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Temperature variability and long-run economic development*

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Abstract

This study estimates causal effects of temperature variability on economic activity. For identification I use a novel research design based on spatial first-differences. Economic activity is proxied by nightlights. I distinguish between day-to-day, seasonal, and interannual variability and find that the type of variability matters. The results suggest an economically large and statistically significant negative effect of day-to-day variability on economic activity at most temperature levels. Regarding seasonal variability, I find a smaller but also negative effect. The estimated effect of interannual variability is positive at low and negative at high temperatures. These effects are robust, they can be identified in urban and rural areas, and they cannot be explained with the spatial distribution of agriculture. The results draw attention to the effect of climate variability, which is projected to change but has so far been mostly overlooked in assessments of the impacts and costs of climate change.

Keywords: climate, temperature, nightlights, day-to-day variability, seasonal variability, interannual variability

JEL Codes: Q54, Q56, R11, R12, R14, O13, O44

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1 Introduction

The debate about how climate and climate change influence economic development has a long history, but with few exceptions it has been all about annual mean climate. Temperature variability has been mostly neglected, although it is generally very common. In many countries temperatures frequently change by several degrees Celsius from one day to the next. Furthermore, in many places temperatures differ by more than 10 degrees Celsius between summer and winter. Differences between years are generally smaller, but annual mean temperature can still change by about 1-2 degrees Celsius from one year to the next, comparable in magnitude to global warming over the last 100 years. Yet despite its ubiquity, little is known about how temperature variability at the time scale of days, months, and years affects economic development.

There have generally been two approaches to establish causal relationships between climate and economic development (Dell et al., 2012). The first approach is an econometric analysis of climate variables (typically averages over 30 years) and economic outcomes such as GDP per capita over a cross-section of observations (e.g. Nordhaus (2006); Mendelsohn and Massetti (2017)). This approach is often criticised because estimates could be biased by omitted variables such as institutions. The second approach uses panel estimation methods and exploits variation of temperature and economic outcomes for the same unit of observation over time (e.g. Dell et al. (2012)). This approach has generally been regarded as more credibly identifying causal effects, but cannot be used for very slow-changing variables, such as seasonal or interannual temperature variability, which need to be measured over periods longer than a year.

In this paper I attempt to estimate the causal effect of temperature variability on long-run economic development. For this purpose I use a novel econometric framework based on differences between geographically proximate observations (Druckenmiller and Hsiang, 2018). This spatial first-differences research design (Druckenmiller and Hsiang, 2018) allows me to examine the effect of slow-changing climatic variables but requires weaker assumptions for the identification of causal effects than a regression on a cross-section of levels. The identification strategy can be interpreted as matching with a continuous treatment variable whereby neighbouring observations are paired. I apply this method to a global dataset consisting of economic activity, measured by satellites as lights at night, and temperature and its variability from climate reanalysis, as well as several climatic and geographic controls. I then use differences between neighbouring geographical units (about 25 km x 25 km) for identification of causal effects.

I distinguish between temperature variability at the time scale of days, months, and years: *day-to-day*, *seasonal*, and *interannual* variability. I measure them using the intra-monthly standard deviation of daily temperature levels, the intra-annual range of monthly mean temperatures, and the inter-annual standard deviation of annual mean temperatures respectively. My empirical results suggest an economically large and statistically significant negative effect of *day-to-day* and a negative but smaller effect of *seasonal* temperature variability on long-run economic development. On average, one additional degree Celsius of day-to-day and seasonal variability reduces economic activity by about 11 percent and 0.6 percent respectively. Regarding *interannual* variability, I find a positive effect on economic activity below and a negative effect above an annual mean temperature of 20 degrees Celsius. Below this temperature, one additional degree Celsius of interannual variability increases nightlights by about 19 percent. At higher temperatures, one degree Celsius of interannual variability reduces nightlights by about 28 percent.

I discuss several theories about why and how temperature variabillity can affect economic activity, including non-linear marginal effects of temperature levels on productivity, adaptation to local average temperatures, and uncertainty. These theories are generally compatible with each other and multiple mechanisms might thus be playing out simultaneously. Most of these theories suggest an overall negative effect of temperature variability on economic activity, in line with the empirical effects that I find. Furthermore, the fact that day-to-day variability is less deterministic than seasonal temperature variability and hence introduces larger uncertainty could explain its more negative effect. Regarding interannual variability, I note that the pattern of estimated coefficients is consistent with an asymmetry whereby the benefits/costs of colder-than-average years are smaller than the benefits/costs of warmer-than-average years.

Any of these mechanisms could affect the spatial distribution of population, productivity, or both. Either case could explain the estimated effects of temperature variability on the spatial distribution of nightlights. I hence use an additional dataset on the spatial distribution of population. I find similar effects of temperature variability if I replace nightlights by population density. At the same time, if I keep nightlights as the dependent variable but control for population density the estimated effects of temperature variability become smaller. These results suggest that some but not all of the effect of temperature variability on nightlights can be explained with effects of temperature variability on the spatial distribution of population.

Furthermore, I examine whether these results are primarily driven by urban areas and whether they can be explained by the spatial distribution of agricultural activity. This is motivated by previously reported insights that nightlights are a better proxy for GDP per capita in urban areas than in rural areas and that the spatial distribution of nightlights also reflects the local sectoral composition of the economy (Chen and Nordhaus, 2019; Gibson, 2020). I find that the estimated coefficients are indeed largest in urban areas, but I find significant effects with the same sign also for less densely populated regions, including the least densely populated areas within countries. Furthermore, the main results are unaffected by controlling for the spatial distribution of agricultural activity.

While this is to my knowledge the first study to examine the long-run effect of temperature variability, the results are in line with previous studies finding negative effects of day-to-day variability on regional GDP (Kotz et al., 2021) and negative effects of seasonal temperature variability on specific economic outcomes such as in agriculture (Mendelsohn et al., 2007a) and health (Hovdahl, 2020). Furthermore, I find positive marginal effects of annual mean temperature at relatively low temperature levels and negative effects at relatively high temperatures, consistent with previous findings of a negative quadratic relationship between annual mean temperature and economic growth (Burke et al., 2015b; Kalkuhl and Wenz, 2020).

The results also contribute to the debate about the the future costs of anthropogenic climate change. With few exceptions (Bathiany et al., 2018; Calel et al., 2020), temperature variability has been missing in this debate and is accordingly also not accounted for in estimated costs. My results suggest that the effect of temperature variability should be included in assessments of future costs and deserves a closer look at its geographical distribution. Climate models project that seasonal variability will tend to decrease in cold and increase in relatively warm countries (Dwyer et al., 2012). These projections, together with my results, suggest that accounting for seasonal variability decreases the costs of climate change in relatively cold countries and increases its costs in relatively warm (and currently poor) countries. The results on interannual temperature variability are generally less robust, but suggest that the benefits or costs of projected changes to interannual variability depend on current annual mean temperature levels. Together with projections of climate models (Bathiany et al., 2018), the results suggest that future changes to interannual temperature variability also tend to increase the costs of climate change in relatively warm (and currently poor) countries.

The use of spatial first-differences reduces omitted variable biases (Druckenmiller and Hsiang, 2018). However, because identification still relies on cross-sectional variation, I conduct a formal sensitivity analysis and several robustness tests. Specifically, I show that any omitted variable would need to be more strongly associated with both temperature variability and nightlights than any of the climatic control variables (annual mean temperature, precipitation, precipitation variability, relative humidity, solar radiation) or geographic control variables (elevation, terrain ruggedness, distance from coast, distance from inland water body) such that controlling for this confounder could make the estimates insignificant. I also compare estimates obtained by using spatial differences in either the North-South or the West-East direction only, and results obtained at different levels of spatial aggregation.

Another concern regarding the identification strategy is reverse causality: climate can have an effect on local economic development, but local economic development can also influence the local climate. To address this concern I use an alternative source of nightlights data which allows me to examine changes of nightlights over time. This enables me to regress changes of nightlights over time on temperature variability observed over an earlier period. By doing so, any feedbacks from local economic development on local climate are excluded by design, but the main results can still be recovered.

The paper is structured as follows. In the next Section, I briefly explain why temperature variability might matter for economic activity, introduce the three measures of climate variability, and explain their geographical distribution (Section 2.2). I then describe the data in Section 3. In Section 4, I present the research design and identification strategy. All results are presented in Section 5: I first present the main results (Section 5.1 and 5.2) and then conduct a series of robustness tests (Section 5.3). In Section 6 I discuss several mechanisms that could explain the results. Finally, I discuss results in light of previous findings and point out implications for future research in Section 7.

2 Climate variability

2.1 How temperature variability can affect economic activity

Temperature affects economic production in both developing and developed countries (Dell et al., 2012; Burke et al., 2015b; Kalkuhl and Wenz, 2020). This effect appears to be non-linear, with possibly positive marginal effects at low and increasingly negative effects at high temperature levels (Burke et al., 2015b; Kalkuhl and Wenz, 2020). These empirical effects have been explained with alternative mechanisms, including possible direct effects of temperature on human cognitive processes and effects on processes external to human beings (Almås et al., 2019). Empirical work provides evidence for an effect of temperature on a range of observable outcomes (Carleton and Hsiang, 2016), including labour productivity (Hsiang, 2010; Behrer and Park, 2019), agricultural productivity (Schlenker et al., 2006), and human health (Deschênes and Greenstone, 2011).

Most of this evidence points to non-linear effects of temperature levels, which means that the marginal effect of higher temperature depends on the baseline temperature level. In this case, the effect of temperature variability on economic activity will depend on the marginal effect at those levels of temperature that become relatively more (or less) frequent. This can be illustrated with a simple example. Consider an average daily mean temperature of 20 degrees Celsius and let us assume that, relative to a day at the baseline temperature of 20 degrees Celsius, one additional day at 15 degrees Celsius increases economic activity by 10 percent, while an additional day at 25 degrees Celsius reduces it by 20 percent. In this example, an increase of temperature variability (assuming a symmetric distribution around the mean) will have a net negative effect on economic activity. This effect of temperature variability is explored for example by Calel et al. (2020) using an integrated assessment model and assuming a non-linear damage function that yields an overall negative effect of larger variability.

This example was based on the assumption that it is only absolute temperature levels that matter for economic production. In other words, it is based on the assumption that a day with 25 degrees Celsius reduces economic activity everwhere by about 20 percent relative to a day with 20 degrees Celsius, regardless of the annual mean temperature. If some adaptation to average climatic conditions is possible, production can be optimised for a certain expected temperature level or range of levels (e.g. through optimising the use of capital and labour in industrial processes according to the average productivity of labour). If such adaptation takes place, larger variability will in most instances be associated with costs, as it means that temperature levels deviate more frequently from their optimal level (or range of levels). Adaptation to average temperature levels has been documented in agriculture, e.g. by the choice of crops in South America (Seo and Mendelsohn, 2008) and can be observed for human physiology (Hanna and Tait, 2015). In both areas, detrimental effects of temperature variability have been reported on respectively crop yields (Wheeler et al., 2000) and temperature-related mortality (Hovdahl, 2020).

These effects of temperature variability relate to realised temperature levels (ex post effects of variability). In addition, temperature variability can affect economic activity through expectations (ex ante effects). To the extent that larger variability implies greater uncertainty about future temperature levels, and to the extent that there are ex post effects of temperature levels, larger temperature variability means larger uncertainty of income and returns to investments. This uncertainty can have a negative effect on economic activity by discouraging investment. Such effects of variability have been documented e.g. for exchange rate fluctuations (Aghion et al., 2009) and volatility of government spending (Ramey and Ramey, 1994). Economic agents can be expected to respond to greater climate uncertainty through risk diversification (Bellemare et al., 2013; Bezabih and Di Falco, 2012; Colmer, 2021), but such diversification might not always be possible, be limited in its effectiveness, and come at a cost.

Adaptation to climate and climate change can also encompass adaptation to temperature variability. Such adaptation can encompass measures to reduce the influence of temperature on production (e.g. use of heat-resistant species in agriculture (Burke and Emerick, 2016), or installation of air conditioning in manufacturing (Somanathan et al., 2018)) and measures that leverage flexibility of production processes (e.g. an allocation of temperature-sensitive production processes to periods in which temperature falls within a certain range). Adaptation of the former type can be expected to always have some cost, while any adaptation of the latter type will require knowledge about temperature variability and often require some anticipation. The latter will thus be more common for temperature variability at shorter time scales, which can be observed and learned about more frequently, and for more deterministic than for more stochastic variability.

Overall, it can therefore be expected that temperature variability has a negative effect on economic activity in a location as compared to a location with the same average climate but lower variability, either due to more frequently observed extreme temperature levels, deviations from locally optimal temperature levels, larger uncertainty, or due to the costs of adaptation to greater variability. Only in few exceptions in which the benefits of variability outweight its costs, e.g. if greater variability allows to realise benefits of certain more frequent temperature levels that exceed the costs of other more frequent levels, will variability have a net positive effect. Because of non-linear effect of temperature levels, the effects of variability are expected to depend on the average temperature level. Furthermore, due to the potential for adaptation, the effect of variability is expected to depend on the time scale of variability as well as its predictability.

2.2 Temperature variability: day-to-day, seasonal, and interannual

Due to human activity, mainly the burning of fossil fuels and the associated emission of greenhouse gases into the atmosphere, temperatures have been increasing since at least the second half of the 20th century. This slow trend has been overlaid by fluctuations on a range of time scales. In this paper I examine variability at the time scale of days, months, and years, that is day-to-day, seasonal, and interannual variability, respectively. In this Section, I first describe how I isolate varibility at different time scales and then explain the global distribution of temperature variability at different time scales with the underlying physical mechanisms of climate.

I define day-to-day temperature variability as fluctuations of temperature within the same month after subtraction of a smooth average annual cycle (Figure 1b,c)[1]. I subtract the

[1]To estimate a smooth average annual cycle, I follow (Moberg et al., 2000) and fit a smooth curve into the multi-year average daily mean temperatures (daily mean temperatures averaged over my reference period 1985-2014). I use a Hodrick-Prescott filter with a smoothing parameter $\lambda = 10,000$ (Figure 5 in the

average cycle because in countries with large annual cycles (large differences of temperature between summer and winter), this cycle means relatively steep trends in spring and fall, which lead to variation of temperature within months. Its subtraction prior to the calculation of intra-monthly standard deviations of daily temperature levels thus ensures that day-to-day variability is isolated from any influence of seasonal variability (Moberg et al., 2000).

Seasonal temperature variability is quantified using the intra-annual range of monthly mean temperatures (Figure 1d,e). I choose monthly means instead of daily means to reduce the influence of potentially rare and extreme days. Furthermore, I use the range of monthly means instead of the standard deviation of monthly means in order to exclude any conflation with day-to-day variability.[2] For both day-to-day and seasonal temperature variability, I average the monthly values of intra-monthly standard deviations and the annual values of intra-annual ranges respectively over my reference climate period (1985-2014).[3]

Interannual variability is calculated as the between-year standard deviation of annual mean temperatures over the 30 year period from 1985-2014 (Figure 1c,f). Before I calculate the standard deviation, I remove a slow trend in order to isolate interannual variability from any warming (or cooling) trends due to decadal climate variability or anthropogenic climate change.

The global maps of temperature variability reflect the influence of astronomy, geography, and climate dynamics (Figure 2). While the maps of day-to-day, seasonal, and interannual variability resemble each other and suggest positive correlations between the variables, I explain in the following how the relative importance of several physical processes differs. I look into the econometric implications of the high degree of spatial correlation in Section 4.

Day-to-day variability is generally larger at higher latitudes. This is primarily due to the influence of high and low pressure systems travelling eastwards at these latitudes, which cause frequent changes between local advection of cold (polar) and warm (tropical) air. Furthermore, day-to-day variability is larger further away from the coastline as water responds slower than land to changes in air temperature between days and fluctuations of temperature close to the coast are thus dampened.

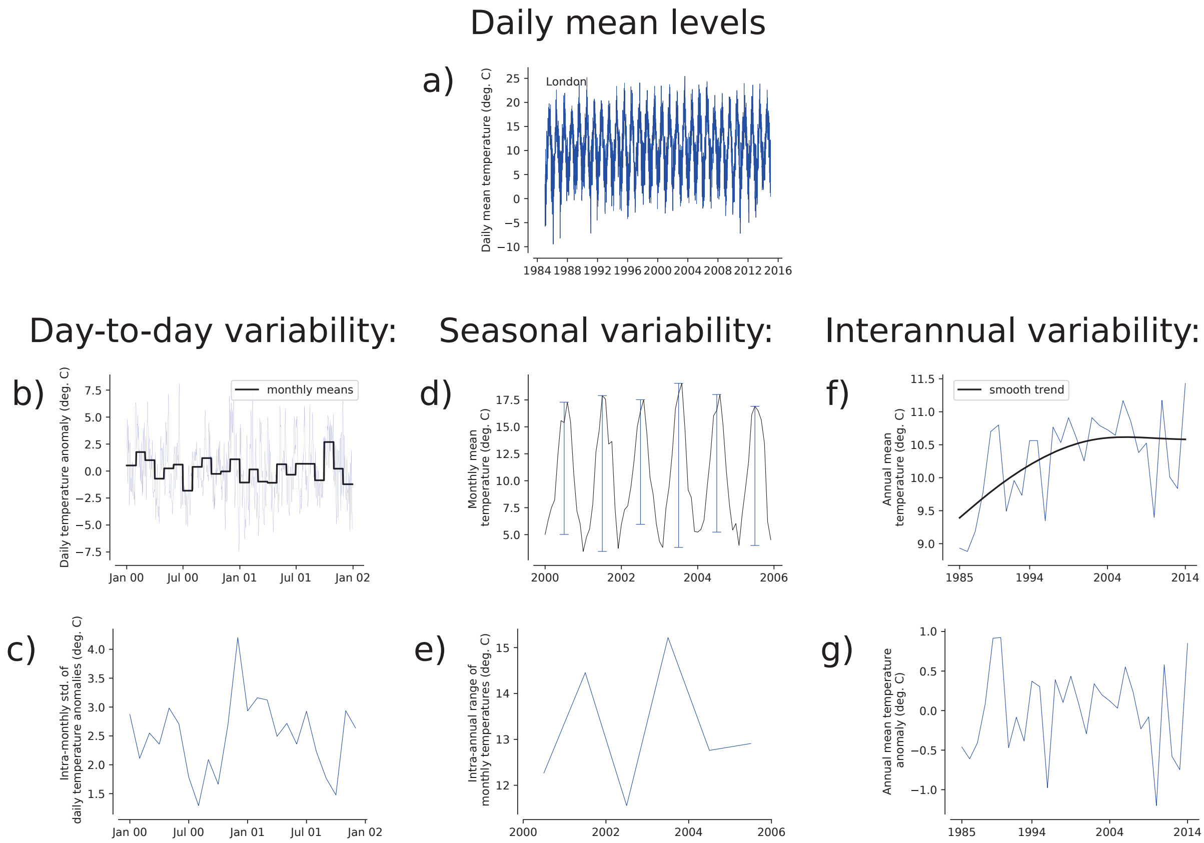
Seasonal variability of temperature is generally larger at high latitudes than at low latitudes due to the tilt of Earth's axis (Figure 2b). Furthermore, because land responds faster to changes in solar radiation than oceans and the land areas are larger in the Northern

Appendix).

[2]The main results are very similar if I measure seasonal variability using the inter-monthly standard deviation of monthly mean temperatures, with a slightly higher significance of the effect of seasonal variability (Table 9 in the Appendix).

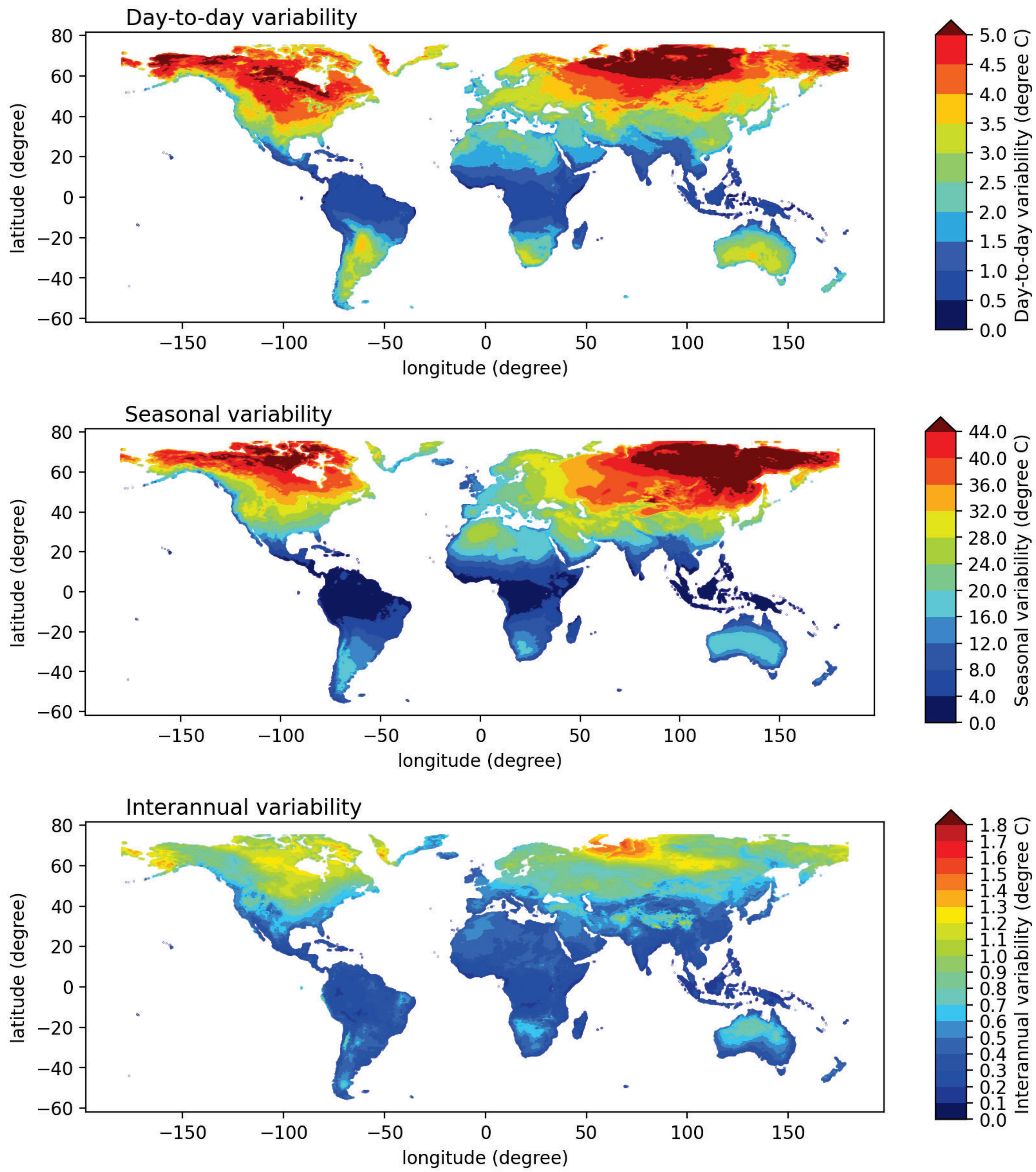
[3]The main results are very similar if I use an earlier time period (1955-1984) (Table 15 in the Appendix); see also discussion in Section 6.1.

Figure 1. Calculation of my three measures of temperature variability: day-to-day, seasonal, and interannual variability.



Notes: The top figure shows daily temperature levels for London from 1985 to 2014 using ERA5 re-analysis (see Section 3). The first column (Figures b, c) show two steps to calculate the day-to-day variability: after subtraction of a smooth average annual cycle (Section 5 in the Appendix), I calculate the intra-monthly standard deviation of daily temperature anomalies (Figure b), which I then average 1985-2014 (Figure c). The second column (Figures d,e) show two steps to calculate seasonal variability: I first calculate the intra-annual range of monthly mean temperatures (Figure d), which I then average 1985-2014 (Figure e). The third column (Figures f, g) show two steps to calculate inter-annual variability: I first subtract a smooth trend from annual mean temperatures (Figure f) and then calculate the inter-annual standard deviation of annual temperature anomalies 1985-2014 (Figure g). Figures b, c, d, e do not show the full time period 1985-2014 for readability.

Figure 2. Geographical distribution of temperature and its variability: day-to-day, seasonal, and interannual variability (top to bottom).



Source: ERA-5 reanalysis (see Section 3.2).

hemisphere than in the Southern hemisphere, seasonal variability is generally larger in the Northern hemisphere and smaller closer to the coast and large inland water bodies (Legates and Willmott, 1990). Because at mid and high latitudes the wind tends to flow from West to East and the temperature of a parcel of air is influenced by the temperature of the surface over which it has been transported (McKinnon et al., 2013; Stine and Huybers, 2012), seasonal variability tends to be larger on the Eastern parts of large continents (America, Eurasia).

Interannual temperature variability is partly driven by external astronomical influences, such as solar cycles of about 11 years, but primarily due to internal climate variability (Mann and Park, 1994). Internal climate variability results from oscillations in the climate system, which are often related to interactions between different components of the climate system, such as the atmosphere and the ocean. Examples are the El-Nino Southern Oscillation (ENSO) and the North-Atlantic Oscillation (NAO) (IPCC, 2013). Interannual variability is generally larger further away from the coasts because the oceans have a larger heat storage capacity and thus a larger year-to-year inertia than land (Figure 2c). Interannual variability is largest in high Northern latitudes and at high altitude due to its amplification by the snow/ice-albedo feedback.

3 Data and descriptive statistics

3.1 Economic variables

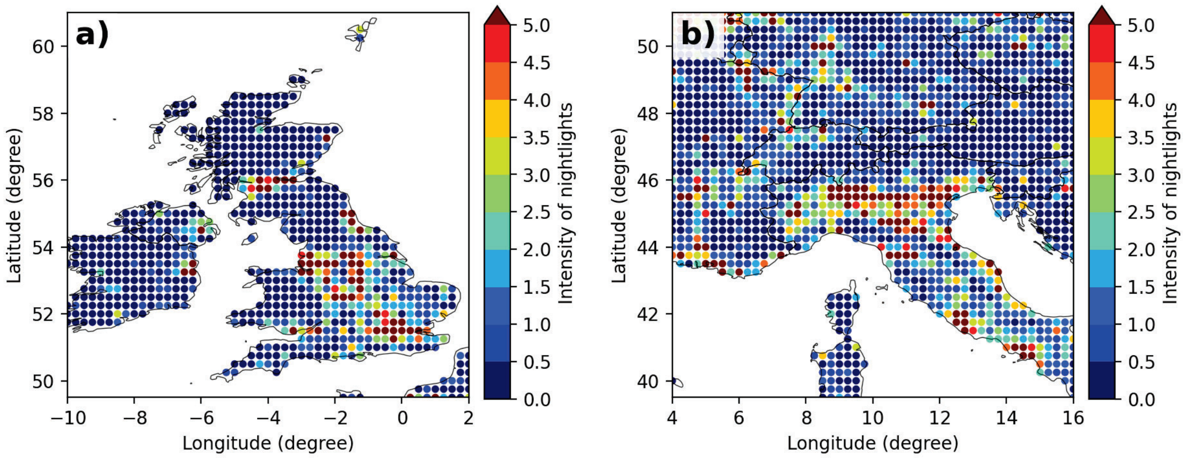
I proxy economic activity by the intensity of lights at night (Chen and Nordhaus, 2011; Henderson et al., 2012; Nordhaus and Chen, 2015). Nightlights are measured by satellites and come with a resolution that outcompetes census-based measures of economic activity. This granularity of the data is particularly important in my research design, as identification rests on the comparability of neighbouring observations. Another advantage of using nightlights instead of population or GDP is that nightlights are consistently measured with the same quality and the same resolution worldwide. I take data on the intensity of lights at night from the satellites of the Visible Infrared Imaging Radiometer Suite (VIIRS) (Elvidge et al., 2017). The VIIRS is a relatively new satellite product which can be regarded as a successor of the popular DMSP data. As compared to the DMSP data, the VIIRS data suffers less from blurring, a lack of sensor calibration, and a limited range of sensitivity (Chen and Nordhaus, 2019; Gibson et al., 2021).

I use annual average radiance values which have undergone some post-processing to remove the effect of clouds and to filter out fires and other ephemeral lights. I use nightlights for the year 2015 with a resolution of 15 arc-seconds, which I aggregate to a resolution of

0.25 degrees. The year 2015 is the earliest year for which VIIRS nightlights are available. As most economic activity occurs on land rather than on water, the average radiance tends to be larger in grid cells with a higher share of land area. This could bias my results if the share of land area correlates with my climatic variables. I address this concern by multiplying the average radiance of a grid cell by the total area of the grid cell and dividing it by its total land area. All grid cells without land area are dropped from the data. Because the distribution of normalised nightlights is highly skewed, I log-transform the data.

At a global scale, the spatial distribution of VIIRS nightlights primarily shows the location of large metropolitan areas. At the regional scale, the spatial distribution of nightlights also shows variation outside metropolitan areas (Figure 3).

Figure 3. Geographical distribution of VIIRS nightlights in a) Great Britain and b) the Alpes in Europe.



Source: VIIRS nightlights.

Although I prefer the VIIRS data to the DMSP data due to technological improvements (Gibson et al., 2021), I also download DMSP data for an additional robustness check for the years 1992 and 2012. The data are processed with the same steps as the VIIRS data. Furthermore, I use population data from the Gridded Population of the World (GPW) dataset version 4.0 (Center For International Earth Science Information Network-CIESIN-Columbia University, 2018). I choose this dataset as it is based on official censuses only and thus independent of my nightlights data. I also use data on the global distribution of cropland and pasture lands (Ramankutty et al., 2008) provided by NASA (Ramankutty et al., 2010), which I aggregate from its native resolution to a resolution of 0.25 degrees.

3.2 Climate variables

I take climate data from the global reanalysis ERA-5.[4] Reanalysis data are produced by feeding an adjusted weather forecast model with the full global record of observational data, including weather station records and satellite data (Parker, 2016). ERA-5 belongs to the newest generation of reanalysis datasets and is provided with a resolution of 0.25 degrees. I choose reanalysis data instead of station-based weather data because of the physical consistency of reanalysis data. Furthermore, meteorological measurements are globally unevenly distributed and I expect that processing with a dynamic model evens out some of the spatial differences in data quality.

The reanalysis data also has the advantage that they includes climate variables in addition to temperature and precipitation. We include additional variables to avoid potential biases due to omitted climate variables. These biases could lead to a misattribution of empirically observed causal effects, but are not necessarily problematic as long as the physical relationships between the variables can be expected to be constant over time or if the estimated relationships are not used for future projections. To avoid misattribution, I also include relative humidity and solar radiation in my regressions. I use daily mean values of all climate variables for the period 1985 to 2014, which is the 30 years period prior to the VIIRS nightlights data, and for the period 1982-1991 (the period before the DMSP nightlights data).[5]

3.3 Geographical covariates

I use the spatial-first differences research design to exclude omitted variable biases from all variables that do not systematically correlate with temperature variability at the spatial scale of my observations (about 25 km). For example, I expect that any differences in institutions between countries cannot bias my results. In order to rule out biases from variables that vary at the scale of about 25 km, I include several geographic controls in addition to my climate controls.

Elevation increases transport costs and is hence a major geographic factor for economic development. Furthermore, elevation is one of them main determinants of local climate. I take data on elevation from the Global Land One-kilometer Base Elevation (GLOBE) dataset in version 1 provided by the National Oceanic and Atmospheric Administration (NOAA) (Hastings et al., 1999). The data has global coverage with a horizontal resolution

[4]The data were obtained from the European Center of Mediumrange Weather Forecast on April 2nd 2020.

[5]In a robustness check, I find that the results are qualitatively the same if I use an earlier period for the climate data (1955-1984) except that the coefficient of interannual variability at relatively low annual mean temperatures is insigificant for the earlier time period (Table 15 in the Appendix).

Table 1. Descriptive statistics.

Variable	Unit	Mean	Std.	Min.	Max.	No. obs.
log Nightlight intensity VIIRS		0.11	0.35	0.00	7.19	233362
log Nightlight intensity DMSP		0.46	0.87	0.00	13.72	233362
log Population density	km-2	1.56	1.88	0.00	13.87	233362
Elevation	km	0.62	0.80	-0.24	6.31	233362
Terrain ruggedness	-	102.42	146.06	0.00	1355.07	233360
Distance from nearest coast	km	0.55	0.52	0.00	2.50	233362
Distance from nearest lake/river	km	0.28	0.50	0.00	6.33	233362
Annual mean temperature	deg C	25.29	13.39	-5.94	48.82	233362
Day-to-day var. of temperature	deg C	2.96	1.44	0.31	6.07	233362
Seasonal var. of temperature	deg C	24.37	14.71	0.74	65.08	233362
Interannual var. of temperature	deg C	0.64	0.30	0.10	1.56	233362
Annual total precipitation	mm	69.50	67.73	0.05	2499.60	233362
Seasonal var. of precipitation	mm	49.79	42.37	0.16	1037.65	233362
Interannual var. of precipitation	mm	0.01	0.01	0.00	0.38	233362
Annual mean rel. humidity	%	89.34	7.03	64.94	98.62	233362
Annual mean solar radiation	W m-2	179.87	57.63	76.34	309.41	233362
Share of cropland	%	10.66	19.64	0.00	100.00	231292
Share of pasture land	%	18.47	27.06	0.00	100.00	231292

Notes: Climate variables computed over period 1985-2014. VIIRS nightlights annual composite for 2015. DMSP nightlights annual composite 2012.

of 0.0083°. I download the data as tiles, merge them, and then aggregate it to 0.25° by averaging.

Previous research has revealed a statistically significant association between terrain ruggedness and economic development in Africa (Nunn and Puga, 2012). Furthermore, terrain ruggedness influences the horizontal and vertical exchange of air, which in turn affect the local climate at the surface. I therefore also include terrain ruggedness as a control variable. Data on terrain ruggedness is taken from a global dataset with a resolution of 1 km (Shaver et al., 2018), which I aggregate to 0.25 degrees.

Economic activity tends to be clustered at the coasts in many countries (Henderson et al., 2018). Furthermore, seasonal variability of temperature tends to be smaller closer to the coast (Section 3.2). I therefore also include distances from the nearest coast and distance from inland water bodies as control variables. Distances from the nearest coast are taken from a dataset provided by the NASA. The dataset covers the whole globe with a uniform horizontal resolution of 0.04°. I also use data on distance from inland water bodies (GloboLakes dataset provided by the CEDA archive) (Carrea et al., 2015). The data were created from ENVISAT satellite images. The data are provided with a 300 m resolution. I aggregate both datasets to a resolution of 0.25 degrees using mean values.

3.4 Descriptive statistics

The final dataset consists of 233,362 complete observations (Table 1). Each observation corresponds to a grid cell of 0.25 degrees width in both latitudinal and longitudinal direction, which corresponds to about 28 km at the equator, about 23 km at 45 degrees latitude, and about 20 km at 60 degrees latitude. The final data excludes grid cells that are not located on land and grid cells on land that are covered by water or ice. Furthermore, due to the spatial coverage of the nightlights data, the dataset is bounded by the latitudes 75 N and 60 S. For the main analysis, nightlights in the year 2015 are combined with time-invariant geographical covariates and climate variables averaged over the period 1985-2014. The exclusion of the year 2015 in the climate data and the averaging over multiple years reduces the influence of (contemporaneous) extreme events, and a 30-years period corresponds to the conventional definition of climate.

4 Econometric strategy

I estimate the model using a spatial first-differences research design. The spatial first-differences (SFD) estimator has recently been proposed as an econometric estimation method that can reduce omitted variable bias for cross-sectional data (Druckenmiller and Hsiang, 2018). The SFD estimator uses only variation between spatially adjacent units of observations. Identification hence relies on the local conditional independence assumption

$$E\left[Y_i|(D_{i-1}, X_{i-1})\right] = E\left[Y_{i-1}|(D_{i-1}, X_{i-1})\right] \forall i \tag{1}$$

whereby observations are indexed with i along a spatial dimension, Y is the outcome variable (log nightlights in the main model of this paper), D is the treatment variable (temperature variability), and X are control variables (climatic and geographic covariates). Equation 1 means that the SFD estimator requires that, conditional on all covariates, *spatially adjacent units of observation* with the same treatment have the same expected outcome. This is a weaker assumption than the assumption underlying a conventional cross-sectional regression of levels, for which conditional on all covariates *all units of observation* with the same treatment need to have the same expected outcome.

The OLS estimator of the SFD design can then be written as

$$\hat{\beta}_{SFD} = (\Delta X' \Delta X)^{-1} (\Delta X' \Delta Y) \tag{2}$$

where Δ refers to the first difference between adjacent units of observations. If the local conditional independence assumption (Equation 1) is satisfied, it implies that

$$E\left[\Delta X' \Delta C\right] = 0. \tag{3}$$

for any potentially omitted variable C. The SFD estimator thus eliminates biases due to omitted variables if the spatial differences of the treatment variable and the spatial differences of a potential confounder are not systematically correlated (Druckenmiller and Hsiang, 2018). Another strength of the SFD research design is a unique robustness test. This robustness test exploits the fact that the estimator can be used with spatial differences in any direction, including North to South (NS) and West to East (WE). If the identifying assumption of SFD is satisfied, the regression coefficients obtained from differences in different directions should be statistically the same (Druckenmiller and Hsiang, 2018). I conduct this robustness test in Section 5.

To illustrate the strengths of the SFD framework, I estimate a simple model in which I explain variation of nightlights by day-to-day temperature variability (and annual mean temperature). The exercise focuses on day-to-day variability as I can use recent estimates of its effect on regional GDP per capita using variation across time for identification as a benchmark (Kotz et al., 2021). Using the sign of this previously reported effect as a reference, the results suggest that the SFD estimator reduces omitted variable biases as compared to a regression with levels. While this first evidence is reassuring, possible omitted variable biases are in more depth discussed in the next Section. Furthermore, what has not been reported before but is important for this paper, the SFD estimator also reduces multicollinearity in the model (Section MISS in the Appendix). The reason for the latter insight is that annual mean temperature and temperature variability at different time scales are influenced by latitude and thus strongly correlated with each other (and with other climate variables such as solar radiation). These correlations are substantially reduced when one uses spatial first differences instead of levels as the influence of latitude is smaller (relative to other variables) if one compares only neighbouring observations (Section B in the Appendix). Taken together, the SFD estimator thus seems to be a promising tool for navigating concerns of omitted variable biases on the one hand and multicollinearity on the other hand, which have been identified as key challenges of empirical work on the effect of weather and climate on socioeconomic outcomes (Auffhammer et al., 2013).

5 Results: Temperature variability and economic activity

5.1 Results of a linear model

I first estimate a linear model relating economic activity as measured by nightlights to seasonal and interannual variability of temperature:

$$\log n_i = \beta_1 \sigma_i^d + \beta_2 \sigma_i^m + \beta_3 \sigma_i^y + \lambda \mathbf{C}_i + \gamma \mathbf{G}_i + \epsilon_i \tag{4}$$

where observations are indexed by i. Units of observations are grid cells with 0.25 degrees width, corresponding to about 25 km at the Equator. The vector n_i contains annual mean nightlight intensity per land area. Day-to-day, seasonal variability and interannual variability of temperature are denoted by σ^d, σ^m, and σ^y, respectively. The matrix of climatic controls C_i includes terms for annual mean temperature, annual total precipitation, relative humidity, solar radiation, and the same three measures of variability of precipitation. The matrix of geographic controls G_i includes grid cell averages of the distance to the nearest coast, the distance to the nearest water body, elevation, and terrain ruggedness. I estimate models with quadratic polynomials for all control variables. Standard errors are clustered at the country level to account for heteroskedasticity and spatial autocorrelation.[6]

The results of my linear model show a significantly negative effect of day-to-day variability on nightlights and no significant effect of either seasonal or interannual variability (Column 1 in Table 4). The estimated effect of day-to-day variability also has the largest magnitude. On average, one degree Celsius of day-to-day, seasonal, and interannual variability reduces the intensity of lights at night by about 0.11 log points (about 11 percent), 0.005 log points, and increases it by about 0.08 log points respectively [7]. As a first robustness test, I compare the results obtained by estimating the model with spatial first-differences in the West-East (WE) direction (Column 1) with the North-South (NS) direction (Column 2), as well as with differences in these two directions pooled (Column 3). Whichever differences I choose I find the same signs of all coefficients with a significantly negative coefficient of day-to-day variability, an insignificantly negative coefficient of seasonal variability, and an insignificantly (except for the direction NS, for which it is significant at $\alpha = 0.1$) positive coefficient for interannual variability.

[6]I also estimate models with standard errors clustered at the level of subnational administrative units, which yields smaller standard errors. This suggests that unexplained factors that determine the intensity of lights at night tend to be correlated within countries (e.g. electrification).

[7]Note that all coefficients are estimated from standardised variables using z-scores.

Table 2. Results of a linear model estimated with SFD.

Dependent variable:	*log Nightlight density*			
Spatial first differences:	Pooled	WE	NS	Pooled
Column:	1	2	3	4
Day-to-day variab. of T	-0.48495***	-0.67404***	-0.39663***	-0.50448***
	(0.13114)	(0.15255)	(0.12107)	(0.12930)
Seasonal variab. of T	-0.22170	-0.06852	-0.27225	-0.28016
	(0.17730)	(0.18190)	(0.17666)	(0.17127)
Interann. variab. of T	0.07396	0.04707	0.08184*	
	(0.04651)	(0.05710)	(0.04431)	
Interann. variab. of $T * \delta(\overline{T} < 20)$				0.17369***
				(0.04441)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$				-0.25220**
				(0.10077)
Effect of increase by 1 deg. C on log nightlights				
Day-to-day variab. of T	-0.11181	-0.15541	-0.09145	-0.11631
Seasonal variab. of T	-0.00500	-0.00155	-0.00614	-0.00632
Interann. variab. of T	0.08169	0.05199	0.09040	
Interann. variab. of $T * \delta(\overline{T} < 20)$				0.19185
Interann. variab. of $T * \delta(\overline{T} \geq 20)$				-0.27857
Climate controls (linear)	x	x	x	x
Climate controls (quadratic)	x	x	x	x
Geographic controls (linear)	x	x	x	x
Geographic controls (quadratic)	x	x	x	x
R2	0.0247	0.0248	0.0252	0.0249
df	448880	224429	224428	448877

Notes: The table shows the results of a linear model (Equation 4) estimated with spatial first-differences. WE = West-East, NS = North-South. Pooled = pooling differences in WE and NS. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.2 The moderating effect of annual mean temperature

Previous authors have found non-linear relationships between annual mean temperature and GDP per capita (Burke et al., 2015a). Similarly, non-linear associations have been found between daily temperature levels and a wide range of outcomes such as productivity and health (Carleton and Hsiang, 2016). This suggests that the effect of temperature variability on long-run economic outcomes might be moderated by the effect of annual mean temperature (Section 2.1). I explore this hypothesis by estimating a flexible model in which I interact temperature variability with dummy variables for bins of annual mean temperature that are

4 degrees Celsius wide:

$$\log n_i = \sum_k \delta_i^k \left(1 + \beta_1^k \sigma_i^d + \beta_2^k \sigma_i^m + \beta_3^k \sigma_i^y + \beta_4^k \overline{T}_i\right) + \lambda \tilde{\mathbf{C}}_i + \gamma \mathbf{G}_i + \epsilon_i \tag{5}$$

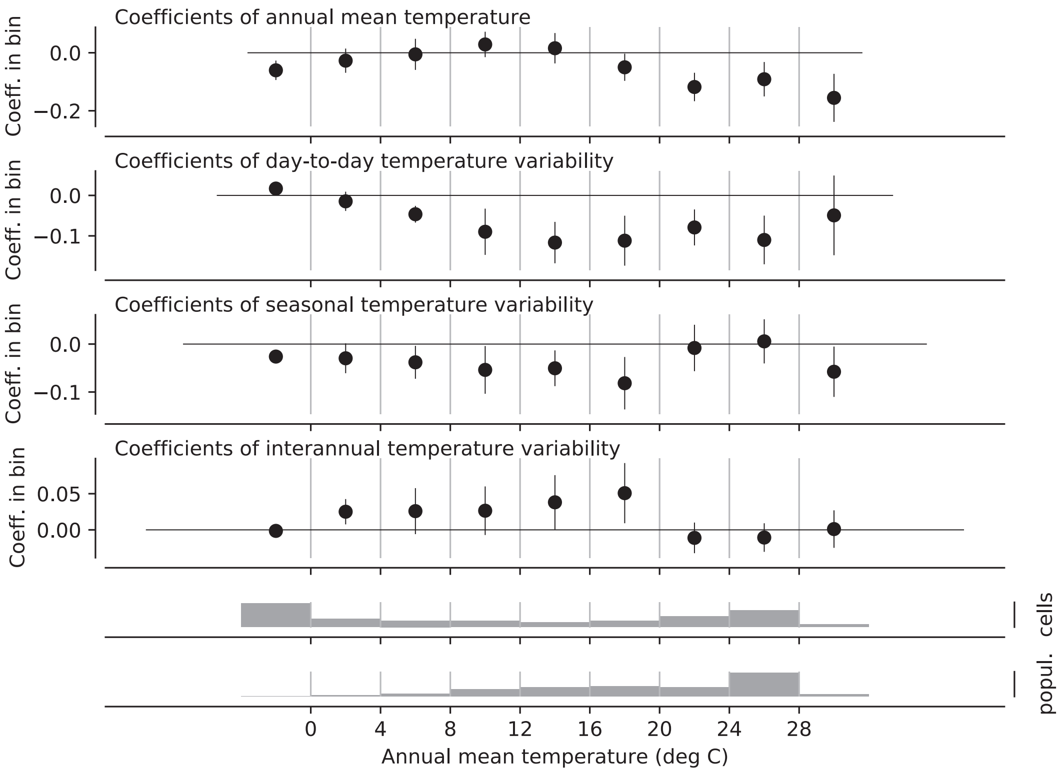
where δ_i^k is an indicator variable for temperature bin k that takes on values 0 and 1, $\overline{T}$ is annual mean temperature, and $\tilde{\mathbf{C}}$ is the same matrix of climate controls as above but excluding annual mean temperature. Consistent with the results of the linear model reported above, the estimated coefficients of day-to-day variability and seasonal variability are negative except at annual mean temperatures below 0 degrees Celsius for day-to-day variability and at temperatures between 20 and 28 degrees Celsius for seasonal variability (Figure 4, second and third row). Annual mean temperature indeed seems to moderate the magnitude of the effect: the estimated negative coefficient of day-to-day variability is largest between 8-28 degrees Celsius. For seasonal variability, the estimated coefficient is most negative between 16-20 degrees Celsius. Annual mean temperature also seems to moderate the effect of interannual variability (Figure 4, fourth row). The estimated coefficients are positive between 0 and 20 degrees Celsius and negative above 20 degrees Celsius.

Regarding annual mean temperature, I find a positive marginal effect at annual mean temperatures between 4-16 degrees Celsius and a negative effect at all other temperature levels (Figure 4, first row). This pattern of marginal effects is consistent with results of previous findings indicating a negative quadratic relationship between annual mean temperature and economic growth (Burke et al., 2015b) except the negative marginal effect at very low temperature levels.

Non-linear effects of temperature levels could generally explain the discontinuity of the estimated coefficients of interannual variability across bins of annual mean temperature (Section 2.1). To explore alternative explanations, I plot all temperature variables across the same bins but do not find any pattern pointing to an alternative explanation of this discontinuity (Figure 7 in the Appendix). A visual inspection of the map of annual mean temperature suggests a positive correlation with average levels of GDP per capita (Figure 6 in the Appendix). To examine possible explanations around the sectoral composition of local economic activity, I also plot the share of land used for agriculture and pasture across bins of annual mean temperature. Again I do not find any suspicious pattern except a substantially smaller share of land used for crops above 20 degrees Celsius than below this threshold (Figure 7). I explore the role of local sectoral specialisation in more detail in Section 6.3.

In sum, my analysis with the binned-model yields negative effects of day-to-day and seasonal variability across most levels of annual mean temperature and an effect of interannual variability whose sign is positive at low and negative at high levels of annual mean temper-

Figure 4. Estimated marginal effects of annual mean temperature and day-to-day, seasonal, and interannual temperature variability across bins of annual mean temperature levels.



Notes: The figure shows the estimated coefficients of a model with linear terms for annual mean temperature, day-to-day, seasonal, and interannual temperature variability in bins of annual mean temperature (Equation 5). The coefficients can be interpreted as marginal effects. The bottom two rows show histograms of grid cells and population within the same temperature bins. The geographic distribution of these bins is shown in Figure 6 in the Appendix.

ature. For parsimony I thus also estimate a model that is as simple as possible but still able to produce these main findings. That is, I estimate a model which includes linear terms for day-to-day seasonal variability and an interaction between a linear term for interannual variability and a dummy variable for annual mean temperature:

$$\log n_i = \beta_1 \sigma_i^d + \beta_2 \sigma_i^m + \delta(\overline{T_i} \geq 20)\left(1 + \beta_3^A \sigma_i^y\right) + \delta(\overline{T_i} < 20)\left(1 + \beta_3^B \sigma_i^y\right) + \lambda \mathbf{C}_i + \gamma \mathbf{G}_i + \epsilon_i \tag{6}$$

where $\delta(\overline{T_i} \geq 20)$ and $\delta(\overline{T_i} < 20)$ are indicator variables that take on the value 1 if annual mean temperature $\overline{T}_i$ is larger or equal/smaller than 20 degrees Celsius and 0 otherwise. As expected from the patterns in Figure 4, I find negative coefficients of day-to-day and seasonal temperature variability (Column 4 in Table 2). For interannual variability, I find a positive effect below 20 degree Celsius and a negative effect above this temperature level. In the next Section I conduct a number of robustness tests using this model, before turning to a discussion of mechanisms in Section 6.

5.3 Robustness tests

I conduct a variety of robustness tests in the following paragraphs. I first examine differences between models using spatial first-differences in different directions, discuss weighing observations by grid cell population, and look at the sensitivitiy of the main results to the inclusion and specification of climatic and geographic control variables. I then conduct a formal sensitivity analysis to address potential biases due to omitted variables. The assumption underlying causal identification with SFD is more likely to be satisfied at finer spatial resolution and I thus also examine the consequences of spatially aggregating my data before estimating the model. Finally, I address concerns of reverse causality using alternative nightlights data that allows me to examine differences in nightlights over time.

5.3.1 Spatial dimension, weights, and control variables

As a first robustness check, I estimate the main model (Equation 6) using spatial first-differences in either the NS direction only (Column 2) or the WE direction only (Column 3 of Table 11 in the Appendix). If my estimated coefficients of temperature variability could be explained with an omitted variable whose association with temperature variability or nightlights were not similar in both directions, I would expect to obtain different estimates. Reassuringly, I find very similar coefficients for the NS and the WE direction.

All of the results presented so far have been obtained without assigning unequal weights to observations. I note, however, that many grid cells in my data contain no or a very small population (Figure 4, bottom two rows), especially at high latitudes in the Northern hemisphere. I hence estimate another model for which I weigh observations by the population of the grid cell (Table 12 in the Appendix). As expected from Figure 4 I find larger coefficients if I weigh by population especially for day-to-day and seasonal variability, but the signs of the coefficients are the same. I prefer the unweighted specification as the spatial distribution of population is a possible outcome of temperature variability. Using population as weights thus suppresses negative effects and attenuates positive effects of variability on nightlights.

As another robustness test I change the model specification for all control variables. I test models with linear terms, linear and quadratic terms, and linear terms interacted with bins of annual mean temperature. The results are presented in Table 11. Overall, he estimated coefficients of temperature variability are similar across specifications (Columns 4, 5, 6).

5.3.2 Sensitivity analysis

In order to quantify the robustness of my key results to omitted variable bias I also conduct a formal sensitivity analysis. Specifically, I calculate how much of the residual variation of temperature variability and the residual variation of nightlights (once all existing terms in the model are controlled for) an omitted variable would need to explain, such that including this additional variable could make my estimates insignificant or even reduce them to zero. Following Cinelli and Hazlett (2020), I quantify the robustness using partial R^2, which means that my results on robustness are not specific to any assumed functional form of the omitted variable in the model, but instead provide an upper bound on the sensitivity to any set of omitted variables including non-linear terms and interactions. The full results are presented in Table 10 in the Appendix.

To make the estimated coefficients insignificant, I find that an omitted variable would need to explain 2.71, 0.74, 0.92, and 0.45 percent of the residual variation of nightlights and simultaneously the same share of the variation of day-to-day, seasonal, and interannual variability below and above an annual mean temperature of 20 degrees Celsius respectively. To reduce the estimates to zero, these robustness values are respectively 2.99, 1.03, 1.28, and 0.94 percent. While these values appear small, they refer to the spatially first-differenced variables and are in fact relatively large. They can be put into perspective by comparing them with the partial R^2 of variables included in the model. This benchmarking shows that none of the climatic and geographic control variables are sufficiently strongly associated with both nightlights and temperature variability. While a few variables are sufficiently strongly associated with temperature variability, none of these explains enough of the residual variation of nightlights. This means that no potentially omitted variable that is similarly strongly associated with temperature variability and nightlights as any of the existing control variables could make my results insignificant if it were included in the model.

5.3.3 Spatial aggregation

The identification strategy rests on the assumption that neighbouring grid cells have the same expected intensity of nightlights conditional on the explanatory variables of the model. This assumption is more likely to hold at relatively high spatial resolutions, as a higher resolution reduces the size of grid cells and hence also the distance between the centroids of neighbouring grid cells. To assess the sensitivity of my results to the spatial resolution of the data, I step-wise spatially aggregate my data. Overall, the estimated coefficients of temperature variability across levels of annual mean temperature are similar for resolutions of 0.25 and 0.5 degrees, except for the coefficient of interannual variability at low temperatures, which is about 80 percent smaller at a resolution of 0.5 degrees (Table 3). At a resolution of 1.0 degree, at which neighbouring observations are about 100 km distance away from each other, only the effect of day-to-day variability remains significant.

I attribute this result to three possible explanations. First, it could be that at a resolution of 1.0 degree, too much of the variation of nightlights is averaged out to recover the true effects of temperature variability. Second, it could be that there are omitted variables which covary with temperature variability and for which the idenfiying assumption of spatial first-differences holds at 0.25 degree and 0.5 degree resolutions, but not at a coarser resolution. Third, it could be that temperature and temperature variability influence the spatial distribution of economic activity at small spatial scales, for instance through the spatial allocation of specific activities to local climatic conditions, but not at larger spatial scales. The results do not allow me to further test any of these explanations. Given that the identifying assumption is most likely satisfied at high spatial resolution, I find the similarity of the results obtained at resolutions of 0.25 degree and 0.5 degree resolutions reassuring.

5.3.4 Reverse causality

It is relatively well established that air temperature tends to be higher in the center of a city than in its surroundings due to what is referred to as the urban heat island. Finding a statistically significant association between temperature variability and nightlights could thus generally also be explained with reverse causality. In that case, spatial differences in temperature variability would result from the spatial distribution of economic activity, rather than temperature variability shaping economic activity. I address this concern by regressing changes of nightlights over time (between 1992 and 2012) on temperature variability measured over an earlier period (1982 to 1991). This means that any effects of nightlights on temperature variability are intentionally excluded by design. For this analysis I use the older DMSP nightlights data, as the VIIRS data is only available since 2015.

I first regress DMSP nightlights in 2012 on climate over the period 1982-2011 (Table 13, Column 1), similar to my main regression with VIIRS data. I find the same key results as for the VIIRS data: a (significantly) negative coefficient of day-to-day and seasonal variability and a negative and positive coefficient of interannual variability of temperature respectively below and above an annual mean temperature of 20 degrees Celsius. The size of the coefficients cannot be compared as the two datasets measure the intensity of nightlights with different devices and on different scales.

To address the concern of reverse causality, I regress the growth of nightlights between 1992 and 2012 on the mean climate of the period 1982 to 1991 (Column 2). Reassuringly, I find the same sign and significance of the coefficients as in Column 1. I take this as evidence that my results are robust to possible confounding effects due to reverse causality. This result holds true also if I include nightlight density in 1992, which is likely associated with temperature variability from 1982-1991 and, as the results confirm (Column 3), also with subsequent changes in nightlights.

6 Mechanisms

6.1 The role of population density

Nightlights are typically considered as a proxy for GDP. This suggests that the spatial distribution of nighlights can be explained by spatial differences in the factors of production (e.g. capital and labour) and by differences in productivity. I do not know of any high-resolution global dataset for capital as an input to production.[8] There are however global high-resolution datasets on population including some that are only based on censuses and thus independent of the nightlights data.

I hence run two additional regressions to identify any effect of temperature variability on the spatial distribution of population. For the first regression I use population density instead of nightlights as dependent variable. For the second regression I keep nightlights as the dependent variable but add population density as control variable. I expect that my first regression recovers the effect of temperature variability on the spatial distribution of

[8]A dataset that comes to mind is a high-resolution dataset on wealth in Africa created using satellite images, household surveys, and machine learning (Yeh et al., 2020), but it is limited to household assets and to one continent.

Table 3. Results of regressions addressing concerns of reverse causality using the DMSP nightlights data.

Dependent variable:	*log NL (2012)*	*Δ log NL (1992 vs. 2012)*	
Time period for climate variables:	1982 - 2011	1982 - 1991	1982 - 1991
Column:	1	2	3
Day-to-day variab. of T	-0.31131***	-0.04719*	-0.07712***
	(0.08156)	(0.02665)	(0.02819)
Seasonal variab. of T	-0.19933	-0.06371**	-0.07539**
	(0.12123)	(0.02934)	(0.03635)
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.12011***	0.02603*	0.02898*
	(0.02794)	(0.01419)	(0.01541)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.11410	-0.01148	-0.01724
	(0.07603)	(0.02808)	(0.02979)
Nightlights in 1992			-0.12585***
			(0.01775)
Climate controls (linear)	x	x	x
Climate controls (quadratic)	x	x	x
Geographic controls (linear)	x	x	x
Geographic controls (quadratic)	x	x	x
R2	0.0473	0.0102	0.0374
df	448877	448877	448876

Notes: The table shows the results of a model with linear terms for day-to-day and seasonal variability and an interaction term for interannual variability (Equation 6) estimated with spatial first-differences. NL = nightlights taken from the DMSP data. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

population, whereas the second regression recovers the effect of temperature variability on economic activity controlling for population density, which could be due to the spatial distribution of capital or differences in productivity. For the second regression I thus deliberately exclude one causal channel of how temperature variability affects nightlights. This means that I am not concerned about any bias due to the inclusion of a control that is an outcome of my treatment variables, but rather deliberately aim to detect such bias.

If I use population density as the dependent variable, I find the same signs and similar magnitude for temperature variability as in my regressions on nightlights (Table 2, Column 5). If I keep nightlights as the dependent variable but add population density as a control variable (Column 4), my estimated coefficients keep the same sign but their magnitude becomes smaller. I interpret both these findings as evidence that some of the effect of temperature variability on economic activity as measured by nightlights can be explained with an effect of temperature variability on the spatial distribution of population.

Table 4. Results of regressions to examine the role of population density.

Dependent variable:	*log Nightlight density*		*log Pop. dens.*
Spatial first differences:	Pooled	Pooled	Pooled
Column:	1	2	3
Day-to-day variab. of T	-0.50448***	-0.19917**	-0.24884***
	(0.12930)	(0.08002)	(0.05259)
Seasonal variab. of T	-0.28016	-0.01919	-0.21270**
	(0.17127)	(0.09509)	(0.10271)
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.17369***	0.08577**	0.07165**
	(0.04441)	(0.03543)	(0.03295)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.25220**	-0.11906	-0.10851
	(0.10077)	(0.08230)	(0.07042)
log Population density		1.22692***	
		(0.10451)	
Effect of increase by 1 deg. C on:	*log nightlights*		*log pop. dens.*
Day-to-day variab. of T	-0.11631	-0.04592	-0.32094
Seasonal variab. of T	-0.00632	-0.00043	-0.02684
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.19185	0.09474	0.44272
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.27857	-0.13151	-0.67047
Climate controls (linear)	x	x	x
Climate controls (quadratic)	x	x	x
Geographic controls (linear)	x	x	x
Geographic controls (quadratic)	x	x	x
R2	0.0249	0.3614	0.0700
df	448877	448876	448877

Notes: The table shows the results of a model with linear terms for day-to-day and seasonal variability and an interaction term for interannual variability (Equation 6) estimated with spatial first-differences.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

It seems plausible to assume that population (as measured by census data) and nightlights respond with different response times to climate and climate change. In this case, the data on the spatial distribution of population might not (yet) reflect the effects of temperature variability to the same extent as the data on nightlights. In this case the results in Column 2 and Column 3 could be accordingly biased. To address this concern, I repeat the analysis with climate data for the period 1955-1984. This means that there are 30 years for both nightlights and population density to adjust to temperature variability. The results are very similar except that the coefficient for interannual variability below an annual mean temperature of 20 degrees Celsius is insignificant for the earlier period (Table 16 in the Appendix). Accounting for potentially different response times hence does not change the main insights on the role of population density.

6.2 Urban areas

It is well known that nightlights are a better proxy for GDP per capita in urban areas than in rural areas (Chen and Nordhaus, 2019; Gibson et al., 2021). I therefore examine whether my results are primarily driven by urban areas. To do so, I first categorise all grid cells based on their population density relative to all other grid cells of the same country and then estimate my model on subsets of the data. I find that the magnitude of my estimated effects is largest in urban areas (5 percent most densely populated grid cells; Column 1), which is in line with my results from a population weighted model (Table 12 in the Appendix). At the same time I find significant effects of the same sign also in less densely populated areas, even in the 50 percent least densely populated areas (Column 4). The effect of temperature variability thus seems to be geographically widespread and not limited to urban areas.

6.3 Agriculture

A possible explanation for my empirical effects is that temperature variability affects the local sectoral composition of economic activity. For instance, regions with higher seasonal variability could be relatively more or less suitable for agriculture than regions with lower variability. Because agricultural activity tends to be associated with lower levels of nightlights than other economic activity for a similar total economic output (Chen and Nordhaus, 2019; Gibson et al., 2021), these climatically induced relative sectoral advantages could be reflected in the spatial distribution of nightlights and thus be recovered by my model. I do not know of any data on local sectoral composition with sufficiently high spatial resolution. However, satellite images have been used to classify land use and to construct datasets on cropland and land used for pasture.

I thus include both cropland and land used for pasture in my model. I find that land used for pasture has indeed a significant effect on nightlights, but my estimates of temperature variability remain unaffected by including either one or both of these variables (Table 14 in the Appendix). I interpret these results as no evidence in favour of the explanation that my estimated effect of temperature variability on nightlights can be explained primarily with the spatial distribution of agricultural activity.

7 Conclusion

I combine a global high-resolution satellite-derived dataset on nightlights with climate re-analysis data to examine how day-to-day, seasonal, and interannual temperature variability

Table 5. Results of regressions with subsampling observations based on population density.

Dependent variable:	*log Nightlight density*			
Population density (percentiles):	0-5	5-20	20-50	50-100
Spatial first differences:	Pooled	Pooled	Pooled	Pooled
Column:	1	2	3	4
Day-to-day variab. of T	-0.91061	-0.20431	-0.06931	-0.24728***
	(0.76166)	(0.21245)	(0.07027)	(0.08610)
Seasonal variab. of T	-2.77649*	-0.95826***	-0.15559**	-0.16781*
	(1.46725)	(0.33788)	(0.06782)	(0.10051)
Interann. variab. of $T * \delta(\overline{T} < 20)$	1.25644	0.23916*	0.07875*	0.05253**
	(0.91921)	(0.13205)	(0.04068)	(0.02431)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.24114	-0.02971	-0.04399	-0.17792**
	(0.86465)	(0.18254)	(0.04216)	(0.08717)
Climate controls (linear)	x	x	x	x
Climate controls (quadratic)	x	x	x	x
Geographic controls (linear)	x	x	x	x
Geographic controls (quadratic)	x	x	x	x
R2	0.0926	0.0181	0.0047	0.0228
df	6220	23428	48388	293981

Notes: The table shows the results of a model with linear terms for day-to-day and seasonal variability and an interaction term for interannual variability (Equation 6) estimated with spatial first-differences. Grid cells are sampled based on their ranking (percentile) in terms of population density of the within-country distribution of grid cells. For example, Column 1 shows results for a model which includes only grid cells that are among the 5 percent most densely populated grid cells of the corresponding country. Because I use spatial first-differences, I require that grid cells and their neighbours to the West and North must fulfill this requirements. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

affect economic activity. I use a spatial first-differences research design (Druckenmiller and Hsiang, 2018), which reduces potential omitted variable biases and multicollinearity of climate and geographical variables. I am to my knowledge the first to study how temperature variability at different time scales influences aggregate economic activity. Furthermore, compared to previous work on the short-run effect of annual weather fluctuations (Burke et al., 2015a; Dell et al., 2012), I focus on the long-run effects of climate, including the potential effect of adaptation and economic development over hundreds or thousands of years. Compared to previous work on the long-run effect of climate (Nordhaus, 2006; Mendelsohn and Massetti, 2017), I use a recently developed econometric framework which allows for a more plausible identification of causal effects.

Considering different mechanisms, including possibly non-linear effects of temperature levels, adaptation to local average temperature, larger uncertainty, and costs of potential adaptation to temperature variability, I expect to find predominantly negative effects of temperature variability. I expect these effects to be more negative for variability at larger time scale due to more difficult learning about variability and to be more negative for variability that is less deterministic and therefore less predictable (due to the underlying physical mechanisms, day-to-day and interannual variability are less deterministic than seasonal variability).

I find that day-to-day variability has an economically large and statistically significant negative effect on economic activity across the range of observed annual mean temperatures. On average, one additional degree Celsius of the average within-month standard deviation of daily temperature levels reduces economic activity by about 11 log points (approximately 11 percent). Regarding seasonal variability, I also find a negative but smaller and less significant effect on economic activity. On average, one degree Celsius of the average within-year range of monthly mean temperatures reduces nightlights by about 0.6 percent. My results on interannual variability suggest that it has a positive effect at low temperature levels (about 19 percent per degree Celsius of the between-year standard deviation of annual mean temperatures) and a negative effect at high temperature levels (about 28 percent per degree Celsius).

While I am to my knowledge the first to empirically analyse the effect of seasonal and interannual variability on aggregate economic activity, the results align with previous work finding a negative short-term effect of day-to-day variability on regional GDP (Kotz et al., 2021) and existing literature reporting negative effects of temperature variability on agriculture (Wheeler et al., 2000; Mendelsohn et al., 2007b) and health (Hovdahl, 2020). Furthermore, consistent with previous findings (Burke et al., 2015b; Kalkuhl and Wenz, 2020), I find a positive marginal effect of annual mean temperature at relatively low temperatures and a negative marginal effect at high temperatures, with a globally optimum annual mean temperature of about 20 degrees Celsius.

I explore several explanations for my findings. I show that some of the estimated effects of temperature variability on nightlights can be explained with an effect of temperature variability on the spatial distribution of population. Regarding my estimated effect of interannual variability I find one possible explanation consistent with my results: Below the optimal temperature, the positive effect of unexpectedly warmer-than-average temperatures could be larger than the negative effect of colder-than-average temperatures, whereas above the optimal temperature, the negative effect of unexpectedly warmer-than-average temperatures could be relatively larger. This could be the case, for example, if responding to a colder-than-average year wa generally easier or less costly than responding to a warmer-than-average year.

It is well known that nightlights are a better proxy for GDP per capita in urban areas than in rural areas and to some extent also reflect the local sectoral composition of the economy (Chen and Nordhaus, 2019; Gibson et al., 2021). I therefore examine whether my results are primarily driven by urban areas and whether my results can be explained by the spatial distribution of agricultural activity. I find that the estimated effects of temperature variability are indeed strongest in urban areas, but can also be recovered from less densely populated regions, including the least densely populated areas within countries. Furthermore, my results are unaffected by controlling for the spatial distribution of agricultural activity.

Given that seasonal variability is largely deterministic, I would expect to find little or no effect of seasonal variability on economic activity if mitigating the effect of temperature fluctuations were easy and had low costs. Such mitigation could include, for instance, heating and air conditioning or an allocation of relatively temperature-sensitive activities to certain periods of the year. The significantly negative effect of seasonal temperature hence points to limited adaptation even to deterministic variability. As I find significant effects of temperature variability on population density, my results suggest that some adaptation to temperature variability could occur through the spatial allocation of economic activity.

My results are robust to a variety of robustness tests. Most importantly, I conduct a sensitivity analysis which indicates that an omitted variable that is as strongly associated with nightlights and temperature variability as any of my geographic and climate control variables would not be sufficient to render the estimated coefficients of temperature variability insignificant. Somewhat consistent with this finding, I recover my main results also for models that include no control variables and for models for which all control variables are included with flexible functional forms. Furthermore, my results pass a robustness test unique to my spatial first-differences research design, namely comparing estimates obtained by using spatial differences in orthogonal directions. In an additional robustness test, I show that my results cannot be explained by reverse causality.

My results suggest that more research should be devoted to temperature variability. For example, with my methodology I am not able to separate effects of past climate on past development from effects of the more recent climate on the more recent development. Temperature variability might have influenced the initial spatial allocation of economic activity but could also have shaped subsequent local economic development including sectoral specialisation. Furthermore, research is needed to investigate how the influence of temperature variability changes as economies develop, and to examine specific possible mechanisms in more detail.

This research seems especially important given that climate models project changes to the seasonal cycle (Dwyer et al., 2012) and interannual temperature variability (Bathiany et al., 2018). Given the geographical patterns of these projections, my results suggest that increasing seasonal and interannual variability might add to the economic costs of climate change especially in currently relatively warm regions. Regarding day-to-day variability, future trends seem to be mostly unknown. I thus conclude that temperature variability across time scales deserves more attention in research to improve our understanding of its influence on human societies and to get better estimates of the expected impacts of future climate change.

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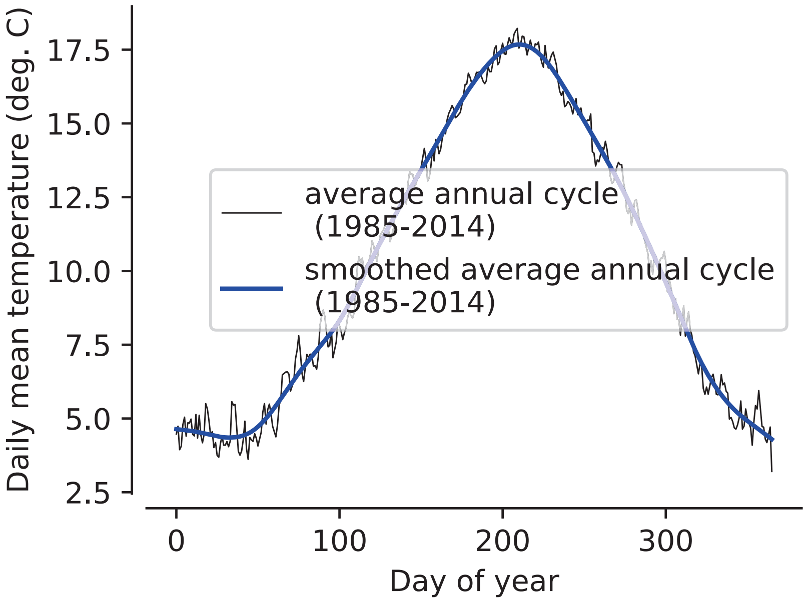
A Annual mean temperature and variability

Figure 5. Subtraction of a smooth average annual cycle: illustration using data for London.



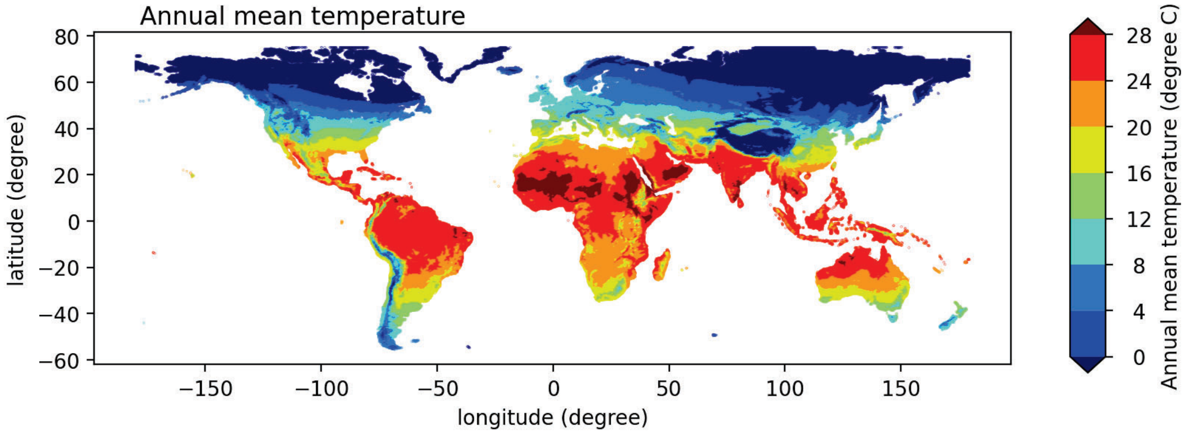
Notes: The figure shows the average annual cycle 1985-2014 and a smooth curve obtained with a Hodrick-Prescott filter with a smoothing parameter $\lambda = 10,000$ *(see also Figure 1 in Section 2.1).*

B Omitted variable biases and multicollinearity

To illustrate the strengths of the SFD framework, I estimate a simple model in which I explain variation of nightlights by day-to-day temperature variability. The exercise focuses on day-to-day variability as I can use recent estimates of its effect on regional GDP per capita using variation across time for identification as benchmark (Kotz et al., 2021). I use two models, one without any other explanatory variables and one that also includes annual mean temperature. I first estimate the two models using levels of all variables and then with the SFD estimator.

I first focus on the model with only day-to-day variability (Columns 1 and 2 in Table 6). I find that using levels yields a significantly positive coefficient, contrary to the result by Kotz et al. (2021). Visual inspection of Figure 2 shows that levels of day-to-day variability are relatively low in the tropics and tend to increase with latitude. Estimates using

Figure 6. Global map of annual mean temperature.



Notes: The figures shows the global distribution of annual mean temperature using the same bins as in Section 5.2. Source is ERA-5 reanalysis for 1985-2014 (see Section 3.2).

levels could thus be confounded by any other variable correlated with latitude, such as institutions/colonial legacies. By contrast, the SFD estimator yields a significantly negative coefficient, consistent with the previously reported result.

Table 6. Results of a model estimated with levels and SFD.

Dependent variable:	*log Nightlight density*			
Estimator:	levels		SFD	
Column	1	2	3	4
Day-to-day variab. of T	0.11857***	0.04641**	-0.76479***	-0.68200***
	(0.03601)	(0.02297)	(0.19528)	(0.18304)
Annual mean temperature		0.12265***		0.89835***
		(0.02853)		(0.11474)
R2	0.0673	0.1055	0.0041	0.0082
df	224454	224453	448909	448908

Notes: The table shows the results of a linear model (Equation 4) estimated with spatial first-differences. Differences in West-East and North-South are pooled. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Because I use different data and focus on long-term rather than short-term effects of day-to-day variability, the comparability of these estimates with previous results is limited. Given that the assumptions that need to be satisfied for an unbiased estimate from levels are stronger than those of the SFD estimator, I expect that the estimates obtained from levels are more prone to omitted variable biases. The results presented in Table 6 include some evidence for it: including annual mean temperature in the model changes the estimated coefficient of day-to-day variability obtained from levels by about 60 percent, while its inclusion changes the SFD estimate by much smaller 10 percent.

This latter result points to another advantage of the SFD estimator as compared to the levels-estimator. Because temperature variability at all frequencies (day-to-day, seasonal, interannual) and annual mean temperature are all influenced by latitude (Section 2.2), levels of these variables tend to be highly correlated. This raises concerns about multicollinearity, which has been recognised as a major challenge of empirically disentangling the effect of multiple climate variables (Auffhammer et al., 2013).

Table 7. Variance inflation factors for a model including all geographic and climatic controls in addition to day-to-day, seasonal, and interannual temperature variability.

	Levels	Spatial first-differences		
Variable		Pooled	NS	WE
Day-to-day var. of temperature	59.11	1.87	1.94	1.81
Seasonal var. of temperature	58.94	1.91	2.00	1.81
Interannual var. of temperature	35.02	1.47	1.50	1.42
Annual mean temperature	141.12	3.83	4.13	3.48

Notes: The table shows the VIF of linear models including annual mean temperature, its day-to-day, seasonal, and interannual variability, as well as all climatic and geographic control variables shown in Table 1. Estimates obtained from spatial first-differences are shown for differences in West-East (WE) and North-South (NS) direction and for differences in the two directions pooled.

A common indicator of multicollinearity in a model is the Variance Inflation Factor (VIF) which is a measure of how much variation of one explanatory variable in a model is explained by all the other explanatory variables. I calculate the VIF for a model in which I include the annual mean of temperature and its day-to-day, seasonal, and interannual variability as well as linear terms of all climatic and geographic control variables (Table 1). Typical critical thresholds for multicollinearity are 5 and 10, corresponding to 80 and 90 percent of all variation being explained by other explanatory variables. I find that multicollinearity is indeed a major concern for the levels-estimator, but is mitigated by using spatial first-differences (Table 7). This analysis of the VIF simultaneously accounts for the correlation of temperature variability at different time scales and its correlation with any of the climatic and geographic control variables. Focusing only on the correlation of temperature variability across time scales, I find that spatial first-differencing also substantially reduces their cross-correlations (Table 8).

Table 8. Pearson correlation coefficients between different temperature variables.

Variable	(0)	(1)	(2)	(3)
Pearson correlation of levels				
(0) Annual mean temperature		-0.83	-0.86	-0.81
(1) Day-to-day var. of temperature	-0.83		0.90	0.89
(2) Seasonal var. of temperature	-0.86	0.90		0.83
(3) Interannual var. of temperature	-0.81	0.89	0.83	
Pearson correlation of spatial first-differences				
(0) Day-to-day var. of temperature		0.60	0.48	-0.11
(1) Seasonal var. of temperature	0.60		0.50	0.09
(2) Interannual var. of temperature	0.48	0.50		0.02
(3) Annual mean temperature	-0.11	0.09	0.02	

Notes: n/a.

C Alternative measures for seasonal variability

Table 9. Results of a model estimated with SFD with two alternative measures for seasonal variability of temperature.

Dependent variable:	*log Nightlight density*	
Seasonal variability:	range	std
Column	1	2
Day-to-day variab. of T	-0.50448***	-0.50031***
	(0.12930)	(0.13259)
Seasonal variab. of T (std)		-0.30724*
		(0.16225)
Seasonal variab. of T (range)	-0.28016	
	(0.17127)	
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.17369***	0.16939***
	(0.04441)	(0.04337)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.25220**	-0.25686**
	(0.10077)	(0.10038)
Day-to-day variab. of T	-0.11631	-0.11535
Seasonal variab. of T (std)		-0.01906
Seasonal variab. of T (range)	-0.00632	
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.19185	0.18710
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.27857	-0.28372
Climate controls (linear)	x	x
Climate controls (quadratic)	x	x
Geographic controls (linear)	x	x
Geographic controls (quadratic)	x	x
R2	0.0249	0.0250
df	448877	448877

Notes: The table shows the results of a model as shown in Equation 6 estimated with spatial first-differences, pooling differences in WE and NS. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D Sensitivity analysis

The sensitivity of my estimated coefficients of temperature variability to the inclusion of omitted and potentially confounding variables in the model is quantified using the robustness value (Cinelli and Hazlett, 2020). The robustness value is the partial R^2 that an omitted variable would need to have with both temperature variability and nightlights to reduce the estimated coefficient of temperature variability to zero. I also quantify the robustness value that would make the estimated coefficients insignificant (at $\alpha = 0.05$). The robustness values of day-to-day, seasonal, and interannual variability are shown in Table 10. Furthermore, the table shows the partial R^2 of the control variables of my model as benchmarks and the critical values for those variables for which the robustness value is exceeded by one of the two partial R^2.

For example, to make my estimated coefficient of day-to-day variability insignificant, a variable that was added to the model would need to have a partial R^2 of at least 2.71 (robustness value) with both out dependent variable (nightlights) and my treatment variable (day-to-day temperature variability). To reduce the estimated coefficient to zero, the robustness value is 2.99. To interpet these values, I can use my climatic and geographic variables that are already included in the model as benchmarks. The first section of the table shows that there are only three variables (annual mean temperature, annual mean relative humidity, and annual mean solar radiation) that have a partial $R^2 \geq 2.71$ (robustness value for significance) for day-to-day variability (Column 2). For these three variables the partial R^2 with day-to-day variability exceeds the robustness value, which means that even a partial R^2 with nightlights smaller than the robustness value could make my estimated coefficients zero/insignificant (if these variables were an omitted confounder). I therefore quantify the critical value for the partial R^2 of these variables with nightlights, which are shown in the bottom section of the table. The critical values are 0.77, 0.80, and 1.76 respectively. I can see in the top part of the table (Column 1) that these critical values are not exceeded by the corresponding partial R^2.

Also the results for seasonal and interannual variability are reassuring. I find that four and one of my control variables respectively explain enough of the variation of temperature variability to be able to render the estimated coefficient insignificant (Columns 4, 6, and 8) but for none of these variables my model has a strong enough association with both nightlights and my temperature variability variables to make my estimated coefficients of temperature variability insignificant (Columns 3, 5, and 7), if these variables were falsely omitted from the model.

The benchmarking of this sensitivity analysis can also be interpreted as a balancing test. Specifically, Columns 2 and 4 in Table 10 show the partial R^2 of all covariates for regressions on my treatment variables, day-to-day (Column 2), seasonal variability (Column 4) and interannual variability (Columns 6 and 8). The results suggest that no single covariate can explain more than 10 percent of the residual variation of day-to-day variability, 4 percent for seasonal variability, or 6 percent of the residual variation of interannual variability.

Table 10. Results of a sensitivity analysis as proposed by Cinelli and Hazlett (2020).

Variable	Day-to-day variability		Seasonal variability		Interann. var. ($\overline{T} < 20$)		Interann. var. ($\overline{T} \geq 20$)	
	$R^2_{Y\sim X_j\|\sigma^d,X_{-j}}$	$R^2_{\sigma^d\sim X_j\|X_{-j}}$	$R^2_{Y\sim X_j\|\sigma^m,X_{-j}}$	$R^2_{\sigma^m\sim X_j\|X_{-j}}$	$R^2_{Y\sim X_j\|\sigma^y_A,X_{-j}}$	$R^2_{\sigma^y_A\sim X_j\|X_{-j}}$	$R^2_{Y\sim X_j\|\sigma^y_B,X_{-j}}$	$R^2_{\sigma^y_B\sim X_j\|X_{-j}}$
Annual mean temperature	0.04115	9.52375	0.04115	1.19277	0.04915	0.97199	0.03630	0.11316
Annual total precipitation	0.00305	0.23419	0.00305	0.09516	0.00411	0.37066	0.00175	0.14781
Annual mean rel. hum.	0.00614	9.25113	0.00614	3.33312	0.01823	1.73334	0.01449	5.28454
Solar rad. annual mean	0.06589	4.59948	0.06589	0.67956	0.06872	0.21369	0.10980	0.68666
Elevation	0.41257	2.64177	0.41257	3.18982	0.55558	0.06992	0.21424	0.17217
Ruggedness	0.27404	0.09342	0.27404	0.19660	0.27126	0.16736	0.29237	0.03908
Distance from nearest coast	0.02488	0.06632	0.02488	2.02610	0.02687	0.43462	0.03704	0.35219
Distance from nearest lake/river	0.24401	0.29917	0.24401	0.20186	0.43069	0.02648	0.17840	0.01711
Robustness values	2.99583		1.03060		1.27824		0.94189	
Critical values								
Annual mean temperature	0.87896		0.88902					
Annual mean rel. hum.	0.90759		0.31125		0.93829		0.16052	
Solar rad. annual mean	1.91905							
Elevation			0.32571					
Distance from nearest coast			0.51895					
Robustness values (significance)	2.71166		0.74064		0.91828		0.45353	
Critical values (significance)								
Annual mean temperature	0.76793		0.77734					
Annual mean rel. hum.	0.79475		0.24619		0.82353		0.11478	
Solar rad. annual mean	1.75567							
Elevation			0.25908					
Distance from nearest coast			0.43408					

Notes: The table shows the results of a sensitivity analysis using a model with spatial first differences pooled in North-South and West-East directions. See text for explanation and an example of how to read the table. All values are shown in percent.

E Robustness checks and population weighted results

Table 11. Results of models estimated with spatial first-differences in different directions and with different control variables.

Dependent variable:	*log Nightlight density*					
Spatial first differences:	Pooled	WE	NS	Pooled	Pooled	Pooled
Column	1	2	3	4	5	6
Day-to-day variab. of T	-0.50448***	-0.69073***	-0.41483***	-0.60062***	-0.55172***	-1.03221***
	(0.12930)	(0.15170)	(0.11675)	(0.15917)	(0.13816)	(0.20010)
Seasonal variab. of T	-0.28016	-0.14383	-0.32325*	-0.22194	-0.23241*	0.44984***
	(0.17127)	(0.17498)	(0.17247)	(0.15297)	(0.13572)	(0.08412)
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.17369***	0.17134***	0.16404***	0.19419***	0.24093***	0.24093***
	(0.04441)	(0.05661)	(0.04454)	(0.04814)	(0.03951)	(0.05338)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.25220**	-0.23005**	-0.25865**	-0.19005**	-0.18553**	-0.10075
	(0.10077)	(0.09922)	(0.11796)	(0.08443)	(0.09012)	(0.09327)
Effect of increase by 1 deg. C on log nightlights						
Day-to-day variab. of T	-0.11631	-0.15926	-0.09564	-0.13848	-0.12720	-0.23799
Seasonal variab. of T	-0.00632	-0.00325	-0.00729	-0.00501	-0.00524	0.01015
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.19185	0.18926	0.18119	0.21449	0.26612	0.26612
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.27857	-0.25410	-0.28569	-0.20992	-0.20493	-0.11128
Climate controls (linear)	x	x	x	x		
Climate controls (quadratic)	x	x	x			
Climate controls (linear in bins)					x	
Geographic controls (linear)	x	x	x	x		
Geographic controls (quadratic)	x	x	x			
Geographic controls (linear in bins)					x	
R2	0.0249	0.0250	0.0254	0.0208	0.0312	0.0051
df	448877	224426	224425	448887	448800	448904

Notes: The table shows the results of a model with linear terms for day-to-day and seasonal variability and an interaction term for interannual variability (Equation 6) estimated with spatial first-differences. WE = West-East, NS = North-South. Pooled = pooling differences in WE and NS. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 12. Results of regression weighted by population.

Dependent variable:	*log Nightlight density*	
Weights:	None	Population
Spatial first differences:	Pooled	Pooled
Column:	1	2
Day-to-day variab. of T	-0.50448***	-2.59440***
	(0.12930)	(0.55076)
Seasonal variab. of T	-0.28016	-0.77874
	(0.17127)	(0.71440)
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.17369***	0.57255
	(0.04441)	(0.41990)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.25220**	-0.45650
	(0.10077)	(0.34151)
Effect of increase by 1 deg. C on log nightlights		
Day-to-day variab. of T	-0.11631	-0.59817
Seasonal variab. of T	-0.00632	-0.01757
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.19185	0.63242
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.27857	-0.50423
Climate controls (linear)	x	x
Climate controls (quadratic)	x	x
Geographic controls (linear)	x	x
Geographic controls (quadratic)	x	x
R2	0.0249	0.2196
df	448877	358789

Notes: The table shows the results of a model with linear terms for day-to-day and seasonal variability and an interaction term for interannual variability (Equation 6) estimated with spatial first-differences. Column 1 shows results of an unweighted regression presented also in the main text. Column 2 shows the results of a regression for which grid cells have been weighted by their population. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

F Spatial aggregation

Table 13. Results of regressions at different levels of spatial aggregation.

Dependent variable:	*log Nightlight density*		
Spatial resolution [deg.]:	0.25	0.5	1.0
Column:	1	2	3
Day-to-day variab. of T	-0.47155***	-0.48211***	-0.36546***
	(0.11773)	(0.11766)	(0.11402)
Seasonal variab. of T	-0.26031*	-0.06202	0.09072
	(0.15822)	(0.16187)	(0.14677)
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.17894***	0.06626	0.02504
	(0.04410)	(0.05318)	(0.04634)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.27164***	-0.25512**	0.00927
	(0.10067)	(0.12744)	(0.14043)
Climate controls (linear)	x	x	x
Climate controls (quadratic)	x	x	x
Geographic controls (linear)	x	x	x
Geographic controls (quadratic)	x	x	x
R2	0.0256	0.0326	0.0377
df	456284	117495	30823

Notes: The table shows the results of a model with linear terms for day-to-day and seasonal variability and an interaction term for interannual variability (Equation 6) estimated with spatial first-differences. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

G Agriculture

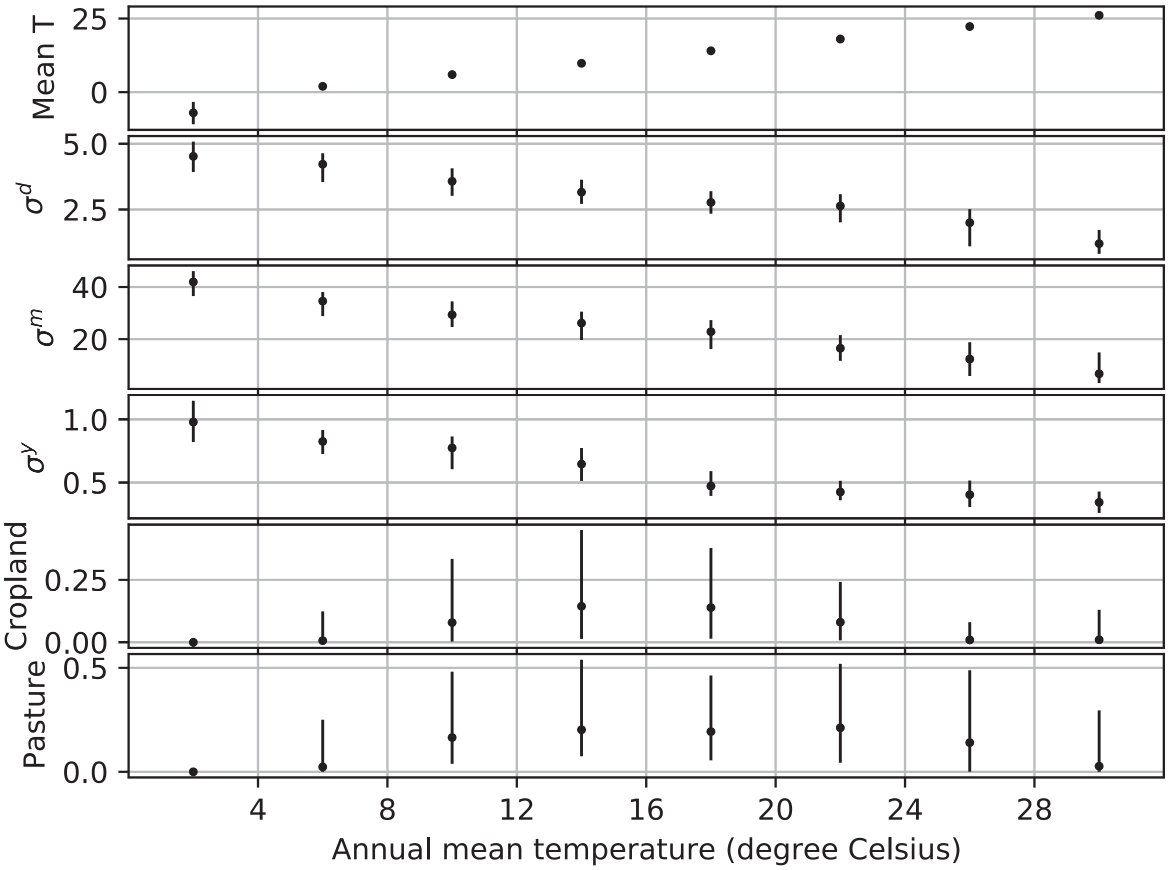
Table 14. Results of regressions to examine the role of agriculture.

Dependent variable:	*log Nightlight density*		
Spatial first differences:	Pooled	Pooled	Pooled
Column:	1	2	3
Day-to-day variab. of T	-0.50895***	-0.51023***	-0.50749***
	(0.12933)	(0.12783)	(0.12773)
Seasonal variab. of T	-0.30296*	-0.31293*	-0.31289*
	(0.18080)	(0.18653)	(0.18356)
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.17643***	0.19750***	0.19352***
	(0.04819)	(0.05019)	(0.05023)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.24130**	-0.23328**	-0.23376**
	(0.10101)	(0.10163)	(0.10149)
Share of cropland	0.06278*		0.05787
	(0.03758)		(0.03868)
Share of pasture		-0.07376***	-0.06962***
		(0.02069)	(0.02169)
Climate controls (linear)	x	x	x
Climate controls (quadratic)	x	x	x
Geographic controls (linear)	x	x	x
Geographic controls (quadratic)	x	x	x
R2	0.0260	0.0263	0.0268
df	445969	445969	445968

Notes: The table shows the results of a model with linear terms for day-to-day and seasonal variability and an interaction term for interannual variability (Equation 6) estimated with spatial first-differences.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

H Bins of annual mean temperature

Figure 7. Median values and interquartile ranges of several variables across bins of annual mean temperature.



Notes: The figures shows both median values and interquartile ranges (errorbars) of annual mean temperature T, day-to-day, seasonal, and interannual temperature variability (σ^d, σ^m, and σ^y respectively), share of land used for crops, and share of land used for pasture (from top to bottom).

I Climate data for 1955-1984

Table 15. Results of a model estimated with SFD for different climate periods..

Dependent variable:	*log Nightlight density*	
Time period (climate):	1985-2014	1955-1984
Column	1	2
Day-to-day variab. of T	-0.50448***	-0.47408***
	(0.12930)	(0.13475)
Seasonal variab. of T	-0.28016	-0.27510
	(0.17127)	(0.19847)
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.17369***	0.08998
	(0.04441)	(0.07277)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.25220**	-0.19300***
	(0.10077)	(0.07264)
Effect of increase by 1 deg. C on log nightlights		
Day-to-day variab. of T	-0.11209	-0.10534
Seasonal variab. of T	-0.00623	-0.00612
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.19115	0.09902
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.27755	-0.21240
Climate controls (linear)	x	x
Climate controls (quadratic)	x	x
Geographic controls (linear)	x	x
Geographic controls (quadratic)	x	x
R2	0.0249	0.0247
df	448877	448877

Notes: The table shows the results of a model as shown in Equation 6 estimated with spatial first-differences, pooling differences in WE and NS. Nightlights are for the year 2015. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 16. Results of a model estimated with SFD examining the role of population for different climate periods.

Dependent variable:	*log Nightlight density*					
Time period (climate):	1985-2014			1955-1984		
Column	1	2	3	4	5	6
Day-to-day variab. of T	-0.50448***	-0.19917**	-0.24884***	-0.47408***	-0.23948***	-0.19127***
	(0.12930)	(0.08002)	(0.05259)	(0.13475)	(0.08937)	(0.06001)
Seasonal variab. of T	-0.28016	-0.01919	-0.21270**	-0.27510	0.01886	-0.23967*
	(0.17127)	(0.09509)	(0.10271)	(0.19847)	(0.10388)	(0.12798)
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.17369***	0.08577**	0.07165**	0.08998	0.03276	0.04666
	(0.04441)	(0.03543)	(0.03295)	(0.07277)	(0.03694)	(0.07052)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.25220**	-0.11906	-0.10851	-0.19300***	-0.08325	-0.08948
	(0.10077)	(0.08230)	(0.07042)	(0.07264)	(0.06454)	(0.05596)
log Population density		1.22692***			1.22651***	
		(0.10451)			(0.10442)	
Effect of increase by 1 deg. C on log nightlights						
Day-to-day variab. of T	-0.11209	-0.04426	-0.05529	-0.10534	-0.05321	-0.04250
Seasonal variab. of T	-0.00623	-0.00043	-0.00473	-0.00612	0.00042	-0.00533
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.19115	0.09439	0.07885	0.09902	0.03605	0.05135
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	-0.27755	-0.13103	-0.11942	-0.21240	-0.09162	-0.09847
Climate controls (linear)	x	x	x	x	x	x
Climate controls (quadratic)	x	x	x	x	x	x
Geographic controls (linear)	x	x	x	x	x	x
Geographic controls (quadratic)	x	x	x	x	x	x
R2	0.0249	0.3614	0.0700	0.0247	0.3613	0.0689
df	448877	448876	448877	448877	448876	448877

Notes: The table shows the results of a model as shown in Equation 6 estimated with spatial first-differences, pooling differences in WE and NS. Nightlights are for the year 2015. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.