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Temperature variability and long-run economic development

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ABSTRACT

This study examines the effects of temperature variability on long-run economic development. To identify causal effects, a novel econometric strategy is employed, based on spatial first-differences. Economic activity is proxied by satellite data on nightlights. Drawing on climate science, the study distinguishes between temperature variability on three time scales: day-to-day, seasonal, and interannual variability. The results indicate that day-to-day temperature variability has a statistically significant, negative effect on economic activity, while seasonal variability has a smaller but also negative effect. The effect of interannual variability is positive at low temperatures, but negative at high temperatures. Furthermore, the results suggest that daily temperature levels have a non-linear effect on economic activity with an optimal temperature around 15 degrees Celsius. However, most of the estimated effects of variability cannot be explained with this non-linearity and instead seem to be due to larger uncertainty about future temperature realisations. The empirical effects can be found in both urban and rural areas, and they cannot be explained by the distribution of agriculture. The results indicate that projected changes of temperature variability might add to the costs of anthropogenic climate change especially in relatively warm and currently relatively poor regions.

1. Introduction

The influence of climate on economic development has been the subject of a longstanding debate, but most studies have focused on annual mean climate while ignoring temperature variability. This is despite the fact that temperature fluctuations are common, with temperature in many places frequently changing by several degrees Celsius from one day to the next, and by more than 10 degrees Celsius between summer and winter. Although changes in annual mean temperature between years are typically smaller, fluctuations of around 1–2 degrees Celsius from one year to the next are common, which is comparable in magnitude to global warming over the last 100 years. This current lack of evidence on the effects of temperature variability at the time scale of days, months, and years means that possible costs of larger variability are not included in most estimates of the costs of future climate change.

Advancing our understanding of the consequences of temperature variability has possibly been hindered by the challenge of identifying its causal effects. In recent years, the marginal effect of climate on economic activity has primarily been estimated with panel regression models using annual observations and unit and year fixed effects (Dell et al., 2012; Burke et al., 2015a). While this approach has generally been regarded as more credibly identifying causal effects than cross-sectional regressions, it cannot be used for variables that need to be measured over periods longer than a year and that change relatively slowly, such as seasonal and interannual temperature variability. Furthermore, larger variability is likely to affect not only realised temperature levels but

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also expectations about their future occurrence, and empirical estimates obtained from year-to-year variation in realisations will not take these expectations fully into account.

In this paper I estimate the causal effect of temperature variability at different time scales on long-run economic development. For identification I use a novel econometric framework based on differences between geographically proximate observations (Druckenmiller and Hsiang, 2018). This spatial first-differences research design allows me to identify the effect of slow-changing climatic variables under weaker assumptions than a regression on a cross-section of levels. The identification strategy can be interpreted as matching based on geographical proximity with a continuous treatment variable. I apply this method to a global dataset consisting of grid cells with a size of approximately 25 km $\times$ 25 km that contain information on economic activity, measured by satellites as the intensity of light at night, and temperature and its variability from climate reanalysis, as well as several climatic and geographic controls.

Temperature variability at different time scales has different underlying physical mechanisms, predictability, and projected changes under future climate change. Drawing on climate science, I therefore distinguish between temperature variability at the time scales of days, months, and years: *day-to-day*, *seasonal*, and *interannual* variability. To measure these variables, I calculate 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.

The results suggest economically large and statistically significant negative effects of *day-to-day* and *seasonal* temperature variability on long-run economic development. On average, one sample standard deviation of day-to-day variability (1.44 degrees Celsius) and seasonal variability (14.71 degrees Celsius) reduces nightlights by 16 and 9 percent, respectively. These effects are similar in magnitude to the estimated non-linear effect of annual mean temperature in terms of their standard deviations. 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. Based on elasticities reported in prior studies (Gibson et al., 2021; Gibson and Boe-Gibson, 2021), these changes in nightlights can be translated approximately 1:1 into changes in GDP for relatively densely populated places in relatively highly developed countries. In less densely populated and less developed contexts, elasticities from Indonesia (Gibson et al., 2021) suggest that changes in GDP are approximately one fifth of changes in nightlights.

These empirical estimates can be explained with different mechanisms through which temperature variability can affect economic activity, including non-linear effects of realised daily temperature levels (ex post effects) and greater uncertainty about future temperature levels (ex ante effects). Because I use cross-sectional variation of long-term averages for identification, my estimates capture both ex post and ex ante effects (Hsiang, 2016). This contrasts most previous work that used time-series variation with annual frequency and thus captured primarily ex post effects (Pretis et al., 2018; Kotz et al., 2021b; Rudik et al., 2021). Robustness tests that model the influence of daily temperature extremes more flexibly suggest that my estimates are primarily related to ex ante mechanisms of larger uncertainty.

The study is one of the first applications of spatial first-differences for causal identification and particular attention is therefore paid to the validity and strengths of this empirical approach in this setting. Notably, I find that the use of spatial first-differences not only reduces the risk of omitted variable biases, but also resolves concerns about multicollinearity, a common issue in climate econometrics (Auffhammer, 2018). All results are scrutinised with a large number of robustness tests, including analysis of reverse causality and spatial spillovers. Additional confidence in the approach is gained by the fact that the estimates of the effect of day-to-day temperature variability are similar in magnitude to earlier results obtained from time-series variation (Kotz et al., 2021b). Also the empirical estimates for daily temperature levels agree well with prior studies that used time-series variation (Deryugina et al., 2018), indicating a globally "optimal" daily temperature of around 15 degrees Celsius and a similar optimum for annual mean temperature.

Previous research suggests that nightlights are a better proxy for GDP 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 therefore also examine whether the results are primarily driven by urban areas and whether they can be explained by the spatial distribution of agricultural activity. I find that the estimated coefficients are indeed largest in urban areas, but I also find significant effects with the same sign 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 land used for crops and pasture, suggesting that agricultural activity is not an important explanation of the results.

This is to my knowledge the first study to examine the long-run effect of temperature variability accounting for both ex ante and ex post effects and examining variability at multiple time scales. The results generally agree with previous studies finding negative effects of day-to-day variability on regional GDP (Kotz et al., 2021b), negative effects of daily and seasonal temperature variability on regional GDP in the US (Rudik 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 fact that day-to-day variability is less predictable than seasonal temperature variability and hence introduces larger uncertainty potentially explains its more negative effect. Regarding interannual variability, the pattern of estimated coefficients is consistent with an asymmetry whereby the benefits or costs of colder-than-average years are smaller than the benefits or costs of warmer-than-average years, possibly due to heating being less costly and generally more widespread than cooling (Rode et al., 2021).

Because identification is obtained from cross-sectional variation, my empirical estimates include effects of temperature variability on economic activity throughout human history. This is important because it is plausible that differences in climate might have affected the spatial distribution of population and economic development in earlier periods more than in recent times as earlier human societies were presumably relatively vulnerable to fluctuations in weather (Ashraf and Michalopoulos, 2015). I address this question by also using changes in nightlights between 1992 and 2012, with an alternative identification strategy based on long-differences, by replacing nightlights with population density, and by controlling for population density in my main estimation. The results indicate that temperature variability is strongly associated with the spatial distribution of population, but that there remain residual effects of variability on nightlights once population density is controlled for. Furthermore I find similar effects of variability on changes in nightlights between 1992 and 2012 as I find for levels in nightlights in 2015, but I do not find significant results for the long-differences estimation. Taken together, the evidence is thus consistent with climate having affected location choices and economic activity in the past and with subsequent path-dependent development (Henderson et al., 2017, 2018).

These nuances are important because with few exceptions (Calel et al., 2020; Kikstra et al., 2021; Rudik et al., 2021), temperature variability is not accounted for in estimated costs of climate change. Taken together, my results are ambiguous regarding the effect of future changes to variability. While the results from long-differences suggest no effect of changes in variability on economic development between 1992–2012, the internal validity of these results is limited because of the limitations of tracking development over time with changes in nightlights, as opposed to using nightlights to examine cross-sectional variation (Chen and Nordhaus, 2019), and their external validity is limited by the relatively small changes of variability in the past relative to future projections. Given the magnitude of the estimated effects of temperature variability relative to the estimated effects of annual mean temperature, the results above all ask for more attention to the costs of variability. Furthermore, if the signs and geographic distribution of the estimates are indicative of the economic costs of future changes in temperature variability, they have important distributional implications. Because climate models project that seasonal variability will tend to decrease in cold and increase in relatively warm countries (Dwyer et al., 2012), the results suggest that accounting for seasonal variability will decrease the costs of climate change in relatively cold countries and increase them in relatively warm (and currently poor) countries. Regarding interannual temperature variability, the results suggest that future changes to interannual temperature variability will also tend to increase the costs of climate change in relatively warm (and currently poor) countries more than in relatively cold countries (Bathiany et al., 2018). Also observed trends of day-to-day variability over the last decades suggest additional economic costs of climate change in relatively warm countries (Kotz et al., 2021a).

The paper is structured as follows. In the next Section, I briefly explain why temperature variability might matter for economic activity (Section 2.1), 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 and then conduct several robustness tests. 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

Annual mean 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 marginal effects at high temperature levels (Burke et al., 2015b; Kalkuhl and Wenz, 2020). These empirical results have been explained with alternative mechanisms, including effects of daily temperature levels on human cognitive processes (Almås et al., 2019) and effects of daily temperature levels on production unrelated to labour, such as crop failures in agriculture.

Temperature variability can add to the costs of annual mean temperature if the relationship between daily temperature levels and economic production is non-linear. In that case, the net costs of variability in any given location depend on the relative frequencies of different levels. This effect of temperature variability is explored for example by Rudik et al. (2021) and by Calel et al. (2020) and Kikstra et al. (2021) using integrated assessment models with non-linear damage functions, which yield an overall negative effect of larger variability. Such effects are also a possible explanation of the negative effect of diurnal temperature ranges reported in prior work (Mitton, 2016). These effects are particularly pertinent if larger variability is associated with more frequent and intense extremes. Alternatively, temperature variability introduces costs if there are heterogeneous locally optimal temperature levels. Such locally optimal temperature levels have been documented for example for 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 possible costs of temperature variability are associated with realised temperature levels (ex post effects of variability). In addition, temperature variability can affect economic activity through expectations (ex ante effects of variability). To the extent that larger variability implies greater uncertainty about future temperature levels, and assuming there are effects of realised temperature levels on production, 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). Regarding climate, the effect of rainfall variability on output volatility was examined e.g. by Malik and Temple (2009). Economic agents can be expected to respond to greater climate uncertainty through risk diversification (Bellemare et al., 2013; Bezabih and Di Falco, 2012; Ashraf and Michalopoulos, 2015; Colmer, 2021; Buggle and Durante, 2021), but such diversification might not always be possible, be limited in its effectiveness, and come at a cost.

Overall, it can therefore be expected that ceteris paribus temperature variability has a negative effect on economic activity, either due to more frequently observed detrimental temperature levels, more frequent deviations from locally optimal temperature levels, or larger uncertainty. Only in situations in which greater variability means more frequent beneficial temperature levels and this positive ex post effect is larger than possible negative ex ante effects, 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, the effect of variability is expected to depend on the time scale of variability because more frequent fluctuations can be learned about more easily while they allow for less time for adjustments, as well as on 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, which I refer to as day-to-day, seasonal, and interannual variability, respectively. In this Section, I first describe how I measure variability at different time scales and then explain the global distribution of temperature variability at different time scales with the underlying physical processes of weather and climate.

The construction of the three measures of temperature variability is illustrated in Fig. 1. All three measures are calculated from timeseries of daily temperature levels in several steps, as explained in the following.

Day-to-day temperature variability is defined as fluctuations of temperature within the same month. These fluctuations are generally observed on top of gradual trends due to seasonality. To isolate the measure of day-to-day temperature variability from such trends, which are considered separately in the measure of seasonal temperature variability that is described further below, I first subtract a smooth average annual cycle from the daily timeseries (Fig. 1b,c). 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 λ = 10,000 which subtracts trends extending over multiple years but not fluctuations from one year to the next. I subtract the average cycle because large annual cycles mean relatively steep trends in spring and fall and are thus associated with additional 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 defined as the annually recurring differences in temperature between the relatively warm and the relatively cold seasons of a year. I hence quantify seasonal temperature variability using the intra-annual range of monthly mean temperatures (Fig. 1d,e). I choose monthly means instead of daily means to reduce the influence of potentially rare and extreme days. An alternative measure is the standard deviation of monthly mean temperatures. The range of monthly means is chosen to further reduce any overlap with the measure of day-to-day variability and to allow for better comparison of this measure across the globe and thus easier interpretation of the results, because some locations close to the Equator exhibit complex patterns of seasonality with several peaks during the year which are all included in the standard deviation of monthly means, but not in their range. In a robustness test, I find that the main results are however 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 (Fig. 5). 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 the period 1985–2014, which is the 30 years period preceding the year of the nightlights data.

Interannual variability is calculated as the between-year standard deviation of annual mean temperatures over the same 30 year period (Fig. 1f,g). 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 anthropogenic climate change.

The global maps of temperature variability reflect the influence of astronomy, geography, and climate dynamics (Fig. 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 (Fig. 2a). 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 land responds faster than water to changes in air temperature between days.

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

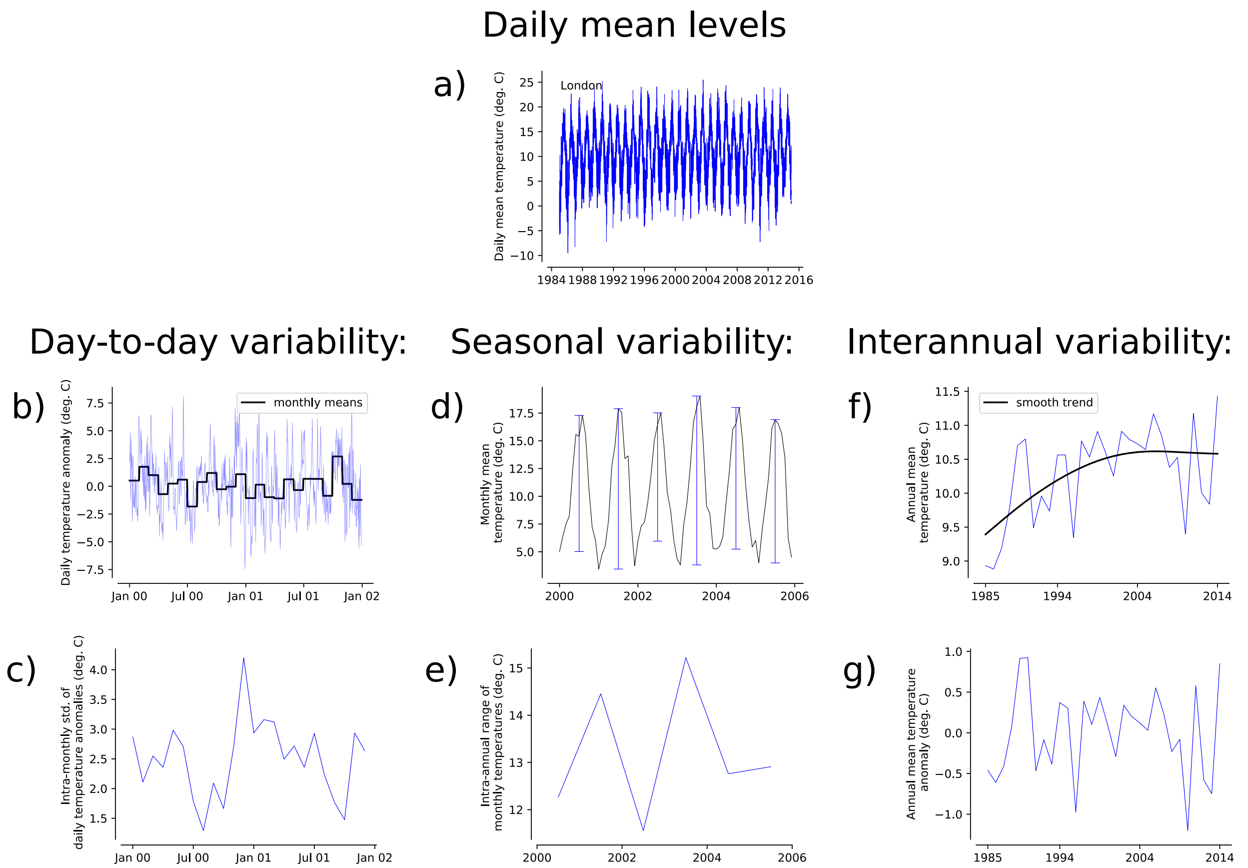

Fig. 1. Calculation of my three measures of temperature variability: day-to-day, seasonal, and interannual variability. *Notes:* The top figure shows daily temperature levels for London from 1985 to 2014 using ERA5 reanalysis (see Section 3). The first column (b, c) illustrates the calculation of day-to-day variability: first, a smooth average annual cycle is calculated and subtracted from the daily mean values, yielding daily temperature anomalies; after that, intra-monthly standard deviations are calculated, yielding monthly values (c). These monthly standard deviations are then averaged over 1985–2014. The second column (d, e) illustrates the calculation of seasonal variability: first, monthly means are calculated (d); after that, the intra-annual range of monthly mean temperatures is calculated for every year (e). These yearly values are then again averaged over 1985–2014. The third column (f, g) illustrates the calculation of inter-annual variability: first, annual mean temperatures are calculated; a smooth trend is then subtracted from these annual values (f), yielding annual temperature anomalies (g). In a second step, the inter-annual standard deviation of these annual anomalies is calculated over 1985–2014. Figures b, c, d, e do not show the full time period 1985–2014 for readability.

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 (Fig. 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

Economic activity is proxied 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 (annual composites VNL V1) (Elvidge et al., 2017). I use nightlights for the year 2015 with a

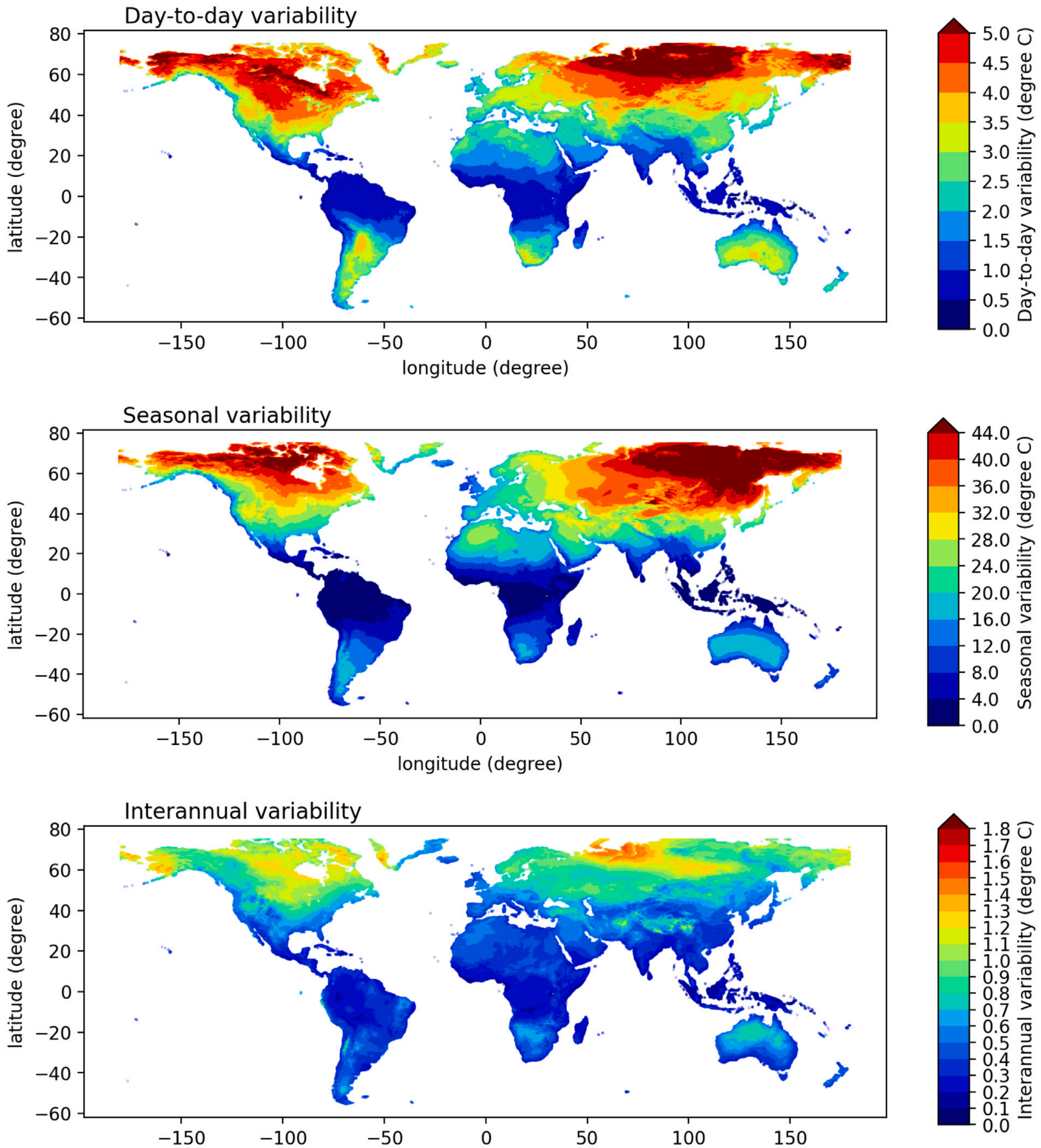

Fig. 2. Geographical distribution of temperature and its variability: day-to-day, seasonal, and interannual variability (top to bottom).
Source: ERA-5 reanalysis (see Section 3.2).

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 were available at the time of the analysis. Because interest is in the effect of climate, typically defined over 30 years, on the level of economic development, climatic averages of 1985–2014 are combined with nightlights for 2015. Robustness tests with an average of nightlights 2015–2019 and with the recent version 2 of the VIIRS nightlights data yield essentially the same results (Fig. 5).

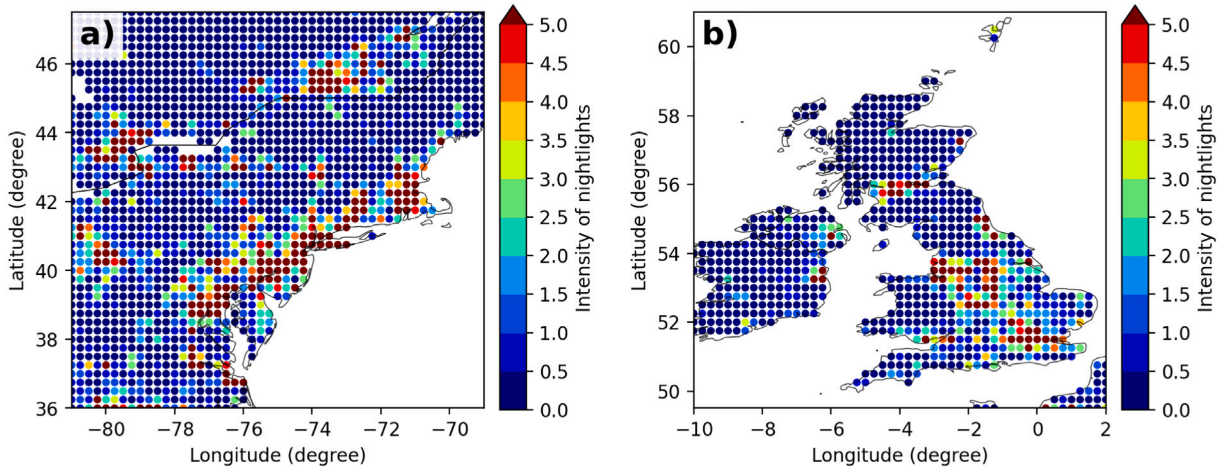

Fig. 3. Geographical distribution of VIIRS nightlights: (a) North-Eastern coast of the USA and (b) the British Isles.
Source: VIIRS nightlights.

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 add one and then log-transform the data. In a robustness check, I use the inverse hyperbolic sine instead of this transformation (Bellemare and Wichman, 2020) and the results are almost identical (Fig. 5)

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 (Fig. 3). Although I prefer the VIIRS data to the older DMSP data due to the technological improvements mentioned above (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 (CIESIN, 2018). I choose this dataset as it is based on official censuses only and thus independent of my nightlights data. Consistent with the data on nightlights I use data for 2015. 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 use climate data from the global reanalysis ERA-5. 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 heterogeneity in data quality.

The reanalysis data also has the advantage that they include climate variables in addition to temperature and precipitation. I include several additional variables in my model to reduce 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). In another robustness check, I find that the results are qualitatively very similar if I use an earlier period for the climate data (1955–1984) (Fig. 5).

3.3. Geographical covariates

The use of the spatial-first differences research design reduces omitted variable biases from all variables whose spatial gradients do not systematically correlate with the gradients of 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. Furthermore, in order to reduce biases from specific variables, I also include several geographic controls.

Table 1
Descriptive statistics. Number of observations: 233,362.

Variable	Unit	Mean	Std.	Min.	Max.
log Nightlight intensity VIIRS		0.11	0.35	0.00	7.19
log Nightlight intensity DMSP		0.46	0.87	0.00	13.72
Elevation	km	0.62	0.80	−0.24	6.31
Terrain ruggedness	–	102.42	146.06	0.00	1355.07
Distance from nearest coast	1000 km	0.55	0.52	0.00	2.50
Distance from nearest lake/river	1000 km	0.28	0.50	0.00	6.33
Annual mean temperature	deg C	25.29	13.39	−5.94	48.82
Day-to-day var. of temperature	deg C	2.96	1.44	0.31	6.07
Seasonal var. of temperature	deg C	24.37	14.71	0.74	65.08
Interannual var. of temperature	deg C	0.64	0.30	0.10	1.56
Annual total precipitation	mm	69.50	67.73	0.05	2499.60
Seasonal var. of precipitation	mm	49.79	42.37	0.16	1037.65
Interannual var. of precipitation	mm	0.01	0.01	0.00	0.38
Annual mean rel. humidity	%	89.34	7.03	64.94	98.62
Annual mean solar radiation	W m^{-2}	179.87	57.63	76.34	309.41
log Population density		1.56	1.88	0.00	13.87
Share of cropland	%	10.66	19.64	0.00	100.00
Share of pasture land	%	18.47	27.06	0.00	100.00

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

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 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

4.1. Research design and identification

For causal identification, the spatial first-differences research design is used. This spatial first-differences (SFD) design has recently been proposed as a strategy that can reduce omitted variable bias for cross-sectional data (Druckenmiller and Hsiang, 2018). This is especially useful for the analysis of climate variability, which is a characteristic of climate and not weather and for which identification therefore arguably requires the "Ricardian" approach of comparing locations with different climate (Hsiang, 2016; Auffhammer, 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). Eq. (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 (Eq. (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.

The SFD framework can also be compared with a spatial regression-discontinuity (RD) research design. In contrast to an estimation with RD, the SFD estimator does not require a discontinuity of the treatment variable. Instead, the marginal effect is recovered from all changes in the outcome (nightlights) and treatment variable (temperature variability) along the North–South or East–West direction. This reduces the risk that estimates primarily reflect correlations of gradients in temperature variability and nightlights in places with sharp gradients of temperature variability because of extraordinary geographical features, where the identifying assumption for a model with polynomial terms of all control variables might be violated. This concern is addressed with a robustness check in which the top 5% and bottom 5% of observations in terms of temperature variability are excluded and which yields very similar results as the main estimation (Fig. 5).

Grid cells at a distance of about 20–30 km can generally be expected to have relatively similar climates. This might raise the question whether differences in temperature variability as observed over 30 years are due to systematic differences in climate or instead due to singular events in this time period that affected one location more than the other. If the latter concern was correct, the SFD estimator would identify a short-term effect of weather rather than a long-term effect of climate (Hsiang, 2016). To address this concern, I vary the time periods over which temperature variability (1955–1984 and 1985–2014) and nightlights (2015 and 2015–2019) are observed and find similar results (Fig. 5). This can be interpreted as additional evidence that my estimates reflect the marginal effects of climate rather than weather.

In the presence of spatial spillovers, the estimates obtained from spatial first-differences will be biased due to a violation of the SUTVA assumption (Druckenmiller and Hsiang, 2018). Such spatial spillovers can result from flows of people, capital, or goods between adjacent locations. For example, economic activity in a specific location might be negatively affected by outward-migration to neighbouring locations. If this migration was partly influenced by local temperature variability, the empirical estimates would be biased because the treatment (i.e. temperature variability) of one unit of observation (i.e. location) would affect the outcome (i.e. economic activity) of another unit of observation (i.e. location). The presence of spatial spillovers can be examined with a model that includes spatial lags of the treatment variable (Druckenmiller and Hsiang, 2018). In a robustness test, I therefore also include spatial lags of annual mean temperature and the different measures of temperature variability before taking spatial first differences. The results suggest that spatial spillovers are not important in this setting (Fig. 5).

4.2. Model specification

Previous studies suggest that the relationship between temperature levels and socio-economic outcomes is often non-linear (Carleton and Hsiang, 2016). This non-linearities are important because their presence can mean negative effects from larger temperature variability (see Section 2.1). In a first regression, I therefore follow previous studies and estimate a degree-day model with bins of daily temperature levels:

$$\begin{aligned} \Delta \log\left(n_i + 1\right) = {} & \beta_1 \Delta\sigma_i^d + \beta_2 \Delta\sigma_i^m + \beta_3 \Delta\sigma_i^y + \sum_k \tilde{\beta}_4^k \Delta d_i^k \\ & + \lambda \Delta\tilde{\mathbf{C}}_i + \gamma \Delta\mathbf{G}_i + \Delta c_i + \epsilon_i \end{aligned} \tag{4}$$

where observations are indexed by i and Δ is the spatial first difference operator. 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. In a robustness check, I use the inverse hyperbolic sine instead of the logarithmic transformation (Bellemare and Wichman, 2020) and the results are almost identical (Fig. 5).

Day-to-day, seasonal variability and interannual variability of temperature are denoted by σ^d, σ^m, and σ^y, respectively. The variables d^k count the number of days with daily mean temperature falling into temperature bin indexed k. Bins are 2 degrees Celsius wide and the bin [10, 12) degrees Celsius is omitted.

The matrix $\tilde{\mathbf{C}}$ represents climate controls including terms for annual total precipitation, relative humidity, solar radiation, and the same three measures of variability of precipitation. The matrix of geographic controls $\mathbf{G}$ includes grid cell averages of the distance to the nearest coast, the distance to the nearest water body, elevation, and terrain ruggedness. In the main specification I estimate models with quadratic polynomials for all control variables, but in robustness checks also linear and linear-in-bins specifications are tested (Fig. 5). Standard errors are clustered at the country level to account for heteroskedasticity and spatial autocorrelation. 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). The variable c contains country fixed effects, which become country-pair-specific border fixed effects after taking spatial first-differences.

Non-linear effects of temperature levels reported in prior studies also suggest that the effect of temperature variability on economic activity might be different in locations with different annual mean temperature. To allow for this flexibility, I also estimate a model

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

where δ_i^k is an indicator variable for annual mean temperature falling into bin k that takes on values 0 and 1, $\overline{T}$ is annual mean temperature, and all other variables are the same as in Eq. (4).

The results of this estimation (SI Figure S2) suggest a more parsimonious model that includes linear terms for the effect of day-to-day and seasonal variability and a linear-in-bins specification for interannual variability

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

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. The matrix $\mathbf{C}$ also includes terms for annual mean temperature, in addition to the controls included in the matrix $\tilde{\mathbf{C}}$.

Economic development can also affect the local climate. To examine whether there is evidence for reverse causality, I estimate a model that excludes effects of economic development on climate by the design of the estimation. To do so, I combine changes in nightlights over time (here: 2012 vs. 1992) with temperature variability over an earlier period (here: 1982–1991):

$$\begin{aligned}\Delta\left(\log\left(n_i^{2012}+1\right)-\log\left(n_i^{1992}+1\right)\right) = & \beta_1 \Delta\sigma^d_{i,1982-1991} + \beta_2 \Delta\sigma^m_{i,1982-1991} \\ & + \delta(\overline{T_i} < 20)\left(1+\Delta\beta_3^A \sigma^y_{i,1982-1991}\right) \\ & + \delta(\overline{T_i} \geq 20)\left(1+\beta_3^B \Delta\sigma^y_{i,1982-1991}\right) \\ & + \lambda \Delta\mathbf{C}_i + \gamma \Delta\mathbf{G}_i + \Delta c_i + \epsilon_i \end{aligned} \tag{7}$$

For this model, an alternative source of nightlights data is used that is available since 1992 (Section 3.1). This estimation strategy uses the fact that temperature variability is part of the climate of a location and that differences between locations change only over long time periods. This is somewhat confirmed by a robustness check based on Eq. (6) using climate data from 1955–1984 which yields very similar results as using climate data from 1985–2014 (Fig. 5).

The empirical estimates obtained from spatial first-differences include effects of temperature variability on economic activity during earlier and during more recent time periods. To disentangle the two, I use an alternative empirical strategy based on long differences. This approach combines changes in temperature variability between an earlier time period (here: 1982–1991) and a later time period (here: 2002–2011) with changes in nightlights at the end of the two periods (here: 1992 and 2012). The model can be written as:

$$\begin{aligned}\log\left(n_i^{2012}+1\right)-\log\left(n_i^{1992}+1\right) = & \beta_1\left(\sigma^d_{i,2002-2011}-\sigma^d_{i,1982-1991}\right)+\beta_2\left(\sigma^m_{i,2002-2011}-\sigma^m_{i,1982-1991}\right) \\ & + \delta(\overline{T_i} < 20)\left(1+\beta_3^A\left(\sigma^y_{i,2002-2011}-\sigma^y_{i,1982-1991}\right)\right) \\ & + \delta(\overline{T_i} \geq 20)\left(1+\beta_3^B\left(\sigma^y_{i,2002-2011}-\sigma^y_{i,1982-1991}\right)\right) \\ & + \lambda\left(\mathbf{C}_{i,2002-2011}-\mathbf{C}_{i,1982-1991}\right)+\epsilon_i \end{aligned} \tag{8}$$

4.3. Comparison of estimation strategies

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., 2021b). I use two alternative model

Table 2
Results of models estimated with different empirical approaches.

Dependent variable:	*log Nightlight density*					
Estimation strategy:	Levels		Levels + Country FE		SFD + Border FE	
Column	1	2	3	4	5	6
Day-to-day variab. of T	−0.0685*	0.0788	−0.2613***	−0.1123*	−0.7256***	−0.6459***
	(0.0408)	(0.0871)	(0.0907)	(0.0634)	(0.1859)	(0.1746)
Annual mean temperature		0.1765*		0.4082***		0.8799***
		(0.0998)		(0.0866)		(0.1112)
(Intercept)	0.4731***	0.0354				
	(0.0842)	(0.2164)				
Country FE			x	x		
Border FE					x	x
R2	0.0047	0.0142	0.1781	0.2035	0.0085	0.0128
N	233 362	233 362	233 362	233 362	456 317	456 317

Notes: The table shows the results of a linear model similar to Eq. (5) but without interaction terms. Columns 1 and 2 show the results for a simple regression using the cross-section of levels. Columns 3 and 4 show the results for the same analysis but the model also includes country fixed effects. Columns 5 and 6 show results for the same model but estimated using spatial first-differences and fixed effects for country borders; differences in West–East and North–South direction are pooled. All variables are scaled using the standard deviations reported in Table 1. Standard errors clustered by country in parentheses. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

specifications, one without any other explanatory variables and one that also includes annual mean temperature. Furthermore, I use three estimation strategies: a cross-sectional regression with levels, a cross-sectional regression with levels and country fixed-effects, and a cross-sectional regression with spatial first-differences and country-border fixed-effects. The three strategies come with step-wise weaker forms of the conditional independence assumptions (Eq. (1)), considering all observations as conditionally independent, only observations in the same country, or only direct neighbours.

I first focus on the model with only day-to-day variability (Columns 1, 3, and 5 in Table 2). I find that all three estimation strategies yield a significantly negative coefficient, generally consistent with the result by Kotz et al. (2021b). The estimated coefficient is largest and most significant when using spatial first-differences, followed by the model with levels and country fixed effects. 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. However, 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.

To further examine these biases, I next compare results for models that also include annual mean temperature (Columns 2, 4, and 6 in Table 2). The estimated coefficient obtained from levels without FE becomes insignificant. For the model with FE, the estimated coefficient shrinks to about 42 percent of its magnitude and becomes less significant. For the model with spatial first-differences, the estimated coefficient decreases slightly but remains large and highly significant. Using the sign and approximate magnitude of the estimates in Kotz et al. (2021b) as a reference, these 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 examined and discussed in the next Section.

The greater robustness of the estimates obtained with spatial first-differences when also including annual mean temperature in the model points to another advantage of the SFD estimator as compared to estimation strategies that rely on levels. 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).

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 3).

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 (SI Table S1). Such comparisons of correlation coefficients between variables can generally be considered as a first check of the validity of the spatial first-differences framework. Reassuringly, I find that all correlations $|.| > 0.2$ between log nightlights and geographic controls, as well as between temperature variability and geographic controls, are smaller for spatial first-differences than for levels (SI Table S2 and S3, respectively). 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).

Table 3
Examination of multicollinearity based on the variance inflation factor (VIF).

Variable	Levels	Spatial first-differences		
		Pooled	NS	WE
Annual mean temperature	44.63	3.80	4.09	3.45
Day-to-day var. of temperature	56.59	1.96	2.01	1.90
Seasonal var. of temperature	54.43	1.97	2.06	1.90
Interannual var. of temperature	34.49	1.49	1.52	1.45

Notes: The table shows the VIF of a linear model that includes annual mean temperature, its day-to-day, seasonal, and interannual variability, as well as all climatic and geographic control variables shown in Table 1 as controls. 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.

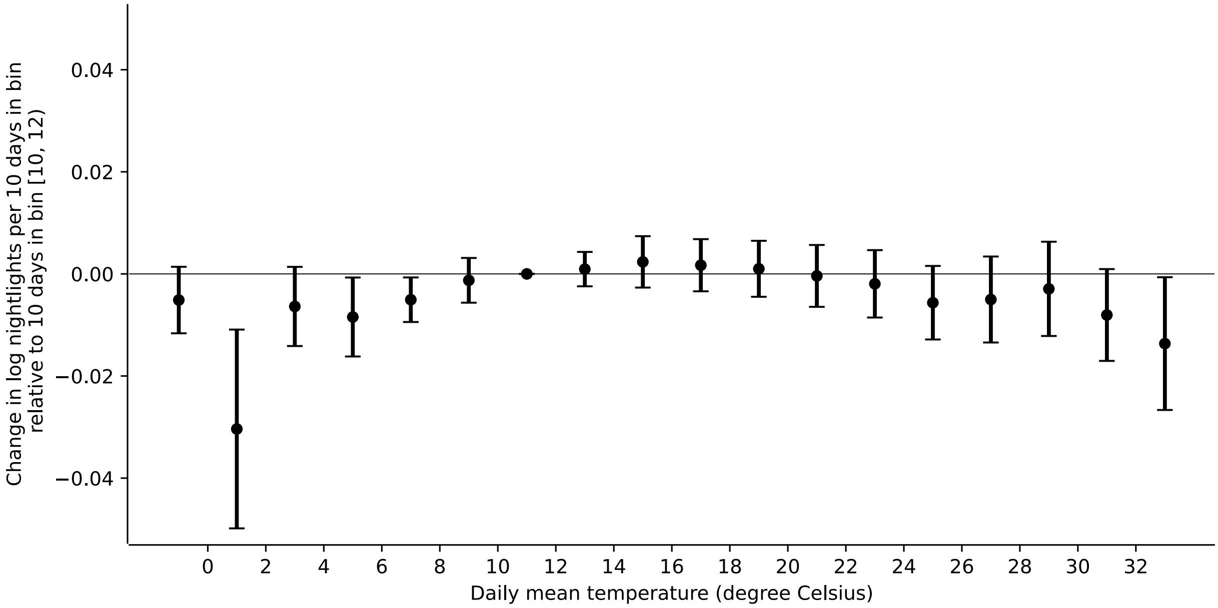

Fig. 4. Non-linear effects of daily mean temperature levels on log nightlights. *Notes:* The figure shows by how much 10 additional days with daily mean temperature within a given bin change log nightlights relative to 10 days in the bin [10, 12) degrees Celsius. The model also includes the same geographic and climatic control variables as the models shown in e.g. Table 4 and it is also estimated using spatial first-differences (Eq. (4)). Error bars show 95 percent confidence intervals.

5. Results

5.1. Main results

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 reported between daily temperature levels and many different socio-economic outcomes including labour productivity and health (Carleton and Hsiang, 2016). To gain further confidence in my estimation strategy with spatial first-differences and to inform subsequent model specifications, I first estimate a model that includes the number of days with daily mean temperature in different bins instead of annual mean temperature (Eq. (4)). The results suggest a inverse U-shaped relationship between daily mean temperature and economic activity (Fig. 4). Below 14–16 degrees Celsius, warmer days are beneficial, whereas above this range, warmer days have a negative effect on economic activity. Days just above the freezing point seem to be particularly detrimental for economic activity, possibly because of damages to infrastructure from thawing (Melvin et al., 2017). The overall shape of the curve is generally consistent with prior work that used time-series variation and focused on outcomes such as GDP growth rates (Burke et al., 2015a; Kalkuhl and Wenz, 2020) or personal income (Deryugina and Hsiang, 2017). The results also suggest a globally "optimal" daily temperature between 14 and 16 degrees, a similar range as has been reported for the USA (Deryugina and Hsiang, 2017).

This additional evidence on non-linear effects of daily mean temperature emphasises that the effect of temperature variability on long-run economic outcomes might be moderated by the effect of annual mean temperature (Section 2.1). To explore this hypothesis I estimate a flexible model in which I interact temperature variability with dummy variables for bins of annual mean temperature that are 4 degrees Celsius wide (Eq. (5)). I also include annual mean temperature itself as a control. The results suggest that higher annual mean temperature is associated with larger economic activity between 4–16 degrees Celsius and reduces economic activity at lower

Table 4
Results of a linear model estimated with SFD.

Dependent variable:	*log Nightlight density*		
Spatial first differences:	Pooled	WE	NS
Column:	1	2	3
Day-to-day variab. of T	−0.4580***	−0.6193***	−0.3762***
	(0.1209)	(0.1469)	(0.1056)
Seasonal variab. of T	−0.2485	−0.0977	−0.2994**
	(0.1529)	(0.1701)	(0.1506)
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.1763***	0.1822***	0.1634***
	(0.0470)	(0.0575)	(0.0465)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	−0.2762***	−0.2656**	−0.2748**
	(0.1028)	(0.1091)	(0.1131)
Effect of increase by 1 deg. C on log nightlights			
Day-to-day variab. of T	−0.1110	−0.1502	−0.0912
Seasonal variab. of T	−0.0059	−0.0023	−0.0071
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.1763	0.1822	0.1634
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	−0.2762	−0.2656	−0.2748
Climate controls (linear)	x	x	x
Climate controls (quadratic)	x	x	x
Geographic controls (linear)	x	x	x
Geographic controls (quadratic)	x	x	x
Border FE	x	x	x
R2	0.0300	0.0307	0.0317
N	456 310	229 014	227 296

Notes: The table shows the results of a linear model (Eq. (6)) estimated with spatial first-differences. All variables are scaled using the standard deviations reported in Table 1. Standard errors in parentheses. WE = West–East, NS = North–South. Pooled = pooling differences in WE and NS. Standard errors clustered by country in parentheses. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

and higher temperature levels (SI Figure S2). This pattern is again consistent with results of previous studies on the relationship between annual mean temperature and economic growth (Burke et al., 2015b), except the negative marginal effect at very low temperature levels.

Furthermore, this analysis with a binned-model yields negative coefficients of day-to-day and seasonal variability across most levels of annual mean temperature, but an coefficients of interannual variability whose sign is positive at low and negative at high levels of annual mean temperature (SI Figure S2). For parsimony I also estimate a model that is as simple as possible but still able to produce these main findings. This model 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 above or below 20 degrees Celsius (Eq. (6)).

As expected from the patterns in SI Figure S2, the estimation with this more parsimonious model yields negative coefficients of day-to-day and seasonal temperature variability (Column 1 in Table 4). On average, one sample standard deviation of day-to-day variability reduces log nightlights density by about 0.46 sample standard deviations. The sign of this coefficient is consistent with the results of an earlier study (Kotz et al., 2021b). A negative effect of seasonal variability has to the knowledge of the author not been reported in prior work. For interannual variability, I find a positive coefficient below 20 degrees Celsius and a negative coefficient above this temperature level. A possible explanation is the usage of energy, as the coefficients are consistent with an asymmetry whereby the benefits or costs of colder-than-average years are smaller than the benefits or costs of warmer-than-average years, possibly due to heating being less costly and generally more common than cooling (Rode et al., 2021).

The magnitude of the estimated coefficients is substantial. An increase by one standard deviation of day-to-day (1.44 degrees Celsius) and seasonal variability (14.71 degrees Celsius) is associated with a reduction of nightlights by about 16 percent and 9 percent, respectively (Column 1 in Table 4). For interannual variability, the magnitude is about 6 percent below and 10 percent above 20 degree Celsius of annual mean temperature. To translate these changes in nightlights into a reduction or increase in GDP, I use elasticities estimated in previous studies based on the same nightlights data and also obtained from cross-sectional variation (Gibson et al., 2021; Gibson and Boe-Gibson, 2021). These empirically estimated elasticities vary with the level of development of a country and the population density of a region, with generally lower elasticities in less developed and more sparsely populated places (Gibson et al., 2021; Gibson and Boe-Gibson, 2021). An elasticity of 1 has been found to be an approximate average value for China, South Africa, and the USA, whereas a value of about 0.2 has been reported for Indonesia (SI Figure S3 and SI Table S4). This suggests that the coefficients above can be translated into effects on GDP by multiplying them by a number between 0.2 (less developed, less urban) and 1 (more developed, more urban).

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 2) with the results obtained from differences in the North–South (NS) direction (Column 3), as well as with differences in these two directions pooled (Column 1). For all three estimations I find significant coefficients with the same sign and similar magnitude. The coefficients of day-to-day and seasonal variability are most sensitive to this choice, but their confidence intervals overlap (see also Fig. 5a–c).

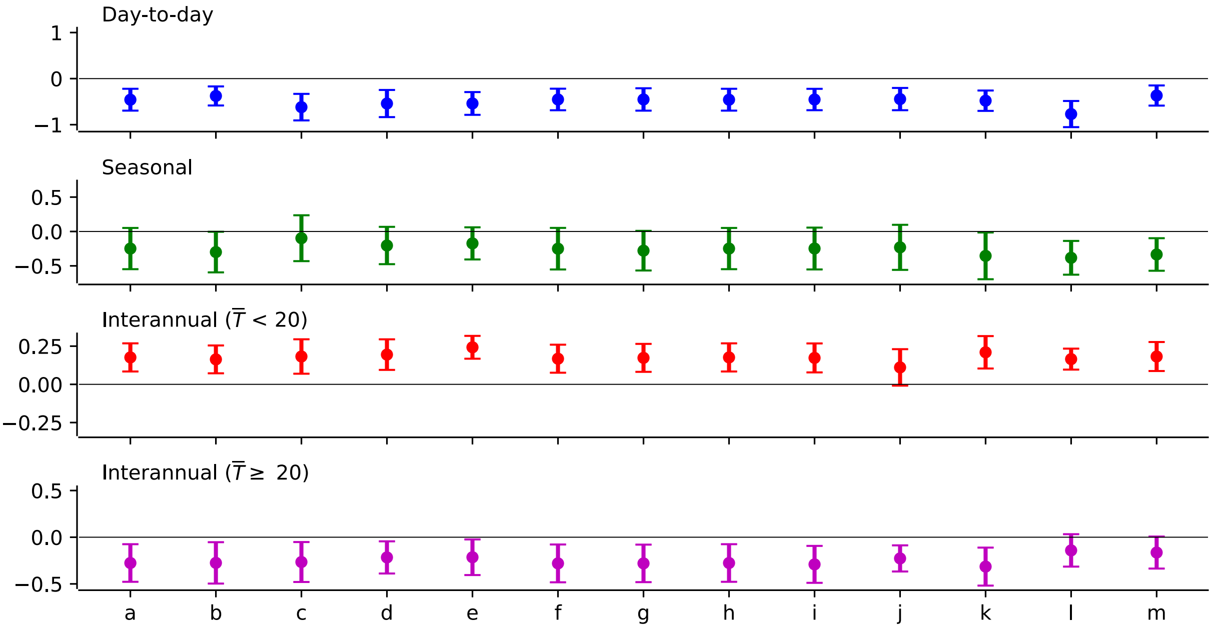

Fig. 5. Robustness tests. *Notes:* The figure shows the coefficients of temperature variability at different time scales for different model specifications. All variables are scaled using the standard deviations reported in Table 1. a. Main specification (Column 1 in Table 4); b. Differences only in WE direction (Column 2); c. Differences only in NS direction (Column 3); d. Only linear terms for all controls; e. Linear terms by 5 degree Celsius bins for all controls. f. Inverse hyperbolic sine transformation instead of logarithm; g. Standard deviation instead of range for seasonal variability; h. VIIRS v2 nightlights for 2015; i. VIIRS v2 nightlights average for 2015–2019; j. Temperature variability calculated from data over 1955–1984; k. Spatial lags included as controls; l. Temperature variability censored to [5, 95] percentiles range; m. Degree-days instead of annual mean temperature as controls (2 deg. C wide). Error bars show 95 percent confidence intervals.

To examine robustness of these estimates further, I conduct a number of additional robustness tests. In a first series of tests I change the model specification for all control variables. In the main specification, all control variables are included with linear and quadratic terms (Table 4 Column 1 and Fig. 5 a). In robustness tests, I find similar estimates for models with linear terms and models with linear terms interacted with bins of annual mean temperature (Fig. 5d, e).

In additional robustness tests I find that the main results are robust to using the inverse hyperbolic sine instead of the logarithm for nightlights (Fig. 5f), using the standard deviation instead of the range to quantify seasonal variability (g), using a more recent version of the VIIRS nightlights data (h), averaging the nightlights data over 2015–2019 instead of only using the year 2015 to address concerns about extreme events in one year (i), calculating all temperature variability variables using data over 1955–1984 instead of 1985–2014 to further examine the influence of extreme events or more generally to disentangle the effect of "climate" from the effect of "weather" (j), including spatial lags of temperature variability to examine robustness to spatial spillovers (k), and censoring temperature variability by dropping the lowest and highest 5% of first-differences to reduce the influence of outliers (l). The effects are also robust to the inclusion of degree-days to disentangle the effect of extremes from the effect of uncertainty (m), which is in more detailed discussed in Section 6.1.

The estimated coefficients are overall very robust to all these changes. The results are overall least significant for seasonal temperature variability, and for interannual variability in places with annual mean temperature above 20 degrees Celsius. In addition to these robustness tests, a formal sensitivity analysis using the methodology proposed by Cinelli and Hazlett (2020) suggests that no potentially omitted variable that is similarly strongly associated with temperature variability and nightlights as any of the included control variables could make my results insignificant if it were additionally included in the model (Linsenmeier, 2021).

5.2. Reverse causality

It is well established that air temperature tends to be higher in the centre of a city than in its surroundings due to what is referred to as the urban heat island. If the spatial distribution of economic activity affected also the variability of temperature, for example through human land use that changes the heat capacity of the surface, the statistical associations between temperature variability and nightlights could generally also be explained with reverse causality. 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) (Eq. (7)). 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. Given the change of dataset, I first regress DMSP nightlights in 2012 on climate over the period 1982–2011 (Table 5, Column 1). 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

Table 5
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	−0.3459***	−0.1130*	−0.1817***
	(0.0880)	(0.0625)	(0.0649)
Seasonal variab. of T	−0.2063	−0.1298**	−0.1558*
	(0.1326)	(0.0650)	(0.0815)
Interann. variab. of $T * \delta(\overline{T} < 20)$	0.1478***	0.0664*	0.0759*
	(0.0333)	(0.0362)	(0.0395)
Interann. variab. of $T * \delta(\overline{T} \geq 20)$	−0.1359	−0.0230	−0.0398
	(0.0924)	(0.0689)	(0.0737)
Nightlights in 1992			−0.2181***
			(0.0298)
Climate controls (linear)	x	x	x
Climate controls (quadratic)	x	x	x
Geographic controls (linear)	x	x	x
Geographic controls (quadratic)	x	x	x
Border FE	x	x	x
R2	0.0517	0.0162	0.0437
N	456 310	456 310	456 310

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 (Eq. (6)) estimated with spatial first-differences. All variables are scaled using the standard deviations reported in Table 1. NL = nightlights based on the DMSP data. Standard errors clustered by country in parentheses. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

of interannual variability of temperature respectively below and above an annual mean temperature of 20 degrees Celsius. The size of the coefficients is more difficult to compare as the two datasets measure the intensity of nightlights with different technological devices and on different scales. I next regress changes in 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 before. I interpret 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. Ex post versus ex ante

Temperature variability can affect economic activity because of non-linear effects of daily temperature levels (ex post effects) and because of larger uncertainty (ex ante effects) (see Section 2.1). Prior studies have attempted to disentangle the two by estimating the effects of variability while controlling for temperature extremes (Kotz et al., 2022). The results of such an analysis are shown as part of the robustness tests in Fig. 5. The results indicate that the estimated coefficients of temperature variability barely change when the non-linear effect of temperature levels are controlled for using a flexible degree-day model as compared to a linear term of annual mean temperature (Fig. 5 a versus m). I interpret this as evidence that at least most of the empirical estimates of temperature variability can be explained with ex ante effects.

6.2. Location choices and the future costs of climate change

Nightlights are frequently considered as a proxy for GDP. This suggests that the spatial distribution of nightlights can be explained by the spatial distribution of population and by differences in productivity. To disentangle the two factors, I estimate two additional models. In the first model, I exchange the dependent variable nightlights with population density. In the second model, I keep nightlights as dependent variable but include population density as a control. The first model thus allows me to recover the effect of temperature variability on the spatial distribution of population, while the second model recovers the residual effect of temperature variability on nightlights after controlling for differences in population.

If I use population density as dependent variable, I find the same signs but smaller magnitude and less significance for the coefficients of temperature variability than in the regressions on nightlights (Fig. 6b versus a). The effect size is especially reduced for seasonal variability, for which I find essentially no effect. If I keep nightlights as the dependent variable but add population density as a control variable, the estimated coefficients change very similarly relative to my main specification (Fig. 6c versus a). I interpret these two findings as evidence that initial location choices and subsequent migration seem to be an important response to differences in temperature variability, but not all of the statistical association between temperature variability and economic activity as measured by nightlights can be explained with an effect of temperature variability on the spatial distribution of population.

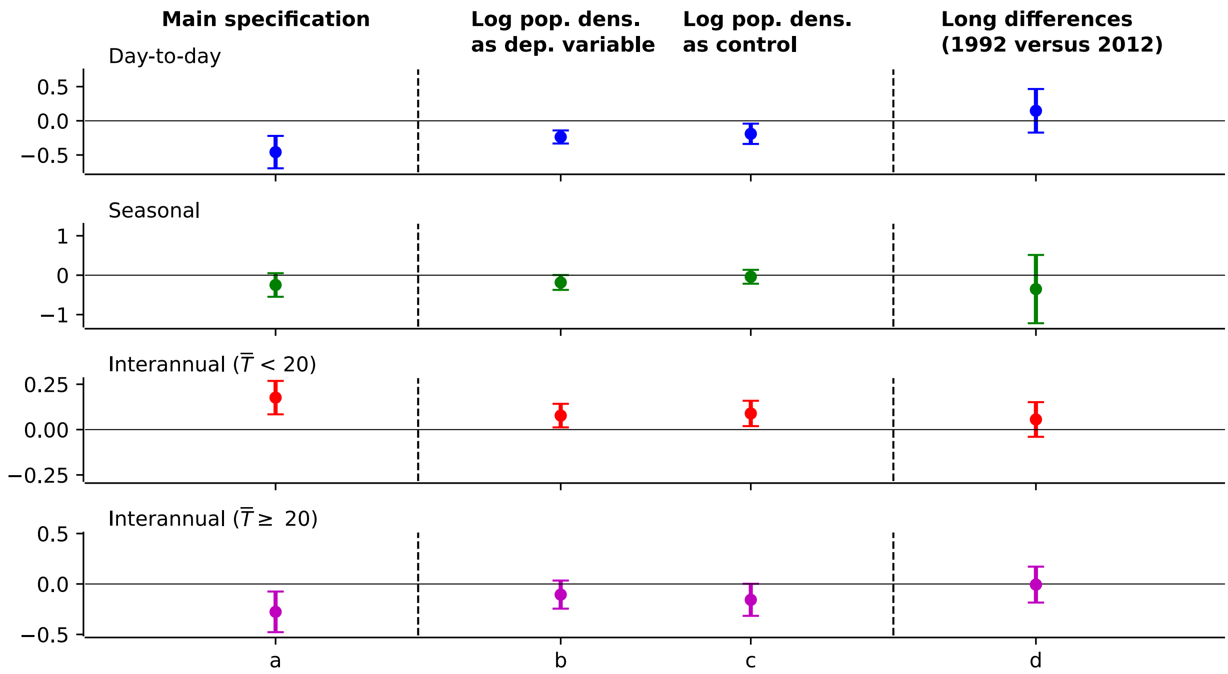

Fig. 6. Results on alternative mechanisms. *Notes:* The figure shows the coefficients of temperature variability at different time scales for different model specifications. All variables are scaled using the standard deviations reported in Table 1. a. Main specification (Column 1 in Table 4); b. Log population density as dependent variable; c. Log population density as an additional control variable; d. Long differences using changes of nightlights between 2012 and 1992. Error bars show 95 percent confidence intervals.

The residual effect on nightlights is presumably either associated with effects of variability on economic development or with path-dependent economic development.

These empirical estimates obtained from spatial first-differences include effects of temperature variability on economic activity that might date back far in time because identification is based on cross-sectional variation. Some evidence on the relevance of temperature variability in more recent time periods can be found in Table 5. They suggest that temperature variability affected economic development also in this relatively recent time period (1992–2012), but because the estimates are again obtained from cross-sectional variation, it cannot be ruled out that they reflect earlier effects and subsequent path-dependent economic development.

To further examine this question, I use an alternative empirical strategy based on changes of both nightlights and temperature variability over time, also referred to as long differences (Eq. (8)). The results indicate no effect of changes in temperature variability between 1982–1991 and 2002–2011 on changes in economic activity between 1992 and 2012 (Fig. 6d). The estimated coefficients are both smaller in magnitude than the coefficients obtained from spatial first-differences and statistically insignificant (Fig. 6d versus a). The combined evidence in Table 5 and Fig. 6d hence suggests that temperature variability affected economic development also during recent time periods, but primarily due to path-dependent development.

An important caveat to the long differences estimation is that nightlights are generally not as informative about changes over time as they are about variation in space (Chen and Nordhaus, 2019). Furthermore, changes in temperature variability between 1992 and 2012 are substantially smaller than projected changes for future scenarios. These limitations suggest some caution regarding the conclusion that future changes to variability will not affect economic development similarly as it did in the past.

6.3. Urban areas

It is well known that nightlights are a better proxy for GDP 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 defined as the 5 percent most densely populated grid cells of every country (SI Table S5). The magnitude of the estimated coefficients appears relatively sensitive to the population density of grid cells, presumably because of large variation in the elasticity of GDP to nightlights between more densely and less densely populated areas (SI Figure S3). Importantly, I find significant effects with the same sign also in less densely populated areas, including the 50 percent least densely populated areas, except for interannual temperature variability above 20 degrees Celsius. Overall, the effect of temperature variability seems to be geographically widespread and not limited to urban areas.

6.4. 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 advantages could be reflected in the spatial distribution of nightlights and thus explain the estimated coefficients.

I examine this hypothesis with satellite data on agriculture including both land used for crops and 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 (SI Table S6). This suggests that the estimated effect of temperature variability on nightlights cannot be explained with the spatial distribution of agricultural activity.

7. Conclusion

In this paper I combine a global high-resolution satellite-derived dataset on nightlights with climate reanalysis data and additional geographical datasets to examine how day-to-day, seasonal, and interannual temperature variability 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. This allows me to study how temperature variability at different time scales influences aggregate economic activity. 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 beliefs about climate and adaptation (Waldinger, 2022). Compared to previous work on the long-run effect of mean climate (Nordhaus, 2006; Mendelsohn and Massetti, 2017), I focus on climate variability and use a recently developed econometric framework which allows for a more plausible identification of causal effects from cross-sectional variation.

An important benefit of using cross-sectional variation in this study is that the total effect of temperature variability can be identified (Hsiang, 2016), including possibly non-linear effects of daily temperature levels (ex post effects) and larger uncertainty (ex ante effects). Evidence from micro-econometric studies suggests that this total effect is negative. I expect the effect 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 predictable. Because of the underlying physical processes of climate, day-to-day and interannual variability are less predictable than seasonal variability.

The results reveal a statistically significant, negative effect of day-to-day variability 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 18 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 this appears to be the first study that empirically analyses the effect of seasonal and interannual variability on aggregate economic activity accounting for ex ante effects of variability, the results align with previous work finding a negative short-term effect of day-to-day variability on regional GDP (Kotz et al., 2021b) 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 daily and annual mean temperature at relatively low temperatures and a negative marginal effect at high temperatures, with a globally optimum annual mean temperature of about 15 degrees Celsius. Modelling these effect of daily temperature levels flexibly with bins suggest that ex ante mechanisms are overall more important than ex post effects in explaining the estimated effects of variability.

The chosen methodology allows me to compare the estimated effects of temperature variability with the estimated coefficients of annual mean temperature. On average, one sample standard deviation of seasonal and day-to-day variability reduces nightlights by 9 and 16 percent, respectively. If these effects are benchmarked with the estimated non-linear effect of annual mean temperature, they correspond to increases of annual mean temperature from 20 degree Celsius to approximately 30 and 37 degrees Celsius, respectively (which correspond to 0.75 and 1.27 times the sample standard deviations of annual mean temperature). These changes in nightlights can be translated into changes in GDP using elasticities of the log GDP - log nightlights relationship from prior studies (Gibson et al., 2021; Gibson and Boe-Gibson, 2021). According to these studies, the elasticity is approximately one in relatively densely populated and well developed places. For less densely and less developed contexts, the elasticity is much smaller, with an estimate from Indonesia suggesting an elasticity of about 0.2 (Gibson et al., 2021).

The results are robust to a variety of robustness tests. This includes a robustness test unique to the spatial first-differences research design, namely comparing estimates obtained by using spatial differences in orthogonal geographical directions. In an additional robustness test, I show that my results cannot be explained by reverse causality. Regarding future climate change, the results are ambiguous. Overall, they suggest that the empirical relationships between temperature variability and economic activity are primarily the result of climate affecting the spatial allocation of population and subsequent path-dependent development (Emerick, 2018; Henderson et al., 2017, 2018). However, limitations of tracking changes in economic activity over time with changes in nightlights (Chen and Nordhaus, 2019) and small changes of temperature variability in the past relative to projected changes in the future limit extrapolations from these findings to future scenarios. If the results are indicative of the sign of the economic effects of future changes to temperature variability, projected changes to seasonal cycles (Dwyer et al., 2012), interannual temperature variability (Bathiany et al., 2018), and day-to-day temperature variability (Kotz et al., 2021a; Wan et al., 2021) suggest that future changes to variability will add to the economic costs of climate change, especially in currently relatively warm regions.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeem.2023.102840.

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