The Subnational Effect of Temperature on Economic Production: A Disaggregated Analysis in European Regions

Holtermann, Linus and Rische, Marie-Christin

Ruhr University Bochum, University of Hamburg

2020

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Linus Holtermann[1] Marie-Christin Rische[2,3]

Abstract

In order to develop efficient strategies to counter the adverse economic consequences of climate change, accurate and spatially detailed assessments of economic damage are required. Estimates to assess the impact of temperature variations on macroeconomic output are usually based on country-level weather aggregates, neglecting that weather realizations tend to vary significantly within countries. Using data from multiple decades for spatially small-scaled European regions, we conduct a disaggregated analysis to mitigate the potential bias arising from spatial aggregation. We examine the economic impacts of temperature by analysing annual variations in two different weather indicators, namely yearly averages representing rise in temperature levels and standardized deviations from the region-specific climate norm representing unusual warm and cold periods. Our spatially explicit approach considers spatial dynamics and the spatial distribution of temperature effects as it captures spatial dependence via spillovers and allows for potential heterogeneous effects sizes for distinct spatial regimes. We find that regional-level growth reacts non-linearly to a rise in temperature levels, with a concave response curve similar to those estimated in earlier country-level studies. Interestingly, baseline temperature levels also moderate the effects of temperature deviations as unusually hot years adversely affect warm regions, whereas overly cold years foster growth. In contrast to most of the literature, we disclose that the relationship between economic growth and temperature variations is not generalizable. The uniform temperature-growth relationship found in the literature for countries at a global scale does not hold at the subnational level. The "world city" regions at the top of the urban hierarchy are not prone to any form of tested temperature variation. The resilience of these city regions can be explained, inter alia, by the prevalence of invulnerable sectors. The uneven effect sizes suggest that spatially differentiated policy measures are needed that should be coordinated between regional and national levels of government to counter the adverse consequences of temperature variations and climate change more efficiently.

JEL classifications: C31, C33, O44, Q51, Q54, R11.

Keywords: temperature, climate change, regional economic growth, heterogenous vulnerability, Europe, spatial spillovers.

[1] Ruhr University Bochum, Department of Geography: Urban and Regional Economics, Universitätsstraße 150, Bochum 44801, Germany. E-Mail: linus.holtermann@rub.de.
[2] Hamburg Institute of International Economics (HWWI), Department of Energy and Environmental Economics, Oberhafenstraße 1, Hamburg 20097, Germany. E-Mail: rische@hwwi.org.
[3] University of Hamburg, Department of Socioeconomics, Welckerstraße 8, Hamburg 20354, Germany.

1 Introduction

Climate change could have far-reaching consequences on large segments of human wellbeing including economic development. It is expected that not only gradual temperatures rise, but also that weather phenomena, hence short-term realizations of the long-term climate distribution, become more "extreme" (Kharin et al., 2007; Orlowsky and Seneviratne, 2011). Because, at least within certain temperature ranges, economies should be able to adapt to gradual changes of average temperatures, impacts of extreme weather events are assumed to cause higher economic losses than impacts of changes in mean conditions (IPCC, 2014).

The interest of scientists and policy makers on the possible harmful impacts of temperature changes on economic production has emerged in recent years. However, the vast majority of studies focuses on the economic effects of increasing temperature levels (e.g. Dell et al., 2012; Burke et al., 2015; Carleton and Hsiang, 2016). Due to more robust prognoses on changes in average weather, these climate change analyses typically concentrate on gradual changes in mean conditions, effectively ignoring the benefits and damages that might be associated with changes in climate variability. Nevertheless, it is essential to incorporate the effects of unanticipated deviations from the historical observed climatic norm (unusual hot and cold periods) into the assessments of economic costs of climate change to draw a more complete picture of the impediments to economic development that climate change might exacerbate. Therefore, in this paper, we focus on both the economic effects of gradual changes in temperature levels and the economic consequences of unanticipated (short-term) temperature anomalies.

The seminal work of Dell et al. (2012) was the first study that addressed the impact of temperature changes on macroeconomic performance. The empirical analysis examines a panel of 125 countries and 53 years and evaluates whether fluctuations in yearly average temperature have an impact on economic growth. The authors find that temperature upswings reduce growth rates, but only in developing countries. For developed countries, they detect no significant effects on economic production. Building on the study of Dell et al. (2012), Burke et al. (2015) show that economic growth reacts non-linearly to temperature. Instead of the income level which is (negatively) correlated with the temperature level, the long-run average temperature of a country – which to some extent describes the present climate – shapes the response towards temperature changes. Their results provide evidence that economic activities in all countries are coupled to climate. While the two studies predict broadly the same economic consequences for specific countries with respect to the rise in temperature level, the causal driver of the outcome is not the same ("income hypothesis" versus "climate condition hypothesis"). The vast majority of nowadays studies supports the climate condition hypothesis proposed by Burke et al. (2015) (see literature review in Appendix A).[1] Surprisingly, all studies on the economic effects of rise in temperature levels find concave response functions that are generalizable across sample units. Up to certain temperature levels, economic systems benefit from the rise in temperature before the relationship

[1] The literature review includes only studies that use Gross Domestic Product (GDP) as dependent variable and base the measurement of weather on physical strength and not on information about outcomes of weather events (e.g. economic or human damage). For the latter, the intensity measures are a function of economic development which complicates the causal interpretation of economic effects potentially stemming from the events (for a detailed discussion, see Kahn (2005) or Felbermayr and Gröschl (2014)). Numerous micro level studies exist that often detect a non-linear impact of temperature. To name a few prominent examples, agriculture yields (Schlenker and Roberts, 2009), labour productivity (Zivin and Neidell, 2014; Zhang et al., 2018), cognitive functions (Hayes and Saberian, 2019; Park et al., 2020), or various aspects of health (Barecca et al., 2016) are prone to temperature thresholds beyond which they decline abruptly.

becomes harmful at higher levels. The literature on the economic effects of temperature deviations from the historical norm, however, is sparse. Only Kahn et al. (2019) addressed this issue, finding persistent negative effects of temperatures above and below the historical norm. Again, the empirical results are generalizable for all samples under investigation.

Following the regional approaches of Kalkuhl and Wenz (2018) and Burke et al. (2019), we attempt to take a step further in understanding the temperature-growth relationship by taking the analysis to a geographically disaggregated level. We exploit the fact that aggregated economic output in Europe is also measured at a smaller spatial scale and use NUTS-3 regions of EU-15 countries as our units of observation. We analyse the causal effect of temperature on macroeconomic performance and examine whether potential temperature effects are driven by income levels or climatic conditions. Furthermore, we scrutinize whether the presumption of a generalizable response function can be maintained by testing if the detected temperature-growth relationship holds for all subnational economic systems. The EU-15 regional economies provide a good testing ground since these economic systems count among the wealthiest economies on earth, which, following the empirical results of Dell et al. (2012), should not be affected by temperature changes, and are at the same time characterized by a strong heterogeneity of economic structures and a large variation in climate conditions.

Our empirical examination contributes to the literature in two main directions. The first contribution relates to the temperature indicators we employ. We apply two different ways to operationalize temperature variations to demonstrate the multi-faceted dimensions of weather. On the one hand, we utilize the measure of yearly temperature averages to examine how growth rates change as yearly average temperature changes (rise in temperature levels). On the other hand, we utilise an index of weighted standardized anomalies to investigate the relationship between economic growth and monthly temperature deviations from the historical norm within a region (unusually hot and unusually cold temperature manifestations). Second, we choose a regional approach to mitigate the spatial aggregation problem. Since weather realizations tend to vary substantially within countries, we focus on small-scaled regions instead to reduce the spatial aggregation bias and potential smoothing of local weather events. In addition, our regional approach addresses the critique of Burke et al. (2015) that large scale temperature changes generate emergent impacts on regions beyond what a region might experience in response to an isolated change in their individual temperature because spillovers might transmit weather effects from interconnected economic units. We utilize spatial econometric techniques to capture the spatial correlation of unobserved climatic factors as well as economic interlinkages between regions. In contrast to country-level studies, the regional approach offers the advantage that large subnational variations in regional growth rates and potential moderators of vulnerability are not averaged to country-wide values, which allows us to gain more detailed insights into the (spatial) distribution of temperature effects. We investigate whether differently structured subnational economic systems show a homogenous response to a comparable temperature change or not. The disclosure of potentially uneven economic impacts between economic units is pivotal to calibrate more sophisticated damage functions in the Integrated Assessments Models (IAMs) which are a widely used instrument of forecasting climate change consequences (e.g. Nordhaus, 1992). Moreover, the identification of potentially heterogeneous response patterns between and within countries provides important implications for the configuration of policy interventions at different spatial scales.

For our assembled panel data covering 954 regions over a 31-year climate period from 1982 to 2012, we find five main results. First, our estimations confirm the findings of Burke et al. (2015) as we find a non-linear and concave relationship between average temperature and economic growth, with a turning point at 9.2 °C. Since we cannot detect significant moderations of the temperature-growth link by regional or national income, the results provide evidence that average temperature conditions shape the responses towards temperature fluctuations. Second, large agglomerations that constitute focal points in the global network of cities are unaffected by changes in average temperature, regardless of the prevailing climatic conditions. In contrast to Burke et al. (2015), the heterogeneous response pattern suggests that the relationship between economic growth and annual average temperature is not generalizable for all (regional) economic systems. The disclosure of significant spillover-effects underlines the relevance of the heterogeneous response function since indirect temperature effects are determined by both the strength of spatial dependencies and the vulnerability of "neighbouring" regions. Third, the divergent impact of the rise in temperature levels in the large city regions at the top of the urban hierarchy can be explained, inter alia, by their sectoral composition which is characterized by the prevalence of invulnerable sectors.

With respect to temperature deviations, we find two further main results. First, temperature deviations from the historical norm within a usual range exert no adverse effects on growth, but severe anomalies beyond critical intensity thresholds in both directions – too hot and too cold years – lower regional growth rates in a statistically meaningful way. Albeit rare events, if deviations from anticipated conditions in unusually hot or unusually cold years become more extreme in the future, the additional damage will be perceptible in the wealthy European economies. Interestingly, the impacts of deviations from the long-run norm are also coupled to climatic conditions insofar that overly hot years adversely affect warm regions in our sample, whereas too cold years foster growth. The opposite holds true for cold regions. Second, the results of temperature deviations validate the findings of the yearly average temperature estimates regarding the heterogeneity of response functions and the role of sectoral channels.

The remainder of the paper is structured as follows. Section 2 presents the estimation strategy, the spatially explicit estimation approach, and the operationalization of the weather indicators of interest. Section 3 describes the data. The empirical results are reported and discussed in section 4, separated by weather indicator and investigation focus. Section 5 concludes.

2 Empirical strategy

2.1 Research design

Weather is a rather local and temporary phenomenon whose realizations might vary significantly across space within large-scaled economic units. The country-wide average temperature might not be a relevant or adequate measure for the exposure of certain local productive units. By looking at spatial and temporal aggregates, it is not possible to determine if opposing temperature effects occur within economic units and periods and whether these effects offset each other. For instance, compensations due to at least two temperature situations with opposing impacts within the spatial boundary of an economic unit (e.g. unusually high temperatures in southern locations and unusually low temperatures in northern locations) or within a period (e.g. too cold summer paired with too cold winter) could not be detected in unit-by-period aggregates. The likelihood that such compensations occur within the aggregated measures increases with the spatial extension of the economic unit and the length of the time frame across which the aggregation is performed.[2] In general, a wider dispersion of weather conditions experienced across locations and moments within a summarized unit leads to greater smoothing of the response (Hsiang, 2016). In particular for temperature deviations, national averages of climate variables may be close to the historical norm while there is significant heterogeneity at the regional level within countries. Thus, we expect that larger economic units that cover more heterogeneous local weather conditions produce a smoother and flatter response to unit-by-year weather indicators which enhances the risk that the temperature effect attenuates to zero. For these reasons, we investigate spatially small-scaled regions instead of countries to mitigate the smoothing of weather manifestations by spatial aggregation. The choice of regional economic units that exhibit a notably higher within-unit spatial correlation of weather than national economies allows us to identify the actual prevailing weather conditions and related economic consequences more precisely. For instance, the standard deviation of yearly average temperature observations within the spatial boundaries of our European regions is on average 0.71 °C, while the same indicator is 1.61 °C within countries.[3] Unfortunately, higher frequency data of economic output that would allow us to address the issue of temporal compensation within a year are not available for our sample of regions.

In addition, our regional approach considers that the economic effects of temperature are potentially not ubiquitous across space as we take into account that temperature effects might not be homogeneous between regions due to potential effect size moderations that may arise from prevailing climatic conditions as well as from inherent socio-economic factors. The potentially heterogeneous temperature effects are not regionally confined as the spatially explicit statistical approach abolishes the isolated view on economic units and captures potential spatial multipliers of weather effects through growth spillovers. As pointed out by Dell et al. (2014) and Burke et al. (2015), the neglection of cross-border interactions could result in an underestimation of effect sizes. Moreover, our empirical set-up accounts for the spatial correlation of omitted (unobserved) weather variables and unsystematic interlinkages between regions (for a detailed justification of the spatial econometric model, see Appendix B.I). Overall, our disaggregated analysis avoids the assumption that observations are independent and identically distributed in space which typically would enhance the risk of Type I errors when examining temperature effects in an interdependent economic framework at the regional level (Moulton, 1986; Fisher et al., 2012).

The empirical analysis follows a three-step procedure. In the first step, we test whether the economic production of European regions is affected by temperature at all or whether these highly developed economic systems are resilient to temperature changes (see section 4.1). Since higher temperature levels are negatively correlated with income levels for our regional observations, we also inspect moderation effects of income to test whether the income level might

[2] For example, if the boundary of an economic unit stretches over several degrees of latitude, it is likely that the aggregated unit-specific temperature value assigned to productive units in the north and the south does not portray local temperatures in an appropriate way since the variance in temperature is larger between latitudes than within latitudes and we are averaging over temperatures that are generally increasing with lower latitudes. Obviously, the risk of an imprecise representation of local temperature realizations for the local productive units is increased when aggregating temperature observations over a larger geographical extension.

[3] The computed spatial autocorrelation between temperature observations within distance bands that have a diameter of the average size of a sample region (country) shows a similar picture. The average of Moran´s I coefficients (Moran, 1950) across sample years is 0.90 (0.64), suggesting that spatial autocorrelation in temperature tends to be substantially stronger within selected NUTS-3 regions.

be responsible for potentially more adverse effects in regions that are both hotter and “poorer” (“climate condition hypothesis” versus “income hypothesis”).

In the second step, we test whether the disclosed relationship in step one is generalizable for all regions (see section 4.2). As pointed out by Hsiang et al. (2019), specific observable socio-economic predictors of response heterogeneity are often not randomly assigned. For example, the openness of a region is likely to be correlated with other important moderators for which data are not available at the applied spatial resolution, e.g. capital intensity or quality of infrastructure. Thus, the interpretation of the influence of single determinants of vulnerability is problematic. To mitigate this limitation, we pursue an alternative strategy. To better understand the impact of temperature on economic performance in economically differently structured regions, we rely on regional typologies. We rank the economic units according to their position in the urban hierarchy and assign each region to one of the four classes: MEGA region, predominantly urban, intermediate, or predominantly rural (see section 3.1). Since the process of city formation in Europe was predominantly determined by trade costs and locations near main trade routes, e.g. rivers and the roman road network (Bosker et al., 2013; Bosker and Buringh, 2017), and military conflicts played a key role in the rise and evolution of urban regions throughout European history (Dinececco and Onorato, 2016), we argue that the used classification of region types is independent of the climatic conditions. Therefore, this strategy allows us to identify potentially varying temperature effects between spatial regimes that are neither pre-defined by nor systematically different in climatic conditions and at the same time subsume, on average, differences in potentially important (unobservable) human-made moderators, such as openness, sector structure, or agglomeration economies.

As region types typically come along with specific sector structures, we test whether this transmission channel can contribute to explain possible heterogeneity in temperature responses between region types (see section 4.3). In the last step, we evaluate the effect of temperature on several components of GDP. Since direct interactions of sector shares with temperature would suffer from the same limitations with respect to the interpretation of results as outlined above, we constrain our analysis to clearly identifiable net effects of temperature on growth of sectoral gross value-added (GVA) and apply the same identification strategy that is implemented to assess the temperature effects on aggregated GDP growth.

2.2 Econometric model

Our empirical strategy makes use of a quasi-experimental framework for identifying the effect of random weather events on economic growth proposed by Deschênes and Greenstone (2007). In this research setting, a single region can be regarded as both “control” and “treatment” population, where a given region is “shifted” through time and is compared to itself at different weather manifestations. These weather conditions are exogenously determined by atmospheric changes in the environmental system and thus are fully independent of the economic system. Since economic units are adapted to their usual weather, we use deviations from the region-specific norm to quantify the causal effect of weather fluctuations on economic growth. We rely on a fixed effects panel set-up and apply the within-estimator, which allows us to estimate the impact of weather variables on aggregated economic growth without explicitly modelling the transmission channel of effects (e.g. Dell et al., 2012; Hsiang et al., 2013; Burke et al., 2015). In order to capture spatial dependencies, we augment the conventional panel models by two spatially autoregressive processes:

$$y_{it} = \rho_r \sum_{j=1}^{N} w_{ij} y_{jt} + f_r^1(T_{it}) + f_r^2(P_{it}) + \mu_i + \nu_{r\mathrm{l}t} + u_{it} \tag{1}$$

$$u_{it} = \lambda \sum_{j=1}^{N} m_{ij} u_{jt} + \varepsilon_{it}$$

where regions are indexed by $i = 1, \dots, N$ and years by $t = 1, \dots, T$. y is the annual change in economic production proxied by the growth rate of inflation-adjusted GDP per capita (first difference in natural log of annual GDP per capita × 100). Subscript r indicates the discrete spatial regimes $r = 1, \dots, R$ and hence group-specific coefficients for each region type, which we test for in a later step.[4] The region fixed effects μ_i contain all time-invariant factors that influence a region's average growth rate, such as politics, climate, institutions, and geographical location. The year-specific fixed effects $\nu_{r\mathrm{l}t}$ control for common trends and abrupt events, such as turmoil in energy and financial markets or recessions. We follow Dell et al. (2012) and test for time fixed effects differentiated by larger regions (hence the subscript l). The application of year fixed effects interacted with a dummy variable for Scandinavian regions substantially improves the fit of our model. One possible explanation might be the economic crises in Nordic countries at the beginning of the 90s that did not hit other European economies as severely. T and P denote the temperature and precipitation indicators (see section 2.4). $f(\cdot)$ describes the functional relationships between weather and economic growth.

We control for precipitation because changes in regional precipitation sums tend to be correlated with changes in temperature (Auffhammer et al., 2013). Since typical growth controls might themselves be in part an outcome of weather variations and vice versa do not influence the magnitude of short-run weather fluctuations, all specifications deliberately contain no further control variables to avoid the "bad control problem" (Angrist and Pischke, 2009; Hsiang et al., 2013). The problem with control variables is that they would have to be strictly exogenous from the weather variables; otherwise, they might absorb part of the "total (aggregated) weather effect" on growth which is transmitted by them.

In order to account for spatial interactions between regions, we opt for the so-called Spatial Autoregressive Autoregressive Model (SARAR).[5] The spatial lag of the dependent variable $\rho_r \sum_{j=1}^{N} w_{ij} y_{jt}$ allows for growth spillovers across regions which indirectly transmit the effects of weather shocks in one region to interconnected localities, while spatially correlated (unobserved) unsystematic effects that drive economic performance are captured by a spatially correlated error term $\lambda \sum_{j=1}^{N} m_{ij} u_{jt}$. The respective regional interlinkages are modelled explicitly via weighting

[4] To run separate panel regressions for each region type would be accompanied by the loss of the spatial influence arising from regions that are eliminated from each subsample. Hence, we apply a pooled model that interacts the weather variables with dummy-indicators for each region type. We also interact the year fixed effects with the region type indicators to implicitly allow the year fixed effects to differ across groupings (as it would be the case in subsample specifications). In the case that "sample-wide" models are analysed, r vanishes and a homogenous coefficient is estimated for all regions.

[5] Based on theoretical arguments outlined in Appendix B.I, we refrain from adding weighted averages of weather indicators in neighbouring regions to the model (spatial lag of explanatory variables). From a statistical point of view, an incorporation of both the weather of region i and the average weather of neighbouring regions would result in a severe multicollinearity problem due to the extensive spatial correlation of weather indicators (variance inflation factors > 100).

matrix W (M), where the spatial weights w_{ij} (m_{ij}) indicate the dependency structure between region i and region j (see section 2.3). ρ_r and λ are scalar parameters to be estimated measuring the strength of the spatial dependencies.

A key facet of spatial autoregressive processes in the dependent variable is the presence of endogenous interactions and feedback effects that lead to a scenario where changes in one region set in motion a sequence of adjustments in (potentially) all regions. This spatial multiplier should be considered when interpreting the marginal effects of the econometric model. LeSage and Pace (2009) propose scalar summary measures that allow us to evaluate the total impacts of temperature changes as the sum of effects occurring within a region and potential effects which spill in from "neighbouring" regions that might also be affected by weather events (for technical details regarding the calculation of the scalar summary measures, see Appendix B.II).[6] Estimations of spatial autoregressive panel regressions via ordinary least squares (OLS) would suffer from a simultaneity bias originating from the endogenous spatial interactions. Therefore, we rely on a full Bayesian approach to overcome the endogeneity problem. To account for unknown forms of heteroscedasticity that may arise from spatial outliers and temporal autocorrelation, the disturbances ε_{it} are clustered by regions and follow a multivariate t-distribution (Geweke, 1993). Since we have no a priori information on the effect sizes of weather parameters of interest, we use non-informative priors (a scheme for sampling the posterior distributions is developed in Appendix B.III).

2.3 Spatial interactions

In open economic systems such as those in our regional sample, we expect that spillover mechanisms and externalities matter for economic development. For weighting matrix W, we base our specification on "Economic Distance" (ED) to capture urban hierarchy in spatial dependencies between regions and assume that growth depends stronger on the growth of neighbours with larger economic size penalised by inter-regional distance (Corrado and Fingleton, 2012; Fingleton and Palombi, 2013). Weather and economic growth might have an influence on inter-regional dependencies over time, e.g. weather shocks might affect exports of trade partners (Jones and Olken, 2010; Dallmann, 2019). Hence, we construct W time-invariant using the GDP in 1981 to measure the economic size, so that endogeneity as a byproduct of modelling spatial processes is not an issue. We conduct robustness tests using alternative distance penalty specifications, e.g. inverse distance weighting and exponential distance decay functions. Moreover, we use alternative measures for the economic size of a region and modify the weights attributed to the economic size and distance component to adjust their relative importance in the construction of the spatial weights matrix (for a detailed derivation of spatial weights, see Appendix B.IV).

The weighting matrix M in the spatially autoregressive disturbances models unsystematic effects that drive economic performance in interrelated regions. Those unsystematic effects may arise from omitted weather variables (e.g. atmospheric pressure or wind speed) which are correlated in space and because the spatial scale of "functional economic units" is not congruent with the spatial scale of administrative NUTS-3 regions. Those spatial dependencies are stronger between

[6] Total impacts (TO) = direct impacts (DI) [effect of a change in a region´s z^{th} covariate on own-region growth] + indirect impacts (IN) [effect of a change in a neighbouring region´s z^{th} covariate on own-region growth].

nearby regions and diffuse with increasing distance or order of neighbours. For the corresponding matrix M, we adopt so-called Queen contiguity weights (Q), assuming that regions which share a common boundary are neighbours.

2.4 Construction of weather indicators

Yearly Averages (YA)

The most intuitive way is to use yearly averages of daily weather measures as done by many studies (e.g. Dell et al., 2012; Burke et al., 2015). In settings with fixed effects models, these indicators evaluate the effects of yearly fluctuations around the long-term annual mean. Potential non-linearities in weather effects between units imply that changes in the dependent variable are conditional on different levels of the weather variable ("between-unit" non-linearity). Annual fluctuations, however, might not completely capture all weather dimensions relevant for economic performance. Instead, estimations using these smoothed average of yearly weather conditions quantify the effect of a rise in average temperature levels on economic production.

Weighted Standardized Deviations (WSD)

Due to the adaptation to usual weather conditions, it is likely that excessive short-term deviations from anticipated climatic conditions might be particularly stressful for economic systems. To better account for the temporal variability of intra-annual weather phenomena in each region, we take monthly values and compare them to their respective long-term averages before aggregating them to an annual measure. We utilize the so-called Weighted Anomaly Standardized Precipitation (WASP) index proposed by Lyon and Barnston (2005) which is based on the sum of weighted monthly precipitation deviations:

$$S_N = \sum_{i=1}^{N} \left(\frac{P_i - \overline{P}_i}{\sigma_i} \right) \frac{\overline{P}_i}{\overline{P}_A} \tag{2}$$

For each month, observed precipitation P_i is corrected by the long-term precipitation mean of this month $\overline{P}_i$. The resulting deviation is standardized by the month's standard deviation σ_i. The deviations are then weighted according to the typical contribution of this month to the annual total of rainfall $\overline{P}_A$ in order to account for dry and wet seasons. In this study, the focus is on inter-annual weather variability, hence $N = 12$ (months). In the last step, the sum S_{12} is standardized at a given 0.25 degree weather grid cell over time to obtain a dimensionless measure of the relative severity of annual precipitation surpluses or deficits:

$$WASP_{12} = \frac{S_{12}}{\sigma_{S_{12}}} \tag{3}$$

The WASP values can be interpreted as the number of standard deviations (σ) by which the observed year deviates from the long-run norm. Since temporal variations in the annual WASP index at a given grid cell reasonably fit a normal distribution, index values of -2 (severe drought) and +2 (severe wetness) are regarded as severe anomalies, whereas moderate anomalies describe index magnitudes exceeding ±1 (Lyon and Barnston, 2005). Rather than counting the grid cells above and beyond a specific threshold (e.g. Brown et al., 2013), we take all grid index values of the region and generate a weighted average for each region (see section 3.2). The WASP index is designed for precipitation, but it can easily be adapted to temperature with the simplification that each month's weight is the same for the annual average. We term this regional index the "Weighted Standardized Deviation" (WSD) index.

The WSD index aggregated at the regional level indicates the relative departures of temperature from normality within a region, hence non-linearity in the WSD indicator implies that changes of the dependent variable depend only on the standardized size (intensity) of deviations from the region-specific mean ("within-unit" non-linearity). These variations are independent from the mean itself and represent unanticipated yearly weather anomalies (McIntosh and Schlenker, 2006).[7] Due to the consideration of specific standard deviations, the WSD does not only account for fluctuations around each respective long-term mean, but also for the size of deviations and how typical specific sizes are for a region. The assumption behind that construction is that each region is not only adapted to its long-term weather average but also to the common range of weather fluctuations around it, thus the WSD index can be compared across markedly different climates. In our baseline setting, we assume that adaptation is lagging behind and economic systems are adjusted to a longer-term average than just the sample period mean and chose the years 1960-2012 as reference period to calculate the long-term mean and standard deviation for each month in Equation (2). Such a leading reference period is often used in the literature that evaluates the socio-economic consequences of weather anomalies (e.g. O'Loughlin et al., 2012; Obradovich et al., 2017; Harari and La Ferrara, 2018). We also conduct robustness tests using the years of available economic data (1982-2012) as reference period.

3 Data

3.1 Economic data

Our main source of data on GDP is the European regional database of Cambridge Econometrics (CE) which in turn draws upon the EUROSTAT Regio database and official data from national providers. The dataset covers the years 1982-2012 for 954 NUTS-3 regions in EU-15 states (without Luxembourg) and Norway. NUTS-3 regions are the smallest-sized administrative units for which longer time series of statistically comparable economic data are available across EU member states.[8] NUTS-3 regions correspond to "*Kreise*" and "*Kreisfreie Städte*" in Germany, "*Départements*" in France, or "*Provinces*" and "*Città metropolitane*" in Italy, for example. The closest administrative units in the United States that NUTS-3 could be compared with are counties.

For the region type classification, we follow a two-step procedure. First, we employ the regional typology used in the OECD territorial classification scheme (OECD, 2007) and group the NUTS-3 regions into three classes: predominantly urban (PU), intermediate (IN), and predominantly rural (PR).[9] A limitation of the urban-rural typology is that it does not account for differences in size

[7] The "within-unit" non-linearity has a centering point for each region fixed effect (regional long-run average of the weather variable, which can be regarded as the "normal" environmental state), whereas "between-unit" non-linearity has only a single centering point across the sample distribution of the weather variable. Despite the temporal scale of used intra-annual weather data, the WSD index and the YA indicator are fairly similar when using linear specifications in fixed effects models. In this instance, the WSD index expresses the departure from the climate norm in region-specific standard deviations (σ), while the YA indicator quantifies the departure in the unit in which temperature is measured (°C).

[8] Due to lack of data before 1990, regions in the eastern part of Germany and overseas territories are excluded from the sample. Furthermore, we drop regions that have limited weather data quality or many missing values in the weather records (e.g. island regions).

[9] We skip the prefix "predominantly" in the further course of the paper to conserve space.

and functional aspects of the cities within specific region types (e.g. global networks, economic specialization, and central command functions). Therefore, a distinction in MEGA (ME) and non-MEGA regions is made for urban and intermediate regions. The definition of MEGA cities is based on the ESPON[10] report (2004), which identifies MEGA cities on the basis of functional specialization (population, accessibility, manufacturing specialization, degree of knowledge, political significance, and distribution of headquarters of international firms).[11] NUTS-3 regions that host a MEGA city are considered as a MEGA region, which results in 52 MEGA regions in our sample. The MEGA regions broadly correspond to the centres of agglomerations which possess outstanding importance in the global network of cities, such as London, Paris, or Madrid (summary statistics of socio-economic variables for each region type are reported in Appendix C). Alternatively, we use the definition of world city formation proposed by Beaverstock et al. (1999) to delimit top-tier city regions.

3.2 Weather data

For weather records, we chose the E-OBS data set from the EU-FP6 project ENSEMBLES and the data providers of the ECA&D project. The high-resolution gridded data set is chosen because of its small grid size and the complex underlying interpolation method (see Haylock et al., 2008). For our analysis, we opt for the smallest possible grid size, 0.25 degree regular grid, of version 11 which covers the years 1960 to 2014. The data we apply are the surface mean temperature and daily precipitation sum. With the complete set of daily grid-data, we calculate the required yearly and monthly data for the operationalization of weather indicators (see section 2.4). For mapping the weather data to the economic data, we compute spatially-weighted averages from respective grids for each NUTS-3 region. As a robustness check, we aggregate grid cell weather data to region-year level via weighting by population density in the year 2000 using data from the Corine Land Cover (Gallego, 2010).

4 Empirical results

4.1 The effect of temperature on regional growth

4.1.1 Rise in temperature level

In the first step, we scrutinize the relationship between rise in yearly average (YA) temperature and economic growth. The functional form of the relationship between rise in temperature and per capita growth is a priori unknown, hence we start with a linear specification and add potential non-linearities in a stepwise procedure. We find no statistically significant linear relationship between temperature and growth (see Appendix D: Table D.1). This is not surprising since, from a theoretical point of view, economic systems should not be (fully) adjusted to very cold

[10] ESPON (European Observation Network for Territorial Development and Cohesion) is a research programme currently on hold and partly financed by the European Commission with the aim is to provide targeted scientific evidence on spatial and territorial processes in Europe.

[11] Two limitations emerge from the used classification of regions: first, the classification is held fixed throughout the sample period; second, regions are classified on the basis of indicators that are collected in the year 2000 because comparable data for the indicators are not available at earlier dates. Nevertheless, we argue that relying on these existing typologies offers important benefits: in contrast to developing an own classification scheme, rather arbitrary assignments and the temptation of data mining are avoided. Moreover, the urban hierarchy of European regions, at least at the top, is characterized by a strong path-dependency in the last decades.

temperatures as well. Once average temperature characteristics, hence climatic conditions, are taken into account, estimation results point clearly to a non-linear response of regional growth. Figure 1 displays the non-linear relationship between yearly average temperature and economic growth including spillover-effects from interlinked regions in the effect size quantification. We find a smooth and concave relationship for temperature with an optimum at 9.2 °C (see Figure 1a).[12] The economic growth of cold regions is enhanced as temperature increases, until the optimum is reached. Growth declines gradually with further warming. The impairment of growth rates accelerates with larger deviations of the regional baseline temperature level from the temperature optimum in both directions. The corresponding marginal effects (slopes of the response function) show that regions with baseline temperature levels above 12 °C (below 6 °C) suffer (benefit) from an additional increase of average temperature in a statistically meaningful way (see Figure 1b). An alternative model specification that interacts the linear temperature term with the long-run average of regional temperature corroborates the findings of the quadratic model as both specifications yield nearly identical results.[13]

As world regions with a warmer climate usually coincide with poorer world regions, it is often argued that the size of temperature effects might depend on income, rather than on average temperature levels, as richer regions might be able to better cope with weather shocks and climate change (e.g. Kahn et al., 2005; Dell et al., 2012). The tendency that colder regions are on average richer is also apparent in our sample of European regions (see Figure 1f). Therefore, we expand the linear model which contains the interaction effect between temperature and regional long-run average temperature and allow a temperature-income interaction to enter in order to exclude a potential composite effect between income and baseline temperature level. Regardless of whether regional or national income is tested, the temperature-growth response is only very modestly affected by income moderations while the growth-diminishing effect of higher baseline temperature levels remains unchanged (see Figure 1c-d).

Regarding the regional interlinkages, ρ and λ are significant at the 1% level in all estimations, indicating that spatial dependencies are present (see Appendix D: Table D.2). Hence, the isolated view on regions might lead to a distortion of estimation results. The total economic effect a temperature rise causes in a region is higher than the coefficient suggests. For instance, roughly 19% of the total temperature effect is attributable to the indirect spatial effect in our baseline model. All in all, the non-linear and concave temperature-growth relationship is robust towards the choice of spatial model specification. While direct temperature effects are stable across alternative spatial models and alternate computation methods of the "Economic Distance" matrix, the size of indirect spillover-effects slightly increases when putting more weight on the distance

[12] Polynomial functions tend to be primarily determined by the center mass of observations and are not very flexible at the tails. Since our observations are rather concentrated around 7–10 °C (see Figure 1e), we test for more flexible specifications that consider local basis functions to model non-linearity. The response functions remain stable when using natural cubic splines (depict as orange lines in Figure 1a).

[13] Specifications that include polynomials to model "between-units" non-linearity use within-region and cross-region variations to identify the effects of temperature. Since both year-to-year variation in weather realizations as well as average climate are considered in those specifications, some aspects of adaptation are captured by allowing the marginal effect to vary with climate (Lobell et al., 2011; Burke et al., 2015). Alternatively, an interaction term between a weather variable and the region-specific long-run level of those variable could be used to test for weather effects that are varying with the baseline weather level. In this case, the identification of weather effects is purely based on within-region variations. The marginal effects of both specifications are plotted in Figure 1b.

penalty, e.g. using an exponential distance decay function in the calculation of "Economic Distance" weights (see Appendix D: Figure D.1).[14]

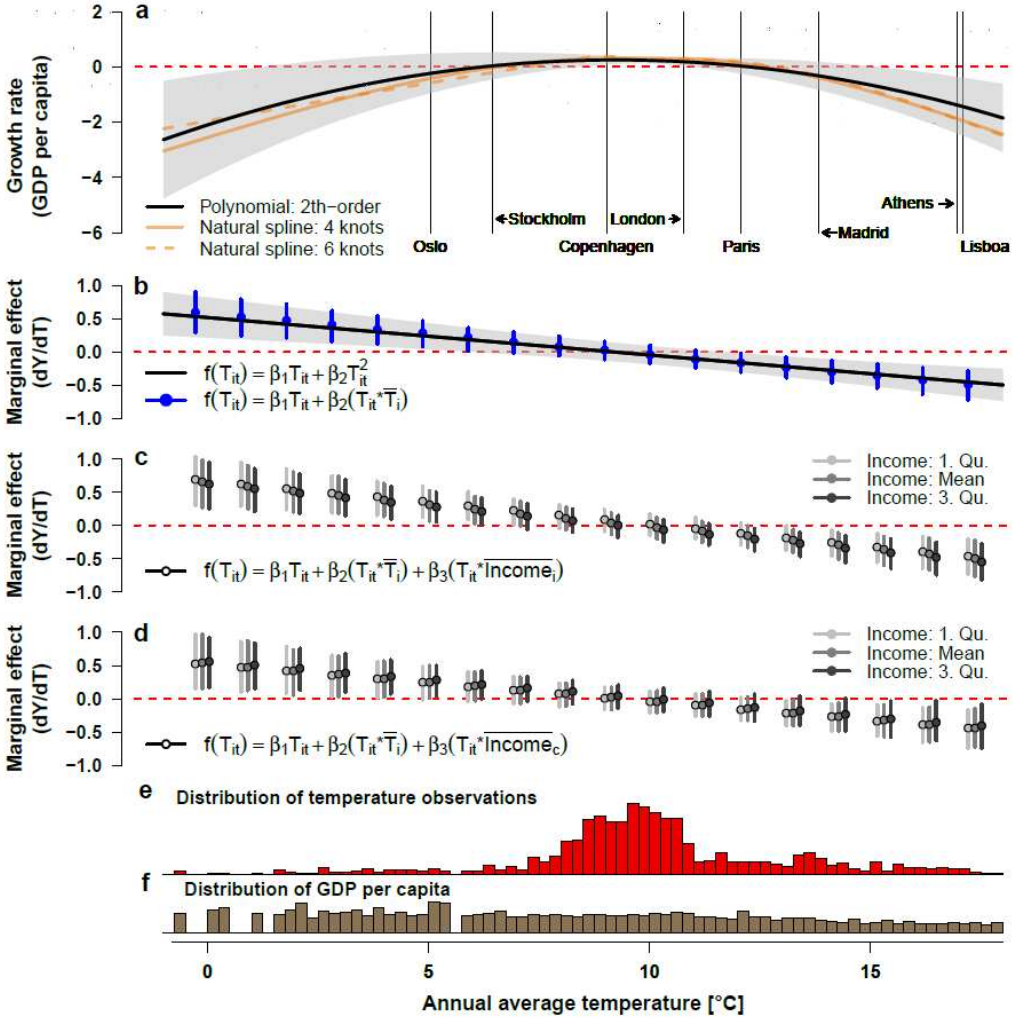


Figure 1: Effect of annual average temperature on regional economic growth.
a) Non-linear relationship between annual average temperature and regional growth of GDP per capita with 90% credible interval (grey). Response function (black line) is calculated on basis of total spatial effects (Appendix D: Table D.1: (2)). Orange lines show responses for alternative forms of non-linearity: natural cubic splines. Vertical lines indicate baseline temperature levels (annual average temperatures) of selected NUTS-3 regions.
b) Black line shows the point estimates for marginal effects of temperature on regional growth for different average temperatures with 90% credible intervals (grey) for the non-linear response function in a). Blue dots indicate point estimates and blue bars 90% credible intervals for marginal effects of temperature evaluated at different average temperatures estimated from a model that interacts temperature in each year with annual average temperature (Table D.1: (3)).
c-d) Grey dots (point estimates for different income levels) and bars (corresponding 90% credible intervals) show marginal effects of temperature on regional growth evaluated at different average temperatures, as estimated from a model that interacts temperature with regional average temperature and regional income in c) and country-level income in d) (Table D.1: (4) and Table D.1: (5)).
e-f) Histograms show distribution of temperature exposure (red) and GDP per capita (brown).

[14] We like to emphasize that apart from the SAR specification which drops the spatially correlated error term, all models are able to remove systematic spatial autocorrelation from the residuals (Moran's I close to zero and statistically insignificant). Thus, the SAR model with "Economic Distance" spatial weights seems inappropriate for our purpose. Regarding the model fit, SARAR specifications are preferable to SAR or SEM specifications (see Appendix D: Table D.2).

Overall, the findings of our spatially disaggregated analysis support the hypothesis that baseline temperature levels determine the response of aggregated production to a change in yearly average temperature. The shape of our regional-level response function corresponds to the shape of the national-level response function found for non-agricultural GDP in rich countries by Burke et al. (2015), which peaks at roughly 10 °C. The detected effect of a rise in temperature level on economic production in our subnational sample is in line with the outcome of spatial theory models developed by Desment and Rossi-Hansberg (2015) that build a complex theoretical framework to elaborate the geographic impacts of global warming as colder regions are the beneficiaries of rising temperature levels which may shift production to the north in the long-run due to comparatively advantageous climatic environments for economic productivity in the course of global warming.[15]

The estimation results are robust to a myriad of robustness tests, including the use of estimation procedures that replace area-weighted weather data by population-weighted weather data, allow for temporal autocorrelation in the dependent variable, and exclude cold regions in Scandinavia (see Appendix D: Figure D.2a). Moreover, we split the regional sample at median income, and we group regions according to whether their income level is above or below the corresponding country-specific income median. For both subsample comparisons, we find similar temperature-growth relationships for both income groups that do not deviate in a noteworthy way from the baseline results (see Figure D.2b). We also find no evidence that the response function is driven by regional responses of one specific country (see Figure D.2c). Lastly, we replace the YA indicator by the WSD indicator in the linear specification that includes an interaction with annual average temperature. Regardless of the used reference period in the computation of the WSD index, we find again that temperature increases are more harmful in regions with higher baseline temperature levels (see Figure D.2d).

4.1.2 Temperature deviations

Unlike the vast body of literature which exclusively investigates the effects of rising temperature levels, we also focus on the potential economic effects of monthly standardized temperature deviations from the historical norm. We proceed in a two-step procedure. First, we disclose the functional form of the anomaly-growth relationship by using the WSD indicator and testing a variety of specifications to model the potentially non-linear response function. Regardless of the used specification to model the within-unit response, temperature deviations within moderate ranges do not affect economic growth, but once critical intensity thresholds are crossed (roughly $\pm 1.75\sigma$), growth rates are rapidly declining with increasing magnitude of temperature deviations from the anticipated weather conditions (see Appendix D: Figure D.3a). Severe anomalies at both tails – indicating either unusually cold or unusually hot years – impede growth at the regional level.

Next, we turn to the moderation effects of average weather conditions. For weather deviations, these conditions might be important since deviations of the same magnitude might have different effects at different average temperature levels. For example, it is conceivable that years with

[15] Spatial shifts of economic production in response to long-lasting changes in temperature levels are likely to be influenced by migration restrictions, constraints of factor mobility, and region-specific adaptation mechanisms. The assessment of production shifts due to rising temperatures is beyond the scope of this paper. However, the documented productivity enhancements originating from a rise in temperature levels in cold regions are likely to trigger the reallocation of production factors to the north.

unusually hot periods are more detrimental if the regional climate is hot rather than cold and vice versa. Therefore, we interact the baseline polynomial specification to model the "within-unit" non-linearity with annual average temperature (see Appendix D: Table D.3).[16] Figure 2 portrays the interdependency between temperature deviations, baseline temperature levels, and GDP growth. The inclusion of temperature level moderation shows clearly that the effect sizes of "within-unit" anomalies are different between regions conditional on the prevailing average weather conditions. Negative deviations from the norm – too cold years – are more harmful to regions that exhibit a low average temperature level, while the opposite holds true for regions that are characterized by a warm climate. The same basic principle is applicable for years with unusually high temperatures as overly hot periods induce higher damage to regions that are endowed with higher temperature levels. For example, adverse effects of severely hot years ($+2\sigma$) become statistically significant only above 10 °C baseline temperature levels, while at an annual average temperature below 7 °C, unanticipated positive deviations exert no significant negative effects on growth (see Figure 2a). This relationship is consistent with the presumption that hotter (colder) regions suffer more strongly from abnormal high (low) temperature realizations.

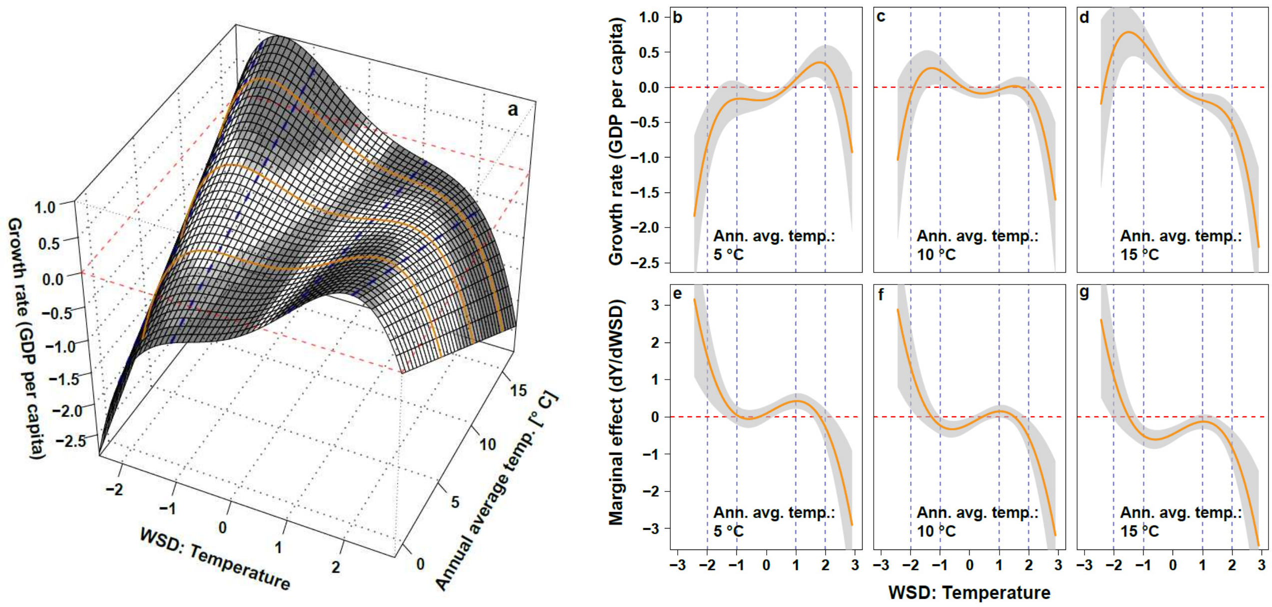


Figure 2: Effect of Weighted Standardized Deviation (WSD) on regional economic growth.
a) Relationship between WSD of temperature and regional growth of GDP per capita moderated by regional climatic conditions (annual average temperature). The WSD is expressed in standard deviations (σ). Black grid lines in 3D plot show response functions depending on annual average temperature levels calculated on basis of total spatial effects (Appendix D: Table D.3: (3)). White areas in the response grid indicate non-significant relationships and grey shaded areas indicate statistically significant relationships at 10% significance level or lower (darker shade represents higher probability that the posterior distribution does not contain zero). Blue dashed lines mark WSD axis tick values for thresholds of moderate and severe anomalies.
b-g) Response functions and corresponding marginal effects for selected manifestations of the moderator variable (displayed as orange lines in panel a). Orange line indicates response function in b-d) and point estimates for marginal effects of temperature anomaly at different intensity levels in e-g) with 90% credible intervals (grey).

A more detailed look reveals that the moderation effect of average temperature does not affect the curvature of the response function. Instead, the response curve rotates approximately clockwise around the anticipated climate norm with increasing baseline temperature levels (see

[16] We opt for the parsimonious model specification reported in column 3 of Table D.3 in Appendix D throughout the subsequent analysis because interactions with higher polynomial terms are statistically insignificant.

Figure 2a-d). As a consequence, the marginal effects of the WSD are shifted downwards when the regional climatic conditions become warmer (see Figure 2e-g). The marginal effects curve is adjusted downwards by roughly 0.05 percentage points in growth with each 1 °C increase in the baseline temperature level. These findings indicate that the role of average temperature conditions to which an economic system is adapted is likewise important irrespective of whether the rise in temperature levels or standardized deviations from the historical temperature norm is under examination. Interestingly, the increase in anomaly intensity of severe anomalies ($\pm 2\sigma$) by one standard deviation, which might likely occur more frequently in Europe in the future due to climate change (see Kharin et al., 2007), causes substantial and statistically significant higher damage at both tails regardless of the prevailing climatic conditions. These results suggest that if severe anomalies become more extreme in the future, the economic damage is likely to increase in all European regions.

Robustness tests show only small discrepancies in response functions when using alternative model specifications (see Appendix D: Figure D.3b). Analogous to the YA temperature set-up, we test whether responses are spuriously driven by income and not by average temperature levels. Again, we find no evidence that income affects the regional response to temperature anomalies (see Figure D.3c-d). Moreover, the structure of the response curve is not largely affected by the use of alternative reference periods in the computation of the WSD (see Figure D.3e), albeit the anomaly distribution is shifted to the right when using earlier periods as reference setting because the study period is warmer, in relative terms, when compared to reference periods in a more distant past. Lastly, the response function is not notably influenced by one specific country (see Figure D.3f).

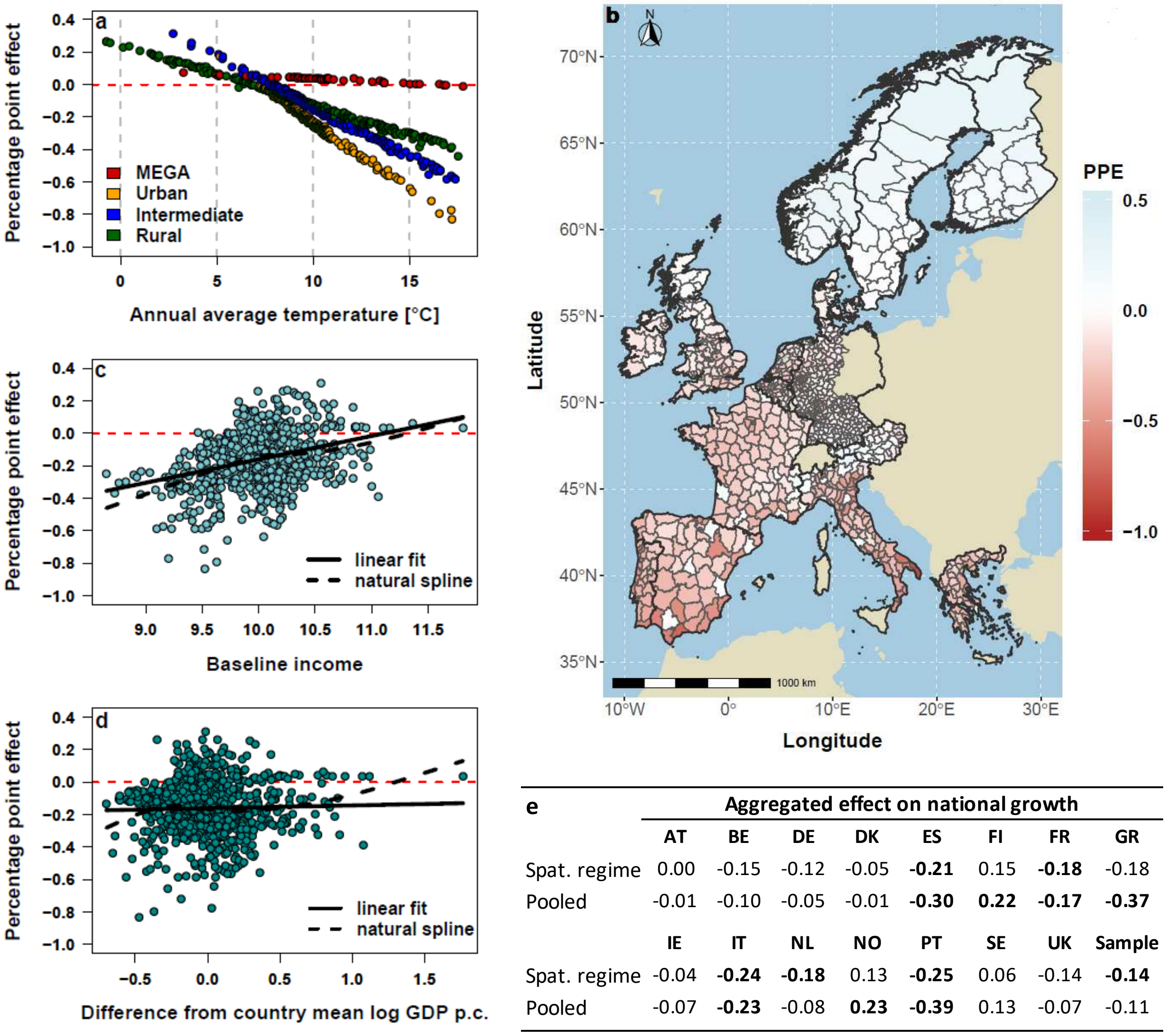
4.2 Heterogeneity in vulnerability across regions

4.2.1 Rise in temperature level

In the next step, we test the hypothesis that the sample-wide concave response function displayed in Figure 1 is generalizable for all regions. We employ an urban-rural classification that is independent of the regional climate environment and captures structural differences between regions including variations in (unobserved) factors that are possibly jointly determined (see section 2.1). Figure 3 summarizes the effects of a uniform 1 °C warming for all sample regions; showing the predicted total impacts on growth rates estimated via spatial panel model with heterogeneous parameters for each region type. We incorporate region-specific spillovers from other regions (spill-ins) because we assume a scenario in which regions warm jointly instead of isolated from each other (global warming). For urban, intermediate, and rural regions, predicted percentage points effects reveal that the positive effect of additional warming by 1 °C decreases with higher annual temperature levels and eventually turns negative above the optimum of the pooled response function (9.2 °C, see Figure 1a).[17] In contrast, an effect on growth is virtually non-existing for MEGA regions at any point of the temperature distribution (see Figure 3a). To test for the significance of these differences in response, we compare the marginal effects based on average scalar measures of total impacts between region types at different temperatures (see Appendix D: Figure D.4). This statistical exercise confirms that marginal effects of MEGA regions differ at conventional significance levels from marginal effects of other region types if baseline temperatures are roughly above 10 °C in the case of urban and intermediate regions, and above

[17] A negative percentage point effect indicates that a region growing at 2% per year in a “normal” temperature year would grow at 1% per year if the temperature were 1 °C hotter.

15 °C in the case of rural regions (Figure D.4: f,i,l); while we cannot reject the hypotheses that the response to a rise in average temperature is the same at any temperature level for pairwise comparisons of non-MEGA region types (Figure D.4: o,r,u).



e	Aggregated effect on national growth							
	AT	BE	DE	DK	ES	FI	FR	GR
Spat. regime	0.00	-0.15	-0.12	-0.05	**-0.21**	0.15	**-0.18**	-0.18
Pooled	-0.01	-0.10	-0.05	-0.01	**-0.30**	**0.22**	**-0.17**	**-0.37**
	IE	IT	NL	NO	PT	SE	UK	Sample
Spat. regime	-0.04	**-0.24**	**-0.18**	0.13	**-0.25**	0.06	-0.14	**-0.14**
Pooled	-0.07	**-0.23**	-0.08	**0.23**	**-0.39**	0.13	-0.07	-0.11

Figure 3: Percentage point effect (PPE) of uniform 1 °C warming.
Percentage point effect of uniform 1 °C warming on regional growth, as estimated using total spill-in effects of the baseline spatial regime model that is differentiated per region types (Appendix D: Table D.4: (1)).
a) Scatterplot of predicted percentage point effect for each region.
b) Map of percentage point effects plotted in a).
c) Percentage point effect plotted against baseline regional income (log of annual average GDP per capita) with linear fit (solid line) and non-linear fit using a natural spline with 4 knots (dashed line).
d) Percentage point effect plotted against difference from country mean log GDP per capita with linear fit (solid line) and non-linear fit using a natural spline with 4 knots (dashed line).
e) Table shows aggregated effects on national growth rates derived from baseline spatial regime model (Table D.4: (1)) and from baseline pooled model (Table D.1: (2)), whereby regional growth effects are weighted by region's annual average fraction of national (sample) GDP. Country-level effects that are significant at the 10% level are displayed in bold.

The resilience of MEGA regions has important implications for spillover-effects. Since regions depend stronger on these economic hubs in our benchmark "Economic Distance" weighting scheme, the growth influencing indirect effects of temperature rise in other regions are largely dominated by the fact that there are no or slightly positive temperature-related spillovers originating from MEGA regions which compensate adverse spillovers from regions that are negatively affected by warming. Hence, the total impact of temperature is primarily determined by the own-region effect, which explains the low scattering of predicted total impacts for regions with similar temperature levels and the same region type (see Figure 3a). We re-estimate the model with alternative specifications of the "Economic Distance" dependency structure. We find that spill-in effects are larger when using an exponential distance decay function and when additionally reducing the weight of the economic mass. As a result, the effect sizes of the total impacts increment by a small amount and predicted total percentage point effects are more diffuse at similar temperature levels which dilutes the differences in effect sizes between non-MEGA regions, but the basic findings remain unchanged (see Appendix D: Figure D.5).

Figure 3b maps the percentage point effects of a 1 °C uniform warming for each region. Regional responses are rather heterogeneous depending on baseline temperature levels (for non-MEGA regions). A north-south gradient is discernible. Additional warming is predicted to increase growth rates by roughly 0.3 percentage points in parts of Northern Europe and to decrease growth by 0.5-0.8 percentage points for non-MEGA regions located in southern Italy, Spain, Portugal, and Greece. Figures 3c and 3d illustrate that an additional warming by 1 °C is going to widen economic inequality between European regions because poorer regions that are disproportionately relatively warm in our sample experience larger adverse effects of warming. However, this relationship can mainly be traced back to income differences between countries rather than within them. Negative percentage point effects decrease only for regions in the upper 2% of the within-country income distribution (see Figure 3d). Nevertheless, the damage of warming in the economic area of the EU-15 is unevenly distributed within countries which makes an essential difference when assessing national effects from the regional estimates (see Figure 3e). Aggregated country-level benefits and damages at the lower and upper tail of the temperature distribution are less pronounced in the regime-specific model than the response function derived from the pooled estimate would imply, because MEGA regions, which are on average accountable for almost 35% of the national production, are unaffected by temperature changes. The disparity in effect sizes between the pooled model and the model with heterogeneous temperature effects is particularly apparent for Greece and Portugal, where roughly 46% of the national production is attributable to MEGA regions.

For the entire sample, the net-effect of uniform warming by 1 °C is a reduction in output growth by 0.14 and 0.11 percentage points depending on the model specification (see Figure 3e). The lower sample-effect in the pooled estimates can be explained by the larger gains of warming in the countries located in the North of Europe that contribute the most to the sample-wide income. The differences between country-level effects derived by the spatial regime model and the pooled model are reduced but not removed when using spatial weights that penalise physical distance more strongly (see Appendix D: Figure D.6). We like to emphasize that the aggregated country-level effects derived from regional estimates show high statistical uncertainties which makes it difficult to develop a general statement about national effect sizes. However, some systematic patterns could be detected. Irrespectively of the configuration of spatial weights, positive effects of warming in Finland, Norway, and Sweden are insignificant in the spatial regime models, while adverse effects in France, Italy, Spain, and Portugal are statistically significant in all model specifications (see Appendix D: Figure D.6).

Overall, the empirical findings indicate that for regions which are generally cooler than the response curve optimum of the pooled estimate (see Figure 1a), the differences in effects of additional warming are statistically not distinguishable between region types, whereas the adverse effects of warming are significantly lower in MEGA regions if regional economies are exposed to relatively high temperature levels as MEGA regions show neither a non-linear response nor negative effects of temperature on economic growth at all. Hence, we can reject the hypothesis that the previously found concave relationship (see Figure 1a) is valid for all regions. Consequently, our results provide empirical evidence in favour of heterogeneous vulnerability and reject the supposition that all regional economic systems are prone to fluctuations in yearly average temperature.

A drawback of the urban-rural typology is that the assignment to a specific region type is held fix throughout the sample period. Aside from a possible transformation of the urban hierarchy at the lower levels over time, we argue that the status and economic relevance of the large city regions at the top of the hierarchy, e.g. London or Paris, are persistent in Europe. Since all non-MEGA regions show roughly the same response to temperature, potential revisions of the classification for these types of regions are not interfering with the interpretation of our main results. With respect to MEGA regions, we test two alternative approaches to define top-tier city regions to verify our findings. First, we employ NUTS-3 regions that host a city that shows evidence of "world city formation" as defined by Beaverstock et al. (1999) to represent city regions that possess outstanding importance in the global network of cities. Second, we employ the classification of metropolitan regions proposed by Dijkstra (2009) to derive two subclassifications to define broader groups of city regions that additionally include centres of smaller agglomerations that constitute hubs within the European or the respective national economy: core regions of capitals and second-tier metropolitan regions, and core regions of all metropolitan regions.[18] Moreover, we test whether regions adjacent to MEGA regions show a similar response as MEGA regions due to potential functional interlinkages. The "world city" regions show nearly the same response to additional warming as our baseline MEGA classification, while the cores of metropolitan regions as classified by Dijkstra (2009) show increasing negative effects of warming at higher temperature levels that are significantly different from the effects found for our baseline definition of MEGA regions (see Appendix D: Figure D.7). Estimation results of broader classifications of top-tier city regions converge to the results of pooled estimates. The effect of the rise in temperature for direct geographical neighbours of MEGA regions is similar to those of non-MEGA regions. The findings of the validation exercise suggest that the economic resilience towards changes in temperature levels is confined to the large city regions at the top of the urban hierarchy, namely MEGA regions respectively "world city" regions.

4.2.2 Temperature deviations

We repeat the analysis with the WSD indicator to evaluate the effects of standardized temperature deviations from the anticipated norm in each region type. We directly apply the model in which the WSD indicator is interacted with annual average temperature since hitherto derived results indicate that baseline temperature levels influence the effects of temperature deviations (see Figure 2). The resulting relationships are plotted in Figure 4 for each region type. The shapes of the responses for MEGA and rural regions at different temperatures depart clearly from those for urban and intermediate regions. The surfaces of the response grids are flatter for MEGA and rural regions. As a result, growth effects do not change much depending on the magnitude of the temperature deviation (intensity of anomaly) or the baseline temperature conditions. MEGA

[18] The group of capital and second-tier metropolitan regions defined by Dijkstra (2009) includes 74 regions (in contrast to 52 MEGA and 40 "world city" regions). The urban classification that additionally includes third-tier metropolitan regions consists of 195 city regions (see Appendix D: Figure D.7).

regions are not systematically affected, the response grid spans around the zero-effect level. Only for a small interval of moderate negative deviations from the norm ($[-1.8\sigma, -1.2\sigma]$), effects on growth are significantly positive for MEGA regions with above 10 °C baseline temperature levels (see Figure 4a).[19] For rural regions, significant effects are mainly found for colder climate conditions (<10 °C). Colder temperatures than usual have negative effects, while warmer ones affect growth positively. For warm baseline temperatures, the pattern is reversed, yet statistical significance is notably weaker (see Figure 4d). All in all, the anomaly-growth relationship disclosed by the pooled estimates – unusually hot (cold) periods are more harmful in hot (cold) climates – holds in an alleviated form for rural regions. The responses of urban and intermediate regions are more similar to those of the pooled estimates, showing basically the same pattern in both region types (see Figure 4b-c). Colder temperatures than expected are associated with significant positive growth effects in regions with warmer usual temperatures (>10 °C), whereas hotter temperatures than expected cause output losses. For cold average temperature levels (<5 °C), the opposite holds true in both region types as positive deviations from the historical norm are beneficial and negative deviations reduce economic performance.

The results of temperature deviations from the anticipated norm corroborate the findings for rise in temperature levels, albeit differences in responses between MEGA and rural regions are less distinct. However, pairwise comparisons suffer from a high degree of uncertainty because the growth-influential years of pronounced deviations from the climatic norm (roughly $\mp 1.75\sigma$) are rare events that on average occur less than three times in a region during the sample period. In addition, statistical uncertainty increases due to sample size reduction through subsampling. Therefore, credible intervals are wide when comparing these severe anomalies which result in a non-rejection of the hypothesis that a respective region type pair has the same response in almost all cases. Only for severe negative anomalies in cold climates, we find that the growth-hampering effects of these anomalies are less pronounced for MEGA and rural regions in a statistically meaningful way (see Appendix D: Figure D.8). In the same way, differences in responses between alternative definitions of top-tier city regions are less distinct when inspecting temperature deviations (see Appendix D: Figure D.9). All alternative classifications to approximate top-tier city regions do not show any statistically significant negative effects of temperature deviations. These findings suggest that the group of regions that exhibit a weaker reaction of economic growth to temperature deviations is not limited to regions that host cities of "world importance" but also includes regions with smaller agglomerations that constitute centres in the European or national network of regions.

In summary, we conclude that both the results for rise in average temperature levels as well as the findings for temperature deviations confirm that the temperature-growth nexus is not homogeneous across regions. Again, the responses to temperature deviations in subsamples that are delimited by the baseline MEGA and "world city formation" definition are only very modestly moderated by baseline temperature levels and effect sizes are in general relatively low for all alternative definitions of top-tier city regions. In contrast, responses of urban and intermediate regions roughly mirror the pooled estimates and show growth-impeding impacts of overly hot and overly cold years conditional on the prevailing climatic conditions. However, all regional subsamples show the common pattern that severe anomalies in the positive direction ($> +2\sigma$) reduce growth rates, albeit the size of the adverse effect differs. This indicates that abnormal

[19] Despite higher effect sizes, more pronounced negative deviations (e.g. -2σ) are statistically insignificant because these weather realizations are rare events which sharply increases the statistical uncertainty. The same phenomenon is apparent at both tails for temperature deviations in rural regions (see Figure 4d).

warm periods beyond a certain threshold impair economic production in some form in all regions. The less distinct responses between alternative definitions of top-tier city regions that do not follow a clear pattern with respect to the number of included regions suggest that the vulnerability in these subsamples of city regions depends less on the position in the urban hierarchy but might instead be determined by (combinations of) region-specific attributes that do not systematically vary between these regional subgroups.[20]

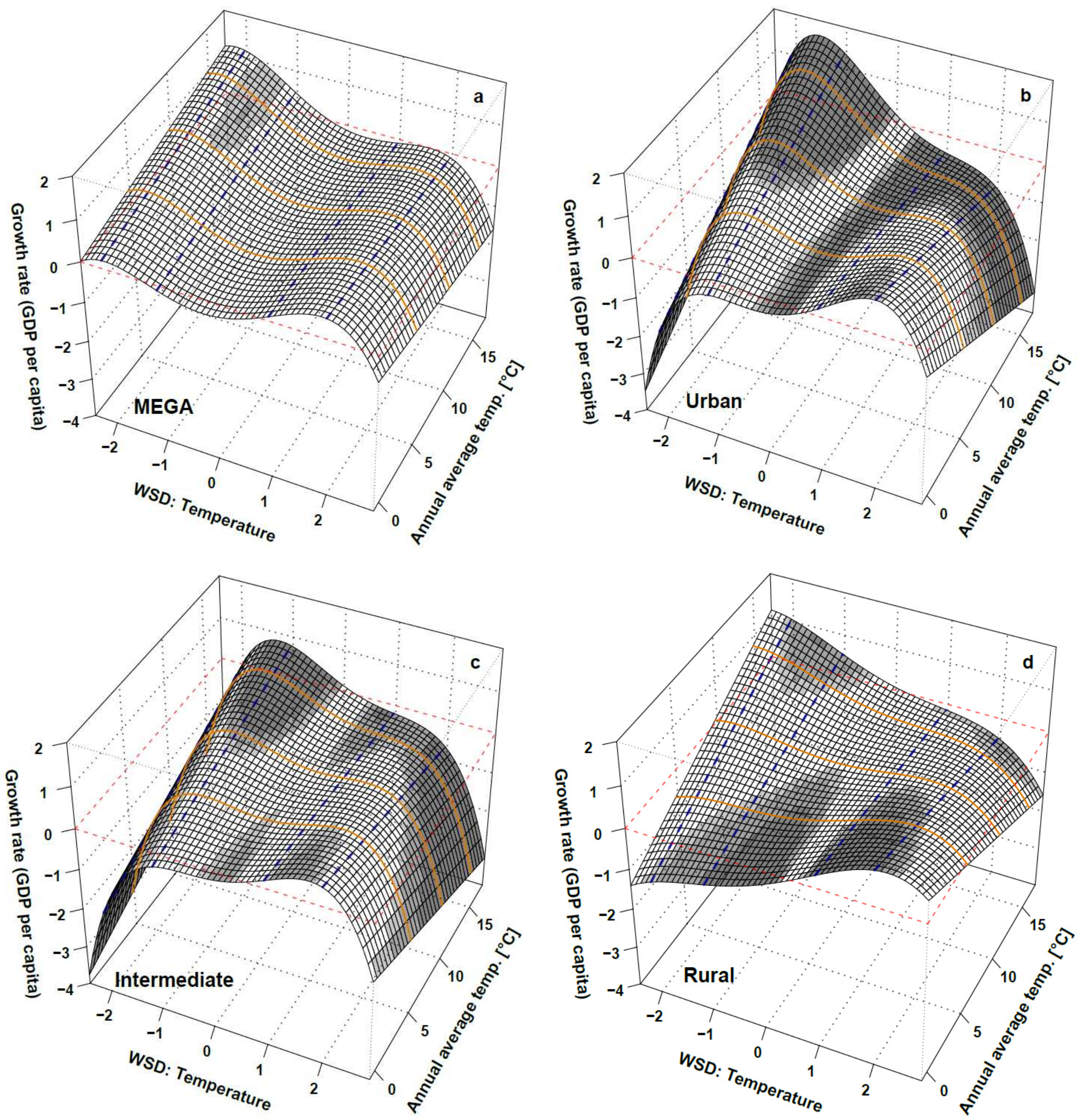


Figure 4: Heterogeneous effects of Weighted Standardized Deviation (WSD) of temperature on regional economic growth.
Non-linear relationship between WSD of temperature and regional growth of GDP per capita moderated by regional climatic conditions (annual average temperature) distinguished by region type. The WSD is expressed in standard deviations (σ). Black grid lines in 3D plot show response functions depending on values of annual average temperature calculated on basis of total spatial effects (sum of direct effects and spill-in effects) estimated via spatial regime SARAR model (Appendix D: Table D.5: (1)). White areas in the response grid indicate non-significant relationships and grey shaded areas indicate statistically significant relationships at 10% significance level or lower (darker shade represents higher probability that the posterior distribution does not contain zero). Blue dashed lines mark WSD axis tick values for thresholds of moderate and severe anomalies.

[20] Due to missing data and an absent identification strategy, we leave this aspect open for future research.

4.3 Components of output growth

4.3.1 Rise in temperature level

In the last step, we are interested in how different sectors react to temperature fluctuations. As region types come along with specific sector structures, different vulnerabilities of sectors might contribute to explain group-specific outcomes. We test if the concave relationship detected for yearly average temperature and aggregated GDP growth can also be found for several components of GDP. To do so, we examine growth rates of gross value-added (GVA) in agriculture, industry, services, and the non-market sector. Figure 5 presents the results. For agricultural and industrial value-added, we find a concave relationship. For baseline temperature levels higher than 13 °C and 10 °C, agricultural and industrial growth suffer from a rise in temperature in a statistically meaningful way (see Figure 5e-f). Although effect sizes are larger for agricultural growth, we like to emphasize that the agriculture sector is only accountable for a small proportion of economic production in Europe (see Appendix C). Contrarily to the growth of agricultural and industrial value-added, the curvatures of response functions are rather flat for services and non-market output growth, showing no signs of significant positive or negative effects over the entire temperature range.

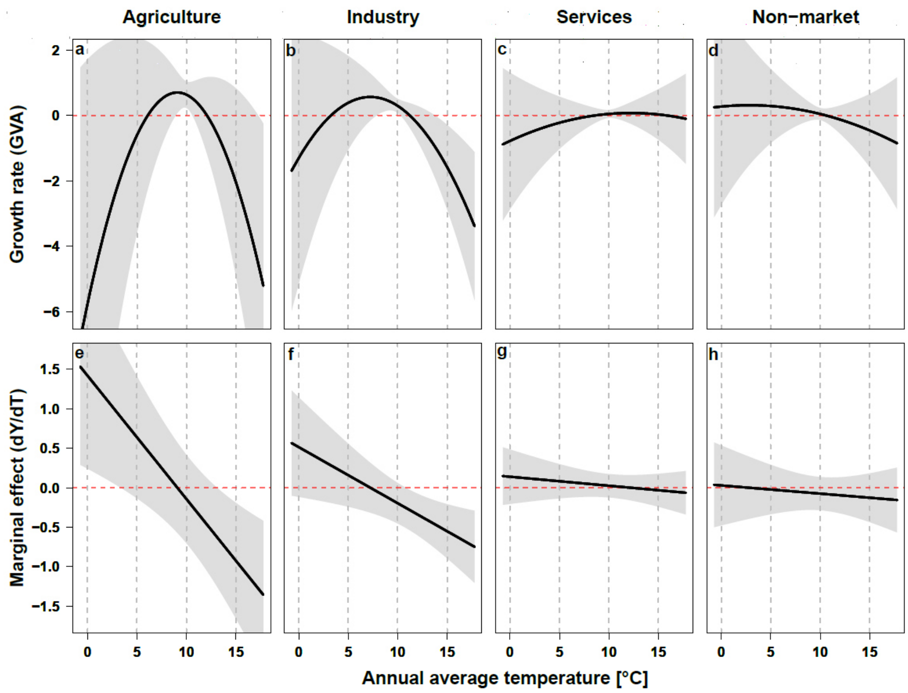


Figure 5: Effect of annual average temperature on components of output growth.
a-d) Non-linear relationships between annual average temperature and growth of gross value added (GVA) for components of aggregated output with 90% credible intervals (grey). Response functions (black lines) are calculated on basis of total spatial effects (Appendix D: Table D.6).
e-h) Black lines show the point estimates for marginal effects of temperature on GVA growth at different average temperatures with 90% credible intervals (grey) for the corresponding non-linear response functions in a-d).

In line with findings in related country-level studies (e.g. Hsiang, 2010; Jones and Olken, 2010; Dell et al., 2012), agriculture and industry are the main sectoral transmission channels through which temperature affects the aggregated economic output. These results go along with our outcome that MEGA regions are not vulnerable to temperature fluctuations. MEGA regions are typically characterized by almost no agricultural production and large shares of services and non-market sector (roughly 75% of total output, see Appendix C). Thus, the invulnerability of the services and non-market sector might partly explain why economic production in MEGA regions is resilient to temperature fluctuations. Nevertheless, it should be mentioned that other regional attributes such as infrastructure specificities, capital intensity, or openness are crucial factors that most likely also play a role in explaining differences in the temperature-growth relationship between region types. Due to data limitations at the used spatial resolution, we constrain the analysis to clearly identifiable net-effects of temperature on sectoral output. These effects provide evidence that the resilience of MEGA regions is fostered by the prevalence of invulnerable sectors.

4.3.2 Temperature deviations

As done for all analytical steps, we repeat the analysis of the GDP components with the WSD indicator. Figure 6 illustrates the results for each sector. Consistent with reactions of sectoral output to the rise in yearly average temperature, the service and non-market sector show only slight responsiveness. If at all, their response grid surfaces are curved “upwards” with increasing intensity of deviations from the anticipated temperature norm following a convex shape. Significant negative effects do not appear. Hence, the invulnerability of the service and non-market sector found for yearly average temperature is also valid for unanticipated temperature deviations. Responses for agricultural and industrial output are more complex. Both response surfaces follow roughly a concave pattern, whereby industrial output shows a reduction in growth rates only in years with severe anomalies ($\mp 2\sigma$). In line with the results of yearly average temperature, agriculture is the most sensitive sector. The moderation effect of the baseline temperature level manifests in the same way as we would expect from our previous results. For all four sectors, we find that for higher average temperature levels positive deviations are more harmful than at lower levels, while the opposite holds true at lower temperature levels.

Overall, the sector-specific effects of temperature deviations correspond to the findings obtained when using the yearly average temperature indicator to evaluate the economic impacts of rise in temperature levels. Again, an advantageous sector structure in MEGA regions explains, inter alia, why economic production in this type of region is not prone to temperature deviations. However, sector-related transmissions of temperature impacts can hardly explain the lower vulnerability of rural regions to temperature deviations (the same tendency, albeit to a lower degree, is also detectable when using the yearly average temperature indicator: see section 4.3.1). The economic performance of rural regions is more reliant on agricultural output and industry shares are on average only slightly below the shares of the other non-MEGA regions (see Appendix C). Hence, rural regions do not exhibit a beneficial sector structure per se. With respect to temperature anomalies, it seems reasonable to assume that other region-inherent factors or interdependencies between sectors play an important role in determining the divergent response of rural regions. Due to the lack of sufficient data, we leave this aspect open for future research.

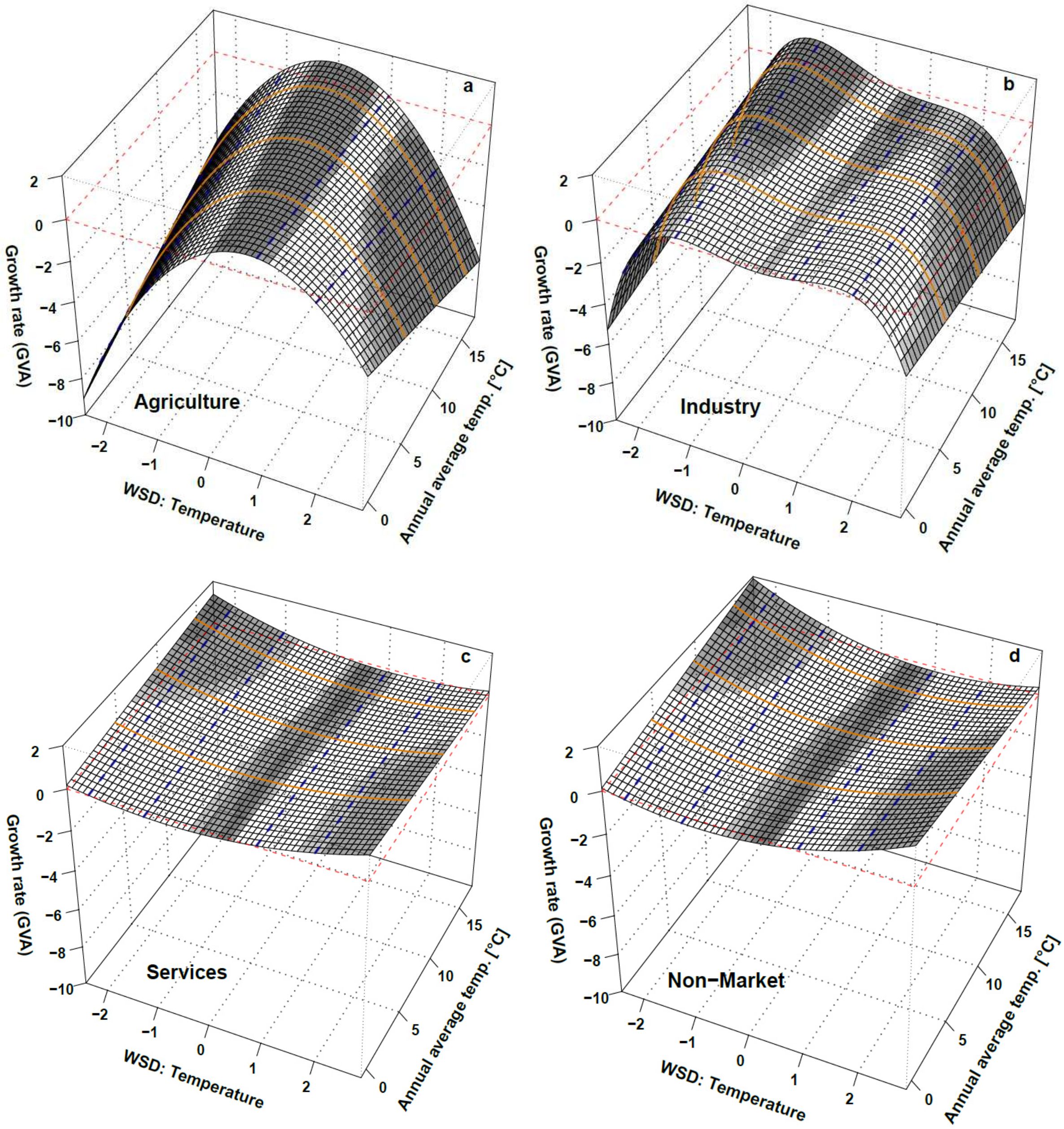


Figure 6: Effect of Weighted Standardized Deviation (WSD) of temperature on components of output growth. Non-linear relationship between WSD of temperature and growth of gross value added (GVA) for components of aggregated output moderated by regional climatic conditions (annual average temperature). The WSD is expressed in standard deviations (σ). Black grid lines in 3D plot show response functions depending on values of annual average temperature calculated on basis of total spatial effects (Appendix D: Table D.7). White areas in the response grid indicate non-significant relationships and grey shaded areas indicate statistically significant relationships at 10% significance level or lower (darker shade represents higher probability that the posterior distribution does not contain zero). Blue dashed lines mark WSD axis tick values for thresholds of moderate and severe anomalies.

5 Conclusion and discussion

In this paper, we conduct a spatially disaggregated analysis of temperature effects on regional aggregates of economic production. We disclose a robust link between temperature and economic growth. Rise in temperature levels and climate variability in the form of standardized temperature deviations from the historical norm induce damage to the macroeconomic output in Europe. Even though warming and the occurrences of severe anomalies cause losses to the aggregated output of the EU-15 economy, temperature effects show heterogeneous patterns within as well as between countries. The spatial heterogeneity of effect sizes poses new challenges for policy actions at different spatial scales to cope with the threat to economic prosperity brought by climate change.

Although yearly average temperature is a rather simple and highly aggregated indicator, we find a non-linear and concave relationship between yearly temperature averages and economic growth. Using a higher spatial resolution of economic activities, the empirical results confirm the "climate condition hypothesis" advocated by Burke et al. (2015) as economic impacts of rise in temperature levels, even in wealthy European economies, depend strongly on the baseline temperature level (climate). The interaction between prevailing climatic conditions and temperature is also a significant moderator of effect sizes when assessing the regional economic impacts of temperature deviations from the climate norm. Warmer (colder) regions suffer more strongly from abnormal high (low) temperature realizations, albeit scenarios in which severe anomalies become more extreme in the future induce damage to all European regions. These findings imply that anomaly intensity thresholds exist for deviations in both directions – overly cold and overly hot years – above which regional growth rates decline disproportionally with further deviations from the anticipated temperature norm.

In contrast to most of the literature, we illustrate that temperature effects are not universally valid; neither for all regions in the sample nor for regions within a country. For both rise in temperature levels and temperature deviations, our results contradict the hypothesis that the response function is generalizable for all (subnational) economic units. Instead, we find differently structured response curves for different region types. Hence, regional economies might be adapted to different optimal temperatures and some regional structures within these economies make them more vulnerable than others. In our sample, top-tier city regions (MEGA respectively "world city" regions) are neither affected by fluctuations in average temperature nor show a sizeable response to temperature deviations from usual weather conditions. As a consequence, our findings provide empirical evidence that a universal temperature-growth response function, as identified by Burke et al. (2015) for countries at a global scale, is no longer valid when shifting the analysis to a lower spatial scale for European regions. These findings suggest that some adaptation possibilities might exist. Since income levels do not moderate the response, the resilience of city regions at the top of the urban hierarchy is not simply driven by the fact that these large city regions are richer but seems to be rather structural. Top-tier city regions are the financial centres of countries and host most of the government functions which results in high shares of the services and non-market sector. The prevalence of these invulnerable sectors fosters the resilience of economic performance towards temperature variations. However, differences in the sector structure between region types are not fully able to explain differences in response. Therefore, it seems likely that other attributes that differ systematically between region types, such as capital intensity, openness, or infrastructure systems, are important factors that determine the vulnerability of regions.

The uneven impacts of temperature at the subnational level have important implications for policy actions. The country-level losses (gains) of additional warming are lower than estimates that neglecting a potential heterogeneity in vulnerability would imply for countries that are exposed to high (low) baseline temperatures levels because the large economic centres (MEGA respectively "world city" regions) are not prone to temperature variations. Since temperature does not affect all regions in a country in the same way, this suggests that policy interventions should be targeted in space and coordinated between national and regional levels of government. If effective adaptation policies are being neglected, a climate change induced rise in temperature levels or anomaly intensity will increase the economic disparity between top-tier city regions and the remaining regions within a country.

Despite the resilience of the top-tier city regions, the effect mechanism that a rise in temperature levels is more harmful in countries with warmer climates is not suspended. Consequently, warming is going to widen economic inequality between European countries since the richer northern countries benefit from temperature upswings while poorer countries in the south are adversely affected by these events. Our empirical results provide no evidence to support the assumption that future economic development will protect against or limit the (regional) impacts of warming. Since the level of economic development does not mediate the vulnerability of economic systems, it is expected that the comparative disadvantage in production conditions arising from warming in the southern regions of Europe will not be reduced if regional disparities might decrease over time, e.g. through convergence processes. Next to human-made shocks, e.g. financial crises such as the "Great Recession" in 2008/2009 that hit regions in Southern European countries harder, changes in environmental conditions must be considered as a threat to economic prosperity in those regions and countries which is likely to exacerbate in the future.

In our spatially disaggregated analysis, we utilise state-of-the-art spatial econometric techniques to test for the presence of spatial spillovers in temperature effects. We detect sizable and highly significant spillovers that facilitate the propagation of temperature effects across space. The uncovering of spatial multipliers of temperature effects indicates that caution should be exercised when interpreting results of studies at the regional level that do not incorporate spatial dynamics. The same holds true for policy interventions. Actions to buffer against warming and temperature anomalies should be coordinated between regions and should take into consideration the temperature effects in neighbouring regions because regional economic activities are often highly interrelated.

Any analysis has its limitations, and we recognise at least three caveats in our approach. First, the applied weather indicators suffer from some limitations. Matching annual weather and annual economic variables relies on strong assumptions regarding the intra-annual distribution of economic activities, e.g. it neglects all kinds of holidays and seasonal fluctuations. Weather impacts might vary with seasons, which is concealed by the temporal aggregation of our indicators. Although the WSD index accounts for intra-annual anomalies, the issue of temporal aggregation could only be completely tackled by higher frequency economic data, which are not available for our regional sample. Second, due to the applied identification strategy that is necessary to isolate the economic effects of temperature changes, our analysis is based on historical data using high-frequency shifts in the climate to ascertain the effects of temperature changes (Hsiang and Burke, 2014; Burke et al., 2015b). This limits the quantitative assessment of the effects of longer-term (gradual) trends of warming. For example, our approach does not fully incorporate long-term adaptation that may occur due to increasing technological progress or because productive units and economic agents adjust their expectations of future climate. Third, our analysis abstracts from a detailed elaboration of transmission channels through which temperature variations affect region types in different ways because required data is missing at the applied spatial resolution. Nevertheless, our study hopefully provides insights that are useful for future work that aims to expose the role of specific transmission mechanisms. The identification of causal mechanisms that drive the uneven impacts at the regional level is essential to understand how the existing patterns of unevenly distributed effect sizes should be valued and possibly counteracted through policy actions. Moreover, the identification of causal effect transmissions is inevitable to evaluate whether intermediate and rural regions can adopt the same mechanisms that promoted resilience in the top-tier city regions.

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Appendix A Literature Review

Study	Indicators (Operationalization)	Empirical findings	Spatial level	Time range	Sample	Methods
Colacito/Hoffmann/Phan (2019): *Journal of Money, Credit, and Banking*	Seasonal temperature averages (however: annual GDP data)	adverse effect of rise in summer temperatures; effect size larger in warm states; "growth effect"	regional	1957-2012	U.S. states	panel models (fixed effects)
Kahn/Mohaddes/Ng/Pesaran/ Raissi/Yang (2019): *Working Paper*	Deviations of temperature from historical norm in both directions (linear: too hot and too cold)	persistent negative effect of temperatures above and below the norm; results are generalizable for all countries and regions; "growth effect"	national & regional	1960-2014	worldwide sample of countries (174 countries) & U.S. states	panel models (fixed effects)
Burke/Tanutama (2019): *NBER Working Paper*	Yearly Averages: rise in level	non-linear response (inverse U-shape); results are generalizable across countries and regions; "growth effect"	regional	varying: depends on country (often more than 20 years)	11,000 districts in 37 countries	panel models (fixed effects): basic spatial models (robustness check)
Acevedo/Mrkaic/Novta/ Pugacheva/Topalova (2018): *IMF Working Paper*	Yearly Averages: rise in level	non-linear relationship: inverse U-shape: cold countries benefit from rise in temperature, while hot countries suffer; non-linear relationship holds for all country groups (advanced economies, emerging markets, low-income countries); "growth effect"	national	1950-2010	worldwide sample of countries	panel models (fixed effects)
Kalkuhl/Wenz (2018): *Working Paper*	Yearly Averages: rise in level	negative impact in temperate and tropical regions and positive impact in cold regions; Findings are generalizable	regional	varying: depends on country (often only a few years)	1,500 regions in 77 countries	panel models (fixed effects)
Burke/Hsiang/Miguel (2015): *Nature*	Yearly Averages: rise in level	non-linear relationship: inverse U-shape: cold countries benefit from rise in temperature, while hot countries suffer; global uniform non-linear response function for all countries; "growth effect"	national	1960-2010	worldwide sample of countries	panel models (fixed effects)
Deryugina/Hsiang (2014): *NBER Working Paper*	Yearly Averages: rise in level	effect size is relative to county´s optimal annual temperature: negative net-effect in most of the warm counties; "growth effect"	regional	1969-2011	USA: counties	panel models (fixed effects)
Brenner/Lee (2014): *Working Paper*	Yearly Averages: rise in level	negative effect of rising temperature levels: but only in countries with high heat index	national	1991-2010	worldwide sample of countries	panel models (fixed effects)
Dell/Jones/Olken (2012): *American Economic Journal: Macroeconomics*	Yearly Averages: rise in level	negative effect of rising temperature levels: but only in developing ("poor") countries; "growth effect"	national	1950-2005	worldwide sample of countries	panel models (fixed effects)

Appendix B Methods

B.I Spatial dependencies

In general, one could argue that the isolated view of economic units in panel regressions is disputable. Due to the strong international interconnections of our modern economic systems, shocks of all kinds of forms might spill over to other countries in some way. In the context of our empirical examination, it is particularly important to consider spatial effects as we focus on small-scaled regions rather than countries that are usually strongly dependent on each other economically. Neglecting this dependence might lead to a misspecified model in cases where these interconnections have a significant influence on economic development (Conley and Ligon, 2002; Fingleton and Palombi, 2013).

Due to our empirical set-up, we face several issues that we have to take into account. The spatial dependence of the weather might become a problem if relevant weather variables are neglected by the model (Auffhammer et al., 2013). Since these omitted processes (e.g. atmospheric pressure or wind speed) are likely to be highly correlated in space, they might lead to a spatially correlated error term as it catches the effect of the missing variables. Since we cannot assume that we have taken into account all relevant variables determining the weather by including temperature and precipitation, a potential spatial correlation of the error term has to be considered. The methodological issue regarding the omitted variables bias is further enhanced by the underlying regional level of the empirical analysis. Due to the administrative character of NUTS-3 regions, the spatial scale of "functional economic units" is not congruent with the spatial scale of regions under investigation. Unsystematic regional effects that driving economic performance are likely to be highly interrelated in neighbouring regions (Fingleton and Palombi, 2012). Clustering errors in groups, as it is often done in panel studies (e.g. Dell et al., 2012; Fischer et al., 2012), might not be an appropriate option for spatial correlation here. The usual assumption of equicorrelated errors within clusters and abrupt termination of correlation between clusters appears less feasible when dealing with geographically small-scaled regions. For example, the spatial correlation of the weather does not follow administrative borders but diffuses with distance or follows geographic barriers like mountains or oceans.

Next to unsystematic dependencies modelled through the spatially correlated error term, we also account for growth spillover-effects from "economic neighbours". The implementation of the spatial autoregressive process in the dependent variable abrogates the assumption that region-level weather shocks occur in isolation but allows impacts of contemporaneous weather events in neighbouring regions to spill over. It is important to consider such growth effects that arise outside the own economic system because otherwise the risk of underestimating the total effect size of weather impacts on growth is enhanced since indirect impacts are neglected. In particular under a scenario of heterogeneous weather effects between region types, the total weather effect depends, to a certain extent, on the composition of neighbours and their vulnerabilities as well as on the strength of spillovers which increase with the degree to which the own regional growth depends on the growth of interrelated regions. We refrain from including spatial lags of weather variables as additional explanatory variables because the inclusion would lead to a severe multicollinearity problem (variance inflation factors > 100 due to the extensive spatial autocorrelation of weather indicators). Furthermore, theoretical reasons plead against such a modelling procedure. For our sample of European regions, it is more realistic to consider the economic situation as a whole since weather effects in one region should not "directly" influence another region's GDP without (first) affecting its own GDP. Otherwise, one would ignore the reaction/capability of the affected region to cope with the weather shocks. Thus, we assume that weather events in "neighbouring" regions have no direct effects on the economic performance of a region, but effects might be transmitted between regions via interlinkages in economic activities (interdependence in the dependent variable: economic growth). We refrain from direct cross-dependences of weather for two further reasons. First, yearly weather conditions are almost the same in nearby regions due to the high spatial autocorrelation of weather (average Moran´s I of yearly temperature (precipitation) in contiguous regions: 0.92 (0.81)). Therefore, it is unrealistic that economic production is shifted to "neighbouring" regions as a direct consequence of yearly weather shocks because these shocks diverge only slightly between "neighbouring" regions. Second, empirical evidence at the micro-level does not reveal any factor reallocation in response to weather shocks in highly developed economic systems (Deryugina and Hsiang, 2014).

These considerations lead us to so-called spatial panel models which, instead of only controlling for spatial autocorrelation, directly model spatial processes by including spatially weighted variables of other regions (Anselin, 1988; Baltagi et al., 2003). Spatial panel models include a spatial lag of the dependent variable and/or a spatial lag in the error term to deal with spatial dependencies between regions (see section 2.2). In a simplified scheme, one can think of the model with a spatially lagged dependent variable as analogous to an autoregressive time series model where serial correlation is addressed by including a temporal lag in the dependent variable. Spatial econometric techniques incorporate spatial lags in each cross-section of the panel to consider spatial dependence between own region and "neighbouring" regions. The respective spatial weighting schemes that model the interdependencies between spatial units can be specified in various ways. A drawback of spatial econometric models is that in the absence of knowledge about the true process of regional interdependence, the spatial weights must be determined by the researcher. Yet, it should be mentioned that newly published research on this topic emphasize that estimates are less sensitive to the choice of spatial weights structure than generally believed (LeSage and Pace, 2014). As the correlation of weather and unsystematic regional interlinkages decline with distance and spillover effects decrease with the order of neighbours, we employ a simultaneous autoregressive specification of spatial processes. This global nature of regional dependencies puts the highest weights on direct neighbours and implies that neighbours are neighbours to neighbours, neighbours to neighbours to neighbours, and so on. Comparisons of the goodness of model fit (see Appendix D: Table D.2) strongly recommend including both sources of spatial dependencies – the spatial correlation in the dependent variable and spatially correlated disturbances – into the panel model (so-called Spatial Autoregressive Autoregressive Model: SARAR). To check the sensitivity of our results, we also run estimations that either contain only the spatial correlation in the dependent variable (so-called Spatial Autoregressive Model: SAR) or the spatial error term (so-called Spatial Error Model: SEM).

B.II Calculation of scalar summary measures for spatial impacts

LeSage and Pace (2009) propose scalar summary measures of the own- and cross-partial derivatives which they labelled direct impacts, indirect (spillover) impacts, and total impacts. As noted by Elhorst (2010), in static panel models the spatial multiplier is independent of the time index, thus the partial derivatives simplify to those in cross-section models:

$$\frac{\partial Y}{\partial X^{z}} = \begin{pmatrix} \frac{\partial y_1}{\partial x_1^z} & \cdots & \frac{\partial y_1}{\partial x_N^z} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_N}{\partial x_1^z} & \cdots & \frac{\partial y_N}{\partial x_N^z} \end{pmatrix} \tag{B.1}$$

$$\frac{\partial Y}{\partial X^{z}} = S^z(W) = \left(I_N - \begin{pmatrix} \rho & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \rho \end{pmatrix} W \right)^{-1} \begin{pmatrix} \beta^z & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \beta^z \end{pmatrix} \tag{B.2}$$

where X^z denotes a certain covariate and β^z the corresponding coefficient (vector of length N). $S^z(W)$ is a matrix $(N \times N)$, where a change in any region´s zth covariate exerts impacts on the own-region outcome (direct impact) and potentially on the outcome of all other regions (indirect impact). The effect size of the indirect impact depends on the level of spatial dependence ρ and the magnitude of β^z. The main diagonals of the matrices (B.1) and (B.2) represent own-partial derivatives $(\partial y_i/\partial x_i^z)$ showing how a change in the zth explanatory variable directly impact each region's outcome (y_i), while the off-diagonal elements are cross-partial derivatives $(\partial y_i/\partial x_j^z)$ showing the spatial spillover impacts from neighbouring regions on the outcome of region i. In the case of a homogeneous coefficient $(\beta_i^z = \beta^z)$, the average of the main diagonal elements of $S^z(W)$ can be used as a scalar summary measure of own-region effects (average direct impact) and the cumulative sum of the off-diagonal elements from each row (or column), averaged over all rows (or columns) are the scalar summary measure for spillover effects from other (to other) regions (average indirect impact). However, in the case of homogenous coefficients, averaging over all rows or all columns will give the same result (spill-in = spill-out). Since we a primarily interested in the total damage/benefit caused by a weather event in a given region, our interpretation of estimation results is consistent with the "to an observation" approach described in LeSage and Pace (2009): the weather shock occurring in neighbouring regions is transmitted via interlinkages in growth from those regions to region i, which is the same as a spill-in effect. The average total impact is the sum of the average direct and average indirect impact. In the case of a row-standardized spatial weights matrix, summary measures of spatial impacts can be derived as proposed by LeSage and Pace (2009):

average direct impact: $$\bar{M}(z)_{direct} = N^{-1} tr\big(S^z(W)\big) \tag{B.3}$$

average total impact: $$\bar{M}(z)_{total} = N^{-1} \iota_N S^z(W) \iota_N \tag{B.4}$$

average indirect impact: $$\bar{M}(z)_{indirect} = \bar{M}(z)_{total} - \bar{M}(z)_{direct} \tag{B.5}$$

When dealing with discrete regimes for region types in our model, a slight modification of the calculation of spatial impacts is necessary, because the coefficients β^z and ρ are now heterogeneous. β^z becomes β_r^z and varies with each regime r as the weather effects are now distinct for each spatial regime (region type). The same applies for ρ as the coefficient that measures the strength of spillovers is now group-specific, hence ρ_r. To account for heterogeneous effects in potential neighbouring regions, expression (B.2) is modified to:

$$\frac{\partial Y}{\partial X^{z}} = S_r^z(W) = \left(I_N - \begin{pmatrix} \rho_r & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \rho_r \end{pmatrix} W \right)^{-1} \begin{pmatrix} \beta_r^z & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \beta_r^z \end{pmatrix} \tag{B.6}$$

Note that the coefficient values of ρ_r and β_r^z on the main diagonals in Equation (B.6) depending on the spatial regime to which an observation belongs. Instead of averaging over the full main diagonal of $S_r^z(W)$, the average direct impact for each spatial regime is the average of diagonal elements belonging to the specific spatial regime. To produce estimates of average indirect impacts for each spatial regime, we follow LeSage and Chih (2016) and use the cumulative sum of off-diagonal elements in rows of $S_r^z(W)$ belonging to a specific group to derive regime-specific indirect spill-in effects ($\partial y_{ir}/\partial x_j\ , j \neq i$). Similarly, we calculate regime-specific indirect spill-out effects by using regime-specific columns in $S_r^z(W)$ instead of rows ($\partial y_j/\partial x_{ir}\ , j \neq i$). In contrast to homogenous coefficients, averaging over rows or columns delivers different results. In particular when "Economic Distance" is used as spatial weights matrix, most of the regions are to a higher degree linked to MEGA and urban regions due to their higher economic size. As a result, the elements in rows of $S_r^z(W)$ are not necessarily the same as in columns. This does not make a difference when averaging over all regions (and thus over all rows or columns) as in the case of homogenous coefficients, but with spatial regimes, we only averaging over regions that belong to the same regime. As the effect of weather on growth might vary due to heterogeneous coefficients for each regime, it becomes important which regions are influenced by the regions of a specific regime (spill-out) and which regions affect the regime-specific regions (spill-in). We are primarily interested in the sum of direct effects and spill-in effects to quantify the total weather impact on growth in each spatial regime (region type).

B.III Estimation procedure and Bayesian update schemes

Allowing for spatial autocorrelation in the dependent variable and/or disturbances leads to inconsistent estimates of regression parameters and standard errors when using OLS. Often in the literature, Maximum Likelihood (ML) or General Methods of Moments (GMM) techniques are applied to estimate spatial regression models (e.g. Lee, 2004; Kelejian and Prucha, 1998). We refrain from those approaches for two main reasons: first, the usage of heteroscedasticity-consistent standard errors in the ML set-up for models with spatial autoregressive processes in the dependent variable is questionable due to the spatial correlation in the variance-covariance matrix; second, the GMM approach requires covariates that are spatially uncorrelated as instrument variables, something that is not given by our weather variables that are highly correlated in space. Instead, we rely on a full Bayesian approach. In Bayesian inference, given the data, the main interest lies in learning about the distribution of the unknown parameters (posterior distributions). Since an analytical solution for our models is not possible, we proceed with sampling techniques based upon Markov Chain Monte Carlo (MCMC) methods in our panel model (Chib, 2008). We employ a Metropolis-within-Gibbs approach (Geweke and Kaene, 2001) to solve the endogeneity problem at hand caused by what Manski (1993) termed "endogenous reflection problem". Model estimates were based on an MCMC sample of 110,000 iterations collected after a burn-in period of 10,000 draws. In order to decrease autocorrelation in the Markov chains, the chains were thinned by storing every 10th draw. The posterior distributions are summarized to obtain point estimates (mean of posterior), standard errors (standard deviation of posterior), and Bayesian credible intervals (5th percentile and 95th percentile of posterior). We apply convergence diagnostics proposed by Gelman and Rubin (1992) and Geweke (1992) to check the convergence of Markov chains.

For the sake of simplicity, $f_r^1(T_{it}) + f_r^2(P_{it})$ in Equation (1) is replaced by $x_{it}\beta$ and balanced panel data are stacked by regional units.[i] Hence our SARAR panel model can be expressed in matrix notation as follows:

$$y = ((D\rho_r W)\otimes I_T)y + X\beta + (\mu\otimes\iota_T) + (\iota_N\otimes\nu) + u \tag{B.7}$$

$$u = \lambda(M\otimes I_T)u + \varepsilon$$

$$\varepsilon = N(0, \sigma^2 V^{-1})$$

$$V = \mathrm{diag}(v_{i=1}, \dots, v_{i=N})\otimes I_T$$

with y as a $NT \times 1$ vector of the dependent variable, X as a $NT \times Z$ matrix of annual observations of the explanatory weather indicators, and u as the $NT \times 1$ error vector. Observations are stacked by successive years $t = 1, \dots, T$ for each region $i = 1, \dots, N$. μ is a $N \times 1$ vector of individual fixed effects and ν is a $T \times 1$ vector of time fixed effects with ι as a vector of ones whose dimension is denoted by the subscript. W and M are the spatial weights matrices ($N \times N$) and I_T is an identity matrix of dimension T used in combination with the kronecker product to expand the time-invariant cross-sectional spatial weights to full (panel) spatial weights. β denotes the regression coefficients ($Z \times 1$ vector), ρ_r is a vector $(R \times 1)$ containing the regime-specific coefficients measuring the spatial dependence of the dependent variable for each region type, and λ is a scalar parameter quantifying the strength of spatial interaction effects involving the disturbances. D is a $(N \times R)$ indicator matrix with dummy variables in each column to indicate if an observation belongs to a specific regime, e.g. the first column is equal to one if a region belongs to the first region type group and zero otherwise. $D\rho_r$ assigns the corresponding regime-specific ρ_r to each cross-sectional observation. In the case of a homogenous coefficient for the spatial dependence of the dependent variable, $D\rho_r$ collapses to a vector $(N \times 1)$ with unitary values $(\rho_r = \rho)$. ε is a $NT \times 1$ idiosyncratic error vector, modelled as distribution that belongs to the scale mixture of the normals family (Geweke, 1993). σ^2 is a positive unknown scale parameter and V is a $NT \times NT$ diagonal matrix containing v_i random scale parameters that are drawn independently across regions from the gamma distribution. This indicates that the specification of unknown form of heteroskedasticity has a constant component σ^2 and a component v_i that varies across regions (clustered by regions). Marginalizing the distribution of ε_i over v_i corresponds to the multivariate t-distribution (Chib, 2008). The hyperparameter τ controls the thickness of the tails in the error distribution and is a free parameter in our model (degrees of freedom). Small estimates for τ would result in a thick-tailed error distribution and indicate heteroscedastic disturbances, whereas large estimates for τ would result in nearly identical variance scalars for all regions and thus favour homoscedastic disturbances (Koop et al., 2007).

Bayesian inference is based on the joint posterior distribution of the parameters given the data. The unnormalized form of the posterior of our model is derived as:

$$p(\beta, \sigma^2, \rho_r, \lambda, v_i, \tau|y) \propto p(y|\beta, \sigma^2, \rho_r, \lambda, v_i, \tau) \times p(\beta)p(\sigma^2)p(\rho_r)p(\lambda)p(v_i|\tau)p(\tau) \tag{B.8}$$

where $p(y|.)$ is the likelihood function and $p(.)$ represents the prior distributions. The joint posterior distribution is analytically intractable but MCMC methods such as the Gibbs sampler

[i] Note the panel is stacked by regions $(y_{i=1,t=1}, y_{i=1,t=2}, \dots, y_{i=2,t=1}, y_{i=2,t=2}, \dots, y_{i=N,t=T})$ and not by cross-sections as often seen in textbooks.

(Casella and Edward, 1992; Geman and Geman, 1984) and the Metropolis-Hastings (M-H) algorithm (Chib and Greenberg, 1995; Hastings, 1970) can be used to generate sequential samples from the complete set of conditional posterior distributions.

First, we follow Lee and Yu (2010) and apply a transformation approach to eliminate fixed effects from the model. This simplifies the complexity of the estimation procedure. Fixed effects can be eliminated from panel models by taking deviations from the time and cross-section means. Therefore, we make use of the time mean operator $J_T = (I_T - \frac{1}{T}\iota_T\iota_T')$ to eliminate the individual fixed effect from each region and the cross-section mean operator $J_N = (I_N - \frac{1}{N}\iota_N\iota_N')$ to eliminate time fixed effect for each year. $Q_N = J_N \otimes I_T$ and $Q_T = I_N \otimes J_T$ denote the expanded mean operators in the panel data set-up and eventually $\ddot{y} = y - Q_T y - Q_N y + \bar{y}$ is the demeaned dependent variable.[ii] In the same way, the fixed effects are eliminated from the exogenous variables. The likelihood function is given by:

$$p(y|\beta, \sigma^2, \rho_r, \lambda, v, \tau) = (2\pi\sigma^2)^{-NT/2}\, |A|^T\, |B|^T\, |V|^{-0.5} \times \exp\{-0.5\, e(\sigma^2 V)^{-1} e\} \qquad \text{(B. 9)}$$

$$e = (B \otimes I_T)(A \otimes I_T)\ddot{y} - (B \otimes I_T)\ddot{X}\beta$$

$$A = I_N - \Psi W$$

$$B = I_N - \lambda M$$

$$\Psi = \text{diag}(\psi_{i=1}, \dots, \psi_{i=N})$$

$$\psi = D\rho_r$$

Ψ is a diagonal matrix $(N \times N)$ containing the assigned regime-specific ρ_r for each region i as diagonal elements. $|A|$, $|B|$ and $|V|$ are determinants of the matrices.

The prior distributions for model parameters must be predefined in the Bayesian approach. To ensure a proper joint posterior distribution, only proper prior distributions are used. We assume that prior distributions are independent.

$$p(\beta) \sim N_Z(\beta_0, S_\beta^{-1}) \qquad \text{(B. 10)}$$

$$p(\sigma^2) \sim IG\left(\frac{a_0}{2}, \frac{b_0}{2}\right)$$

$$p(\rho_r) \sim U\left(\frac{1}{\varpi_{min}^W}, \frac{1}{\varpi_{max}^W}\right)$$

$$p(\lambda) \sim U\left(\frac{1}{\varpi_{min}^M}, \frac{1}{\varpi_{max}^M}\right)$$

$$p(v_i|\tau) \sim G\left(\frac{\tau}{2}, \frac{\tau}{2}\right)$$

[ii] The same can be expressed in sum notation as follows: $\ddot{y}_{it} = y_{it} - y_{i.} - y_{.t} + y_{..}$ with $y_{i.} = \frac{1}{T}\sum_{t=1}^T y_{it}$, $y_{.t} = \frac{1}{N}\sum_{i=1}^N y_{it}$ and $y_{..} = \frac{1}{NT}\sum_{i=1}^N \sum_{t=1}^T y_{it}$.

$p(\tau) \sim E(\tau_0)\mathrm{I}(2, \infty)$

$N(\beta_0, S_\beta^{-1})$ is the multivariate normal density function with mean β_0 and variance S_β^{-1}, $IG\left(\frac{a_0}{2}, \frac{b_0}{2}\right)$ is the inverse gamma density function with the shape parameter $\frac{a_0}{2}$ and the scale parameter $\frac{b_0}{2}$. $U\left(\frac{1}{\varpi_{min}^W}, \frac{1}{\varpi_{max}^W}\right)$ and $U\left(\frac{1}{\varpi_{min}^M}, \frac{1}{\varpi_{max}^M}\right)$ are uniform distribution functions in the interval of the reciprocal of the minimum eigenvalue and maximum eigenvalue of the spatial weights matrices W and M. The uniform priors within a limited range for the spatial parameters ensure that the spatial process is stationary (LeSage and Pace, 2009). The gamma density function for parameter v_i is a hierarchical prior, because v_i depends on the hyperparameter τ, which has its own prior distribution. $E(\tau_0)I(2, \infty)$ is a truncated exponential prior with possible values ranging from 2 to infinity. Truncation of the degrees of freedom is necessary to avoid that the variance of the t-distribution is undefined. Since we have no information from historical data on the parameters of interest, the prior distributions of β and σ^2 are quasi non-informative and make vague probabilistic statements: $\beta_0 = 0$, $S_\beta = 10^{12}$, $a_0 = 10^{-6}$, $b_0 = 10^{-6}$. We set the prior for hyperparameter τ to a value that allocates prior weights to both very fat-tailed error distributions (e.g., $\tau_0 < 10$) as well as error distributions that are roughly normal (e.g., $\tau_0 > 40$): $\tau_0 = 25$.[iii]

Conditional (on the other parameters) posterior distributions are required to obtain random draws (simulated sample) for each parameter via MCMC techniques. The posterior distribution for β conditioned on the other parameters is given by:

$$p(\beta | y, \sigma^2, \rho_r, \lambda, V) \sim N_Z(\beta^*, C^*) \tag{B.11}$$

$$\beta^* = B\ddot{X}(\sigma^2 V)^{-1} BA\ddot{y} + S_\beta^{-1}\beta_0$$

$$C^* = (B\ddot{X}(\sigma^2 V)^{-1} B\ddot{X} + S_\beta^{-1})^{-1}$$

where B and A are defined as in Equation (B.9) and $\ddot{X}$ and $\ddot{y}$ denote the demeaned values (see above). The conditional posterior distribution of σ^2 is given by:

$$p(\sigma^2 | y, \beta, \rho_r, \lambda, V) \sim IG(a^*, b^*) \tag{B.12}$$

$$a^* = \frac{a_0 + NT}{2}$$

$$b^* = \frac{b_0 + e' V^{-1} e}{2}$$

where e is the residuals vector. The conditional posterior distributions for the spatial parameters are of unknown form, hence we use the M-H approach to draw samples:

$$p(\rho_r | y, \beta, \sigma^2, \lambda, V, \rho_{-r}) \propto |A||\tilde{B}| \times exp\left\{-0.5(\tilde{B}A\ddot{y} - \tilde{B}\ddot{X}\beta)'(\sigma^2 V)^{-1}(\tilde{B}A\ddot{y} - \tilde{B}\ddot{X}\beta)\right\} \tag{B.13}$$

$$p(\lambda | y, \beta, \sigma^2, \rho_r, V) \propto |\tilde{A}||B| \times exp\left\{-0.5(B\tilde{A}\ddot{y} - B\ddot{X}\beta)'(\sigma^2 V)^{-1}(B\tilde{A}\ddot{y} - B\ddot{X}\beta)\right\} \tag{B.14}$$

[iii] As robustness checks, we use alternative prior specifications. Estimation results are neither affected by reducing the variance in the normal prior for β nor by setting $\tau_0 > 40$ to indicate beliefs that the error distribution is homoscedastic.

with $\rho_r = (\rho_{r=1}, \dots, \rho_{r=R})$ and ρ_{-r} denotes all elements in ρ_r excluding the element r. The conditional posterior for ρ_r takes the form in Equation (B.13). We hold the other elements in ρ_r constant when updating element r. We proceed the same way when updating the other spatial parameter λ: $\tilde{A} = A(\rho_r^c)$ and $\tilde{B} = B(\lambda^c)$, where c denotes that we hold the spatial parameter constant in the update of the other spatial parameter and rely on the current value of this parameter. For example, when sampling for the spatial parameter ρ_r we use the current value of λ in $|B|$. Similarly, we use the current values (not updated values) of ρ_r in $|A|$ when sampling λ (LeSage and Pace, 2009). This procedure simplifies the update scheme since M-H sampling for each spatial parameter can be executed under the assumption that the other spatial parameters do not exist. The density of the conditional posterior distribution for v_i takes the form:

$$p(v_i | y, \beta, \sigma^2, \rho_r, \lambda, \tau) = G(v^*, \kappa^*) \tag{B.15}$$

$$v^* = \frac{\tau + T}{2}$$

$$\kappa^* = \frac{\tau + \sigma^{-2} e_i' e_i}{2}$$

where v_i is a region-specific scale parameter and e_i is the region-specific residuals vector. Since all regions have the same number of observations in the balanced panel, the number of region-specific observations in v^* is equal to T. The conditional posterior distribution of the hyperparameter τ is given by:

$$p(\tau | y, \beta, \sigma^2, \rho_r, \lambda, v_i) \propto \left(2^{\frac{\tau}{2}}\, \Gamma\left(\frac{\tau}{2}\right)\right)^{-N} \tau^{\frac{N\tau}{2}} \times exp\left\{-\frac{\tau}{2}\left[\sum_{i=1}^{N}(v_i - log\, v_i) + \tau_0\right]\right\} \mathrm{I}(2, \infty) \tag{B.16}$$

where $\Gamma(\cdot)$ is the gamma function defined by $\Gamma(z) = \int_0^\infty x^{z-1} exp^{-x} dx$. Equation (B.16) does not correspond to a known distribution, thus M-H sampling steps are embedded in the MCMC scheme to obtain draws for τ (Koop et al., 2007).[iv]

A single pass through the MCMC sampler is achieved by carrying out the update steps for the parameters in the order as they are listed above. Starting values for β and σ^2 are obtained via a non-spatial regression and starting values for spatial parameters are set to 0.5. For the parameters that govern the error distribution, we set v_i to 1 for all regions and τ to 40 to start with an approximately homoscedastic model and let the data inform us about the tails of the error distribution. For posterior distributions that possess the form of a known distribution, we rely on Gibbs sampling for these parameters. Conditional posterior distributions of the spatial autoregressive parameters ρ_r and λ and hyperparameter τ do not correspond to known distributions. In these cases, we follow a proposal laid out by LeSage and Pace (2009) and use the M-H algorithm with tuned acceptance rates to obtain random draws for the parameters. The modified version of the M-H algorithm can be expressed as follows:

$$\varphi_l^* = \varphi_l^c + \eta \times \phi \tag{B.17}$$

$$\phi \sim N(0,1)$$

[iv] Note that $p(\tau | y, \beta, \sigma^2, \rho_r, \lambda, v_i) = p(\tau | v_i)$, because τ influences only v_i and does not enter the likelihood function (hyperparameter).

$$p(\varphi_l^*, \varphi_l^c) = \ min\left\{1, \frac{p(\varphi_l^*|y,\beta,\sigma^2,V,\varphi_{-l})}{p(\varphi_l^c|y,\beta,\sigma^2,V,\varphi_{-l})}\right\}$$

with $\varphi = (\rho_r, \lambda, \tau)$ and $l = 1, \dots, R + 2$ where φ_{-l} denotes all elements in φ excluding the element l. φ_l^* denotes the candidate value and φ_l^c the current value in the M-H step. A standard normal distribution is used as the proposal distribution ϕ. The tuning parameter η is a constant in the random walk procedure to update φ. The tuning parameter is implemented in the random walk procedure to ensure that the sampling updates move over the entire conditional distribution (LeSage and Pace, 2009). The tuning parameter has an impact on the acceptance rate of the candidate value through acceptance probability $p(\varphi_l^*, \varphi_l^c)$ and affects the selection of the conditional distribution's region from which candidate values are sampled (Doğan and Taşpınar, 2014). Large values for the tuning parameter allow the candidate value to be far from the current value, which reduces the acceptance probability. This increases the risk that the Markov chain may stick at the current value because new values in the random walk will never get accepted. In contrast, small tuning parameter values generate new candidate values that are near the current value, hence many draws are needed to explore the entire distribution. The aim of the tuned M-H steps is to generate draws from densed regions of the conditional distribution and avoid that the sampler getting stuck in low density parts of the distribution. To achieve this aim, the acceptance rate should be near 50% after the burn-in period (Chib, 2001). We follow LeSage and Pace (2009) and start with $\eta = 0.5$ and systematically adjust the tuning parameter when the acceptance rate exceeds the critical threshold of 60% ($\eta' = 1.1\eta$) or falls below 40% ($\eta' = \eta/1.1$).

We like to point out, that the more complex spatial autoregressive autoregressive (SARAR) model nests the spatial error model (SEM) and the spatial autoregressive (SAR) model. In the case where $\rho = 0$, the SARAR model reduces to the SEM, and if $\lambda = 0$, the SARAR model becomes the SAR model. For these reasons, the Bayesian update schemes discussed above can also be used to estimate SEM or SAR models. A further advantage of the Bayesian approach is that posterior distributions of the model parameters can be used to produce a posterior distribution for the scalar summary measures of spatial impacts to assess the magnitude and dispersion of direct effects, indirect spatial (spillover) effects, and total effects (see Appendix B.II).

B.IV Spatial weights

Spatial lag in the dependent variable (W)

Systematic economic spillovers between regions are expressed by the spatial lag of the dependent variable. To represent the direct dependence of growth in region i on growth in neighbouring regions j, we set up a spatial weights matrix: $W = (w_{ij}: i, j = 1, \dots, N)$ is a non-negative matrix that summarises the spatial relations between N spatial units. Each spatial weight w_{ij} reflects the "spatial influence" of region j on region i. We refrain from using spatial contiguity weights because the spatial configuration of boundaries or geographical distance per se does not represent the interconnections of economic activities appropriately. For instance, big cities or economic centres are less remote than their geographical distance would imply, whereas rural regions possess stronger ties to economic hubs and are often isolated from one another (Fingleton and LeGallo, 2008). We model an asymmetric structure of dependence that represents the relative economic distance between regions and reflects that economic flows are not gradually decreasing with distance, but instead are more pronounced between big cities due to lower transaction costs, lower costs of information gathering, better infrastructure, and a similar sector structure. On the other hand, less open rural regions depend more strongly on the nearby economic centres than vice versa. Similar measures of relative economic distance are featured in numerous studies, e.g. Pinkse et al. (2002), Conley and Ligon (2002), Conley and Topa (2002), and LeSage and Fischer (2008). As a reference set-up, we follow Corrado and Fingleton (2012) and Fingleton and Palombi (2013) and construct the spatial weights of matrix W as follows:

$$w_{ij}^{**} = \frac{GDP_j^{ew}}{distance_{ij}^{dw}} \qquad \text{(B.18)}$$

$$w_{ij}^{**} = 0 \qquad i = j$$

$$w_{ij}^{*} = \frac{w_{ij}^{**}}{\sum_{j=1}^{N} w_{ij}^{**}}$$

$$w_{ij}^{*} = 0 \qquad w_{ij}^{*} < 0.01$$

$$w_{ij} = \frac{w_{ij}^{*}}{\sum_{j=1}^{N} w_{ij}^{*}}$$

This construction of W is termed "Economic Distance" (ED) and reflects the urban hierarchy of regions since stronger weights are placed on regions with higher economic mass (proxied by GDP). The weighting factors ew for economic mass and dw for distance are set to unity in our baseline specification but can be modified to adjust the influence of both parameters. Note that the "Economic Distance" matrix is not symmetric. For example, larger urban regions depend less strongly on their surrounding rural regions than vice versa. The strength of spatial influence declines with increasing distance between regions. Following standard conventions, we exclude self-influence (so that W has a zero diagonal). We row-standardized W (relative influence of neighbours) and we set all weights which account for less than 1% of region's total spatial dependencies equal to zero, thus assuming that the economic separation between regions in each of the corresponding location pairs is too large and so interactions are negligible. Since using GDP as a proxy for the economic mass of a region bears the risk of endogeneity with respect to output growth, we construct W time-invariant using the GDP in 1981 to measure the economic size of a region. We conduct a series of sensitivity checks and replace the GDP in the year 1981 with GDP in later years or with total population of a region. The resulting matrices are very similar to the weights matrix of our reference specification and estimation results remain stable in all scenarios (results are available upon request). Thus, we argue that the choice to measure the economic mass of regions before the sample period does not influence our estimation results in a noteworthy way while ensuring the proper treatment of potential endogeneity issues. As a robustness check, we replace the power function for the distance term in Equation (B.18) by an exponential distance decay function to penalize larger physical distance more strongly:

$$w_{ij}^{**} = \frac{GDP_j^{ew}}{exp\ (dw \times distance_{ij})} \qquad \text{(B.19)}$$

In our baseline specification, we set $ew = 1$ and $dw = 1$. Alternatively, we estimate ew and dw with help of a gravity model of national trade data and include the estimated elasticities in the calculation of W. From Equation (B.18) it becomes evident that the calculation of "Economic

Distance" bears a close affinity to the gravity model of trade which can be expressed in the general form as proposed by Chaney (2008):

$$Exports_{\mathrm{OD}} = Constant \times \frac{X_{\mathrm{O}}^{\beta_{\mathrm{O}}} \times X_{\mathrm{D}}^{\beta_{\mathrm{D}}}}{Trade\ barriers_{\mathrm{OD}}^{\gamma}} \qquad (\mathrm{B}.20)$$

where X_{O} denotes a matrix that contains variables that represent the economic mass of the origin region (push factors) and X_{D} is a matrix with variables that explain the economic mass of the destination region (pull factors). $Trade\ barriers$ summarizes bilateral resistance factors to trade flows, e.g. distance, agreements on tariffs, and trade or different currencies. Equation (B.20) is based on the assumption that trade flows are diminished when resistance factors increase. In the econometric analysis, we let the sign of parameter γ determine whether the impact on trade is negative or positive. Anderson and Wincoop (2003) suggest that in addition to the bilateral resistance factors, barriers which each of the origin regions and destination regions faces in their trade with all their trading partners should be included in the gravity model to obtain unbiased results. They labelled those trade barriers as multilateral resistance factors. We control for multilateral resistance factors via fixed effects for origin and destination regions in the gravity equation (Feenstra, 2002). A log transformation of the gravity model leads to a regression model that can be estimated via OLS:

$$\ln(Exports_{\mathrm{OD}}) = \alpha + \beta_{\mathrm{o}}\ln(X_{\mathrm{O}}) + \beta_{D}\ln(X_{\mathrm{D}}) + \gamma\ln(Trade\ barriers_{\mathrm{OD}}) + \theta_{\mathrm{O}} + \theta_{\mathrm{D}} + \varepsilon_{\mathrm{OD}} \qquad (\mathrm{B}.21)$$

where θ_{O} and θ_{D} are the fixed effect terms for the multilateral resistance factors and $\varepsilon_{\mathrm{OD}}$ denotes the error term.

Trade data at the regional level are not available, thus known bilateral trade flows of countries in our sample form the basis of trade estimates. Data on trade flows (measured in Euro) are obtained from Eurostat´s Comext international trade database. We collect all bilateral trade flows available for the years between 1980 and 2012. Detailed trade data before 1980 were not available. Country-level data for push and pull factors are obtained from Eurostat and distance is measured as the mean of inter-regional distances for each country pair.

The coefficients of interest are those of GDP of the destination region and distance. The estimated elasticities are inserted into the related exponents when calculating the spatial weights matrix for "Economic Distance" to perform robustness checks. This approach can be regarded as a version of the spatial Chow-Lin best linear disaggregation method, which disaggregates data at the national level and allocates the disaggregated values to regions on a lower hierarchical level analogous to the decomposition of annual time series into quarterly series (Chow and Lin, 1971). Usually, estimations are conducted on the higher hierarchical level to expose a statistical relationship between a dependent variable that is unknown on the lower level and explanatory variables that are available at both levels. With the help of the estimates on the higher level and the available variables at the lower level, the unknown variable of interest on the lower level is predicted. In the present case, we refrain from predicting detailed inter-regional trade flows, because multilateral resistance factors could not be transferred from the national level to NUTS-3 regions in an appropriate manner. Instead, we rely on the gravity model to provide reliable estimates for the elasticities of interest. Table B.1 shows the estimation results. The estimates are consistent with estimation results in the literature (e.g. Silva and Tenreyro, 2006; Anderson and Wincoop, 2003) and robust across all model specifications. Trade flows diminish with increasing distance and increment with higher economic size (GDP) of the destination. Regardless of the usage of population or GDP per capita as explanatory variable, the respective specific specifications that only include significant variables yield identical results. We use the estimated coefficients to adjust the weight attributes in the calculation of the ED matrix. For example, when using the results of the gravity model in column 2 of Table B.1, we set $ew = 0.7811$ and $dw = -1.4210$ in Equation (B.18).

Table B.1: Estimation results: gravity model of trade

	Gravity model of trade							
	Full model				Generel to specific model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log origin´s GDP	1.3540 ***	0.8749 ***	1.0933 *	0.8776 *	1.2968 ***	0.8756 ***	1.2968 ***	0.8756 ***
	(0.1686)	(0.2052)	(0.5053)	(0.5142)	(0.1688)	(0.1058)	(0.1688)	(0.1058)
Log destination`s GDP	1.2151 ***	0.7811 ***	0.7414	0.5036	1.1096 ***	0.7202 ***	1.1096 ***	0.7202 ***
	(0.1680)	(0.0863)	(0.5163)	(0.1306)	(0.2359)	(0.1295)	(0.2359)	(0.1295)
Log origin´s pop.	-0.2607	0.0027						
	(0.5354)	(0.6815)						
Log destination´s pop.	-0.4737	-0.2774						
	(0.3755)	(0.3011)						
Log origin´s GDP p.c.			0.2607	-0.0027				
			(0.5354)	(0.6815)				
Log destination`s GDP p.c.			0.4737	0.2774				
			(0.3755)	(0.3011)				
Common currency	0.1957 ***	0.2150 ***	0.1957 ***	0.2150 ***	0.1956 ***	0.2141 ***	0.1956 ***	0.2141 ***
	(0.0490)	(0.0531)	(0.0490)	(0.0531)	(0.0490)	(0.0531)	(0.0490)	(0.0531)
Log distance	-1.4248 ***	-1.4210 ***	-1.4248 ***	-1.4210 ***	-1.4249 ***	-1.4211 ***	-1.4249 ***	-1.4211 ***
	(0.1309)	(0.1306)	(0.1309)	(0.0531)	(0.1308)	(0.1304)	(0.1308)	(0.1304)
Origin Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	4,935	4,935	4,935	4,935	4,935	4,935	4,935	4,935
R squared	0.946	0.946	0.946	0.947	0.946	0.946	0.946	0.947

Notes: Columns: (1)-(4) full gravity model of trade, (5)-(6) specific form of the gravity model, where the explanatory variable with the highest p-value is iteratively removed from model specifications (1)-(4) until all remaining variables are statistically significant at the 10% level. Robust standard errors in parentheses, adjusted for two-way clustering for origin and destination. Statistical significance level: 1% ***, 5% **, 10% *.

Spatial Error Term (*M*)

As the correlation of weather and unsystematic regional interlinkages decline with distance, we employ a simultaneous autoregressive specification of the disturbances which puts the highest weights on direct neighbours of each region i and let spatial dependency decay with the order of neighbours. To determine the direct neighbours of each region, we adopt the so-called Queen (Q) contiguity weights for M, assuming that regions that share a common boundary are neighbours:

$$m_{ij}^{*} = \begin{cases} 1, & bnd(i) \cap bnd(j) \neq \emptyset \\ 0, & bnd(i) \cap bnd(j) = \emptyset \end{cases} \tag{B.22}$$

$$m_{ij} = \frac{m_{ij}^{*}}{\sum_{j=1}^{N} m_{ij}^{*}}$$

The set of boundary points of region i is denoted by $bnd(i)$. By construction, the Queen matrix is time-constant and exogenously given.

Appendix C Summary statistics

Table C.1: Typology of regions: summary statistics

	Min.	1. Quartil	Mean	3. Quartil	Max.
MEGA (ME) [52]					
GDP p.c.	12,850	23,230	35,530	40,750	134,400
Population	79,840	644,000	1,112,000	1,777,200	6,336,000
Population density	28	258	2,097	2,611	20,430
Share of agriculture	0.00	0.00	0.01	0.01	0.16
Share of industry	0.03	0.12	0.15	0.23	0.47
Share of services	0.31	0.46	0.53	0.60	0.73
Share of non-market	0.09	0.18	0.23	0.28	0.47
Urban (PU) [320]					
GDP p.c.	8,924	21,210	26,690	29,780	63,560
Population	33,790	150,670	362,700	411,000	1,999,100
Population density	50	340	996	1,241	8,220
Share of agriculture	0.00	0.00	0.01	0.01	0.16
Share of industry	0.05	0.18	0.26	0.33	0.74
Share of services	0.17	0.39	0.44	0.50	0.80
Share of non-market	0.05	0.17	0.22	0.27	0.74
Intermediate (IN) [309]					
GDP p.c.	6,163	18,020	21,180	24,190	50,840
Population	19,050	145,300	343,700	471,500	1,830,000
Population density	14	98	144	193	320
Share of agriculture	0.00	0.01	0.03	0.04	0.15
Share of industry	0.06	0.18	0.24	0.29	0.57
Share of services	0.21	0.38	0.42	0.47	0.61
Share of non-market	0.07	0.19	0.23	0.28	0.65
Rural (PR) [273]					
GDP p.c.	5,720	14,660	19,670	22,820	42,650
Population	16,440	101.500	192,700	246,800	734,700
Population density	2	25	53	80	168
Share of agriculture	0.01	0.03	0.06	0.07	0.23
Share of industry	0.01	0.15	0.22	0.27	0.61
Share of services	0.19	0.36	0.40	0.45	0.66
Share of non-market	0.02	0.19	0.24	0.28	0.76

Notes: Summary statistics for each region type calculated on basis of annual averages: GDP p.c. (in Euro), Population, Population density (inhabitants per square kilometre), and sector shares of total output (gross value-added): share of agriculture (NACE: A), share of industry (NACE: B-E), share of services (NACE: G-N) and share on non-market (NACE: O-U). Number of regions in each regime in square brackets.

Appendix D Robustness checks and additional model specifications

Table D.1: Regression estimates for pooled sample: main results (YA)

YA	**(1) Linear**	**Impacts**	**(2) Polynomial**	**Impacts**	**(3) Interaction**	**Impacts**
Temp.	-0.0381	-0.0381	0.4340 ***	0.4344 ***	0.4838 ***	0.4843 ***
	(0.0631)	-0.0090	(0.1520)	0.1014 ***	(0.1472)	0.1131 ***
		-0.0471		0.5358 ***		0.5974 ***
Temp. sq.			-0.0235 ***	-0.0235 ***		
			(0.0066)	-0.0055 ***		
				-0.0290 ***		
Temp. * $\overline{T}_i$					-0.0516 ***	-0.0517 ***
					(0.0132)	-0.0121 ***
						-0.0637 ***
Rho	0.1920 ***		0.1897 ***		0.1901 ***	
	(0.0171)		(0.0189)		(0.0181)	
Lambda	0.4687 ***		0.4694 ***		0.4708 ***	
	(0.0052)		(0.0068)		(0.0032)	
Observations	29,574		29,574		29,574	
R squared	0.374		0.374		0.374	
Optimum			9.2		9.4	

	(4) Mod.: Income (regional)	**Impacts**	**(5) Mod.: Income (national)**	**Impacts**
Temp.	0.4253 ***	0.4258 ***	0.4303 ***	0.4304 ***
	(0.0159)	0.0995 **	(0.1605)	0.1034 **
		0.5253 ***		0.5338 ***
Temp. sq.				
Temp. * $\overline{T}_i$	-0.0452 ***	-0.0452 ***	-0.0472 ***	-0.0472 ***
	(0.0145)	-0.0106 ***	(0.0151)	-0.0112 ***
		-0.0558 ***		-0.0578 ***
Temp. * Mod.	-0.0683	-0.0684	0.1751	0.1754
	(0.0915)	-0.0159	(0.2426)	0.0420
		-0.0843		0.2174
Rho	0.1902 ***		0.1952 ***	
	(0.0194)		(0.0750)	
Lambda	0.4687 ***		0.4684 ***	
	(0.0073)		(0.0084)	
Observations	29,574		29,574	
R squared	0.374		0.374	
Optimum	9.4		9.2	

Notes: Estimation results of baseline SARAR model for pooled sample using yearly averages (YA) of temperature. All models include precipitation controls, region fixed effects, year fixed effects separated for Scandinavian regions and remaining regions, and errors clustered by regions. Columns: (1) linear, (2) quadratic polynomials, (3) interaction with annual average temperature and precipitation instead of polynomials, (4) as in column 3 but with interaction between temperature and regional income (log of baseline regional GDP per capita), (5) as in column 3 but with interaction between temperature and country-level income (log of baseline national GDP per capita). Income is mean centered such that the weather effects in the first two rows of the table can be interpreted as the effect evaluated at sample average income. Impacts show spatial impacts for each covariate: direct impact (first row), indirect impact (second row) and total impact (third row). Optimum is the estimated temperature optimum of the non-linear response function (calculation based on total impacts). Temperature is measured in °C. Coefficients are derived by the mean of posterior distribution and standard deviation of posterior in parentheses. Statistical significance level: 1% ***, 5% **, 10% * (*** 99%, ** 95%, * 90% credible interval for parameter does not include zero).

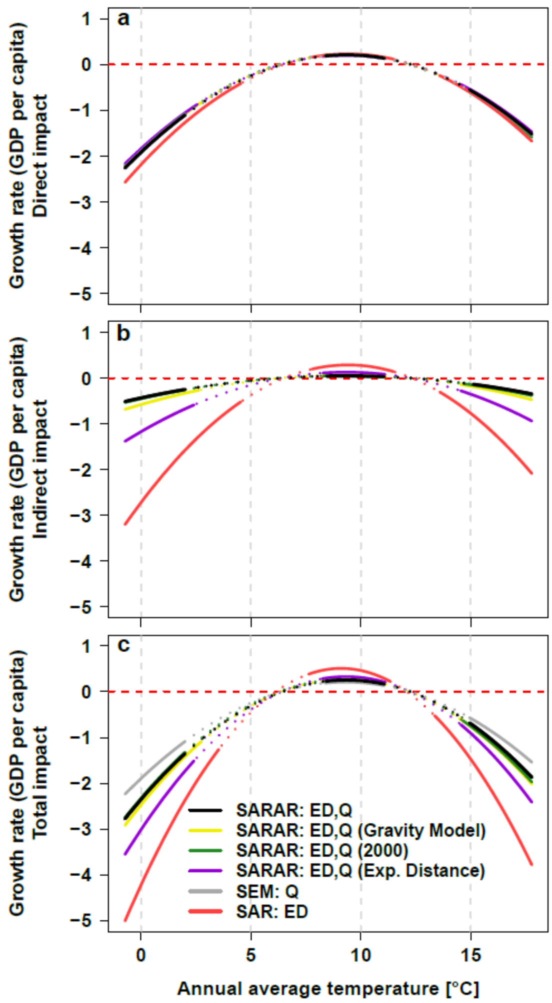

Figure D.1: Alternative spatial model specifications.
Non-linear relationship between annual average temperature and regional growth of GDP per capita calculated on basis of direct spatial impacts (a), indirect spatial impact (b), and total spatial impacts (c). Alternative spatial models: baseline SARAR: Economic Distance (ED),Queen (Q) (see section 2.4), SARAR: ED,Q (Gravity Model): weights for economic mass and distance in ED calculation estimated via gravity model (see Appendix B.IV: column (2) in Table B.1), SARAR: ED,Q (2000): ED calculated with GDP in the year 2000 instead of 1981, SARAR: ED,Q (Exp. Distance): replacing inverse distance weighting by exponential distance decay function (see Appendix B.IV), SEM: Q: dropping spatial lag of dependent variable, SAR: ED: dropping spatially correlated error term. Solid lines indicate a statistically significant relationship at the 10% level or lower. Dotted lines indicate a non-significant relationship. Note that residuals of the SAR model with ED as spatial weights matrix (red lines) are significantly positively correlated in space as indicated by a posterior sample of residuals Moran`s I (see Table D.2).

Table D.2: Spatial model specifications: goodness of fit

Spatial model specification	DIC	Residuals Moran´s I	Rho (ρ)	Lambda (λ)
SARAR: ED,Q	-125,408	-0.052	0.1897 ***	0.4694 ***
SARAR: ED,Q (Gravity Model)	-125,435	-0.055	0.2388 ***	0.3930 ***
SARAR: ED,Q (2000)	-125,355	-0.058	0.1944 ***	0.4674 ***
SARAR: ED,Q (Exp. Distance)	-125,772	-0.042	0.3928 ***	0.3880 ***
SEM: Q	-125,282	-0.066		0.5144 ***
SAR: ED	-121,648	0.215 ***	0.5532 ***	

Notes: DIC: Deviance Information Criterion (Spiegelhalter et al., 2002). Residuals Moran´s I is derived on basis of posterior sample of Moran´s I statistic calculated at each MCMC draw using Queen (Q) spatial weighting to capture short distance spatial autocorrelation. Rho (ρ) and Lambda (λ) denote the coefficients for the spatial lag of the dependent variable and spatial error term, respectively. *** indicates statistical significance at the 1% level (99% credible interval for parameter does not include zero).

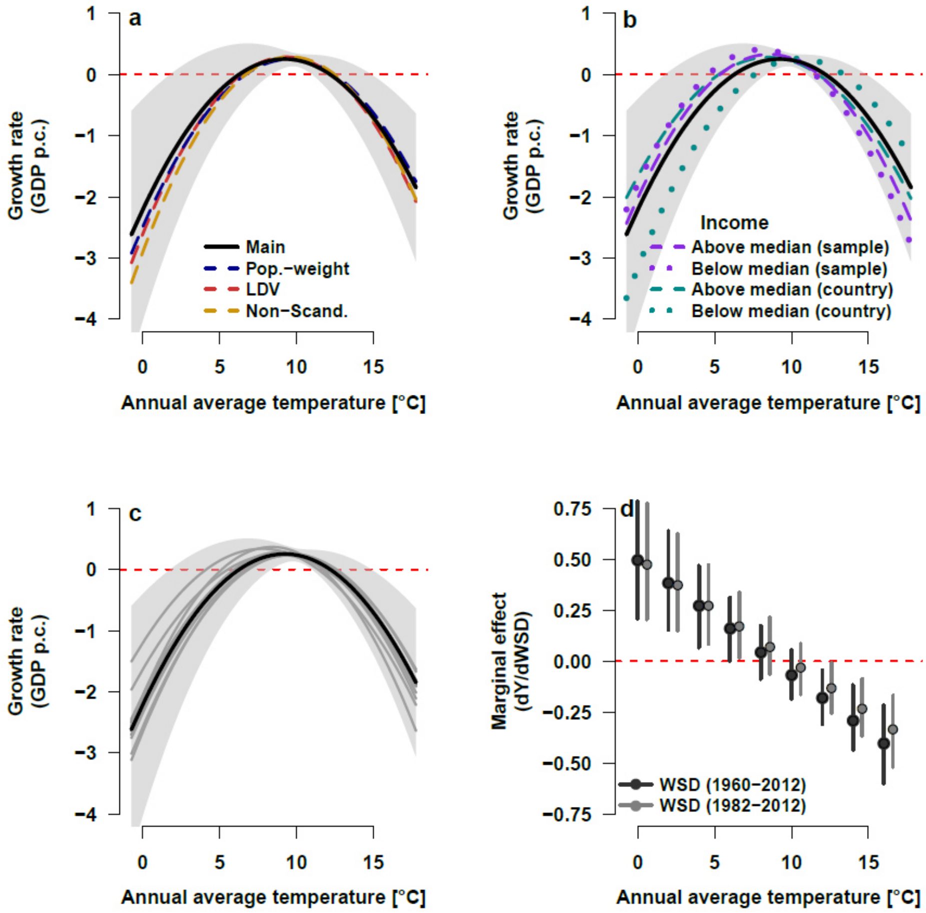

Figure D.2: Robustness tests: yearly average temperature (YA).
Non-linear relationship between annual average temperature and regional growth of GDP per capita (black line) with 90% credible interval (grey) using total impacts of the main SARAR specification (see Figure 1a).
a) Results of model specifications using alternate regional weather data (population-weighted), adding temporal lag of the dependent variable (LDV), and dropping cold Scandinavian regions.
b) Splitting sample by income groups, using the sample median and the country-specific median as criteria to distinguish “poor” and “rich” regions.
c) Response functions (grey lines) of stepwise estimation routine that leaves one country out of sample.
d) Replacing the YA indicator by WSD indicators with alternative reference periods in the linear specification that includes an interaction with annual average temperature.

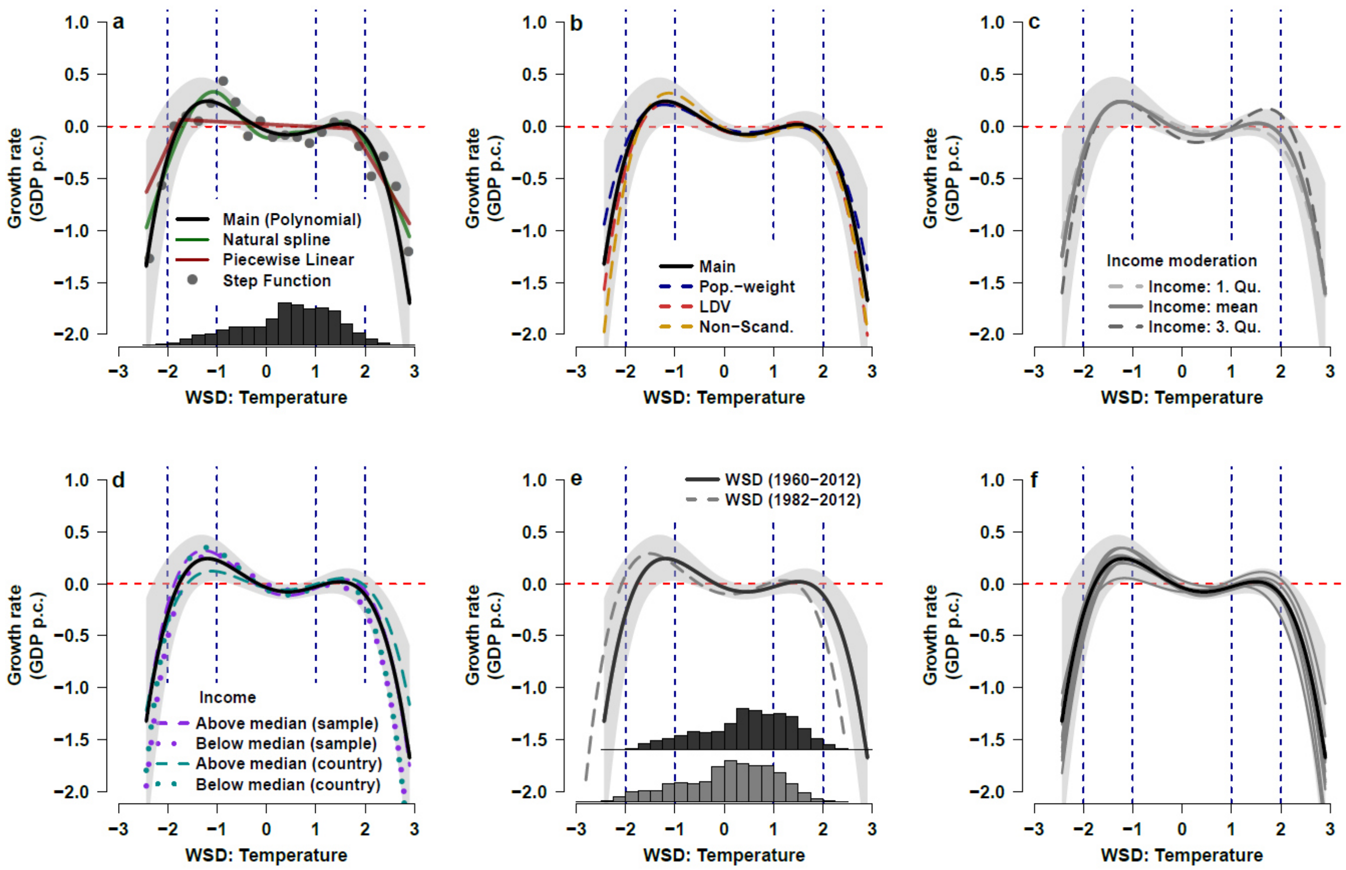

Figure D.3: Robustness tests: Weighted Standardized Deviations (WSD).

a) Non-linear relationship between WSD and regional growth of GDP per capita using alternative specifications to model "within-region" temperature deviations from the historical norm. Black line shows response function of main specification using polynomial regression (4th-order) with 90% credible interval shaded in grey. Green line indicates responses on basis of natural cubic splines with 6 knots. Red line shows response on basis of a piecewise linear regression with breakpoints at -1.75 and 1.75. Darkgrey dots depict results of step function with bin-size of 0.25 standard deviations. Blue dashed lines indicate thresholds for moderate and severe anomalies. Histogram shows distribution of temperature WSD (reference period: 1960-2012).

b) Results of model specifications using alternate regional weather data (population-weighted), adding temporal lag of the dependent variable (LDV), and dropping cold Scandinavian regions.

c) Response functions for the sample mean income (solid line with 90% credible interval shaded in grey), first quartile (dashed line in lightgrey), and third quartile (dashed line in darkgrey) of the regional income distribution. Responses are derived from the model that interacts WSD with regional income (log of baseline regional GDP per capita).

d) Splitting sample by income groups, using the sample median and the country-specific median as criteria to distinguish "poor" and "rich" regions.

e) Response functions of estimations using WSD indicators with alternative reference periods. Histograms show distribution of temperature WSD for the respective reference periods.

d) Response functions (grey lines) of stepwise estimation routine that leaves one country out of sample.

Table D.3: Regression estimates for pooled sample: main results (WSD)

WSD	SARAR (ED,Q)						
	(1)		(2)		(3)		(4)
	Base	Impacts	Interaction	Impacts	GTS	Impacts	GTS
	(1960-2012)		(1960-2012)		(1960-2012)		(1980-2012)
WSD: Temp.	-0.1492 * (0.0856)	-0.1494 * -0.0349 * -0.1842 *	0.5863 *** (0.2107)	0.5870 *** 0.1443 *** 0.7313 ***	0.2874 ** (0.1355)	0.2877 ** 0.0632 ** 0.3509 **	0.3620 *** (0.1252)
WSD: Temp. sq.	0.1562 ** (0.0642)	0.1564 ** 0.0365 ** 0.1930 **	0.2712 (0.2082)	0.2715 0.0664 0.3379	0.1651 ** (0.0657)	0.1653 ** 0.0363 ** 0.2016 **	0.2180 *** (0.0689)
WSD: Temp. cu.	0.0465 (0.0287)	0.0466 0.0109 0.0574	-0.1028 (0.0857)	-0.1029 -0.0251 -0.1280	0.0415 (0.0285)	0.0415 0.0091 0.0507	-0.0158 (0.0231)
WSD: Temp. qu.	-0.0472 *** (0.0165)	-0.0473 *** -0.0110 *** -0.0583 ***	-0.0577 (0.0536)	-0.0578 -0.0142 -0.0720	-0.0453 *** (0.0165)	-0.0453 *** -0.0099 ** -0.0553 ***	-0.0573 *** (0.0167)
WSD: Temp. * $\overline{T}_i$			-0.0754 *** (0.0198)	-0.0755 *** -0.0185 *** -0.0940 ***	-0.0440 *** (0.0105)	-0.0440 *** -0.0097 *** -0.0537 ***	-0.0394 *** (0.0097)
WSD: Temp. sq. * $\overline{T}_i$			-0.0089 (0.0197)	-0.0089 -0.0022 -0.0110			
WSD: Temp. cu. * $\overline{T}_i$			0.0152 (0.0099)	0.0152 0.0037 0.0190			
WSD: Temp. qu. * $\overline{T}_i$			0.0005 (0.0053)	0.0005 0.0001 0.0007			
Rho	0.1900 *** (0.0159)		0.1977 *** (0.0223)		0.1805 *** (0.0214)		0.1911 *** (0.0192)
Lambda	0.4706 *** (0.0019)		0.4648 *** (0.0098)		0.4736 *** (0.0091)		0.4671 *** (0.0073)
Observations	29,574		29,574		29,574		29,574
R squared	0.375		0.375		0.375		0.375

Notes: All models include precipitation controls, region fixed effects, year fixed effects separated for Scandinavian regions and remaining regions, and errors clustered by regions. Columns: (1) Polynomial regression for "within-unit" non-linear response function of weather anomalies (polynomial order is determined by step-wise procedure that started at the 9th-order and eliminates the statistically insignificant highest order from the model until the highest order is significant at the 10% level: polynomial of the 4th-order for temperature anomalies and polynomial of second order for precipitation anomalies), (2) as in column 1 extended with interaction with region´s climatic conditions, (3) specific form of model in column 2 (insignificant interaction terms are iteratively removed from model until all remaining interactions are statistically significant at the 10% level: general to specific (GTS), (4) replication of column 3 with shorter reference period in the calculation of WSD. Impacts show spatial impacts for each covariate: direct impact (first row), indirect impact (second row) and total impact (third row). Coefficients are derived by the mean of posterior distribution and standard deviation of posterior in parentheses. Statistical significance level: 1% ***, 5% **, 1 % * (*** 99%, ** 95%, * 90% credible interval for parameter does not include zero).

Table D.4: Regression estimates for region type subsamples (YA)

YA		(1) Baseline: ED	(1) Spill-In	(2) ED: exp. Dist.	(2) Spill-In	(3) ED: exp. Dist. & ew=0.5	(3) Spill-In
MEGA (ME)	Temp.	0.0838	0.0837	0.1379	0.1372	0.0695	0.0699
		(0.4062)	-0.0122	(0.4157)	-0.0265	(0.4254)	0.0517
			0.0715		0.1106		0.1215
	Temp. sq.	-0.0020	-0.0020	-0.0035	-0.0035	0.0002	0.0002
		(0.0171)	0.0007	(0.0176)	0.0016	(0.0175)	-0.0033 *
			-0.0013		-0.0019		-0.0031
Urban (PU)	Temp.	0.5910 *	0.5918 *	0.5291 *	0.5134 *	0.3867	0.3937
		(0.3177)	0.0776	(0.2935)	0.2305 *	(0.2953)	0.3552
			0.6694 *		0.7619 *		0.7490
	Temp. sq.	-0.0384 ***	-0.0384 ***	-0.0343 **	-0.0344 **	-0.0265 *	-0.0270 *
		(0.0144)	-0.0046	(0.0133)	-0.0317 **	(0.0136)	-0.0229 **
			-0.0430 ***		-0.0481 ***		-0.0499 **
Interm. (IN)	Temp.	0.5102 ***	0.5104 ***	0.4346 **	0.4365 **	0.3404 **	0.3471 *
		(0.1973)	0.0552	(0.1872)	0.2195 *	(0.1735)	0.3599 *
			0.5656 **		0.6560 **		0.7070 **
	Temp. sq.	-0.0301 ***	-0.0301 ***	-0.0265 ***	-0.0266 ***	-0.0210 ***	-0.0214 ***
		(0.0087)	-0.0030	(0.0084)	-0.0128 **	(0.0078)	-0.0228 ***
			-0.0331 ***		-0.0394 ***		-0.0442 ***
Rural (PR)	Temp.	0.2659	0.2660	0.2892	0.2907	0.2130	0.2183
		(0.1942)	0.0486	(0.1832)	0.1868 *	(0.1673)	0.3315 **
			0.3145		0.4775 *		0.5498 *
	Temp. sq.	-0.0182 **	-0.0182 **	-0.0188 **	-0.0189 **	-0.0142 *	-0.0146 *
		(0.0086)	-0.0025	(0.0082)	-0.0108 **	(0.0074)	-0.0207 ***
			-0.0206 **		-0.0296 ***		-0.0353 ***
	Rho: MEGA	-0.0412		-0.0526		0.0906 **	
		(0.0475)		(0.0468)		(0.0435)	
	Rho: Urban	0.2242 ***		0.4456 ***		0.5756 ***	
		(0.0240)		(0.0263)		(0.0197)	
	Rho: Interm.	0.2048 ***		0.4611 ***		0.6121 ***	
		(0.0226)		(0.0235)		(0.0219)	
	Rho: Rural	0.2336 ***		0.4279 ***		0.6147 ***	
		(0.0309)		(0.0246)		(0.0225)	
	Lambda	0.4512 ***		0.3647 ***		0.2430 ***	
		(0.0014)		(0.0087)		(0.0100)	
Observations		29,574		29,574		29,574	
R squared		0.375		0.374		0.375	
Optimum: MEGA			17.7		17.7		17.7
Optimum: Urban			7.8		7.9		7.5
Optimum: Interm.			8.5		8.3		8.0
Optimum: Rural			7.6		8.1		7.8

Notes: All models include precipitation controls, region fixed effects, year fixed effects separated for Scandinavian regions and remaining regions (interacted with region types) and errors clustered by regions. Columns: (1) spillovers are modelled via "Economic Distance" (ED), (2) exponential distance decay function to model the distance penalty in the "Economic Distance" weighting scheme, (3) as in column 2 but down-weighting the influence of economic mass in the dependency structure. Spill-in impacts for each covariate: direct impacts (first row), indirect impacts (second row) and total impacts (third row). Optimum is the estimated temperature optima for each region type (calculation based on total spill-in impacts). Temperature is measured in °C. Coefficients are derived by the mean of posterior distribution and standard deviation of posterior in parentheses. Statistical significance level: % ***, 5% **, 10% * (*** 99%, ** 95%, * 90% credible interval for parameter does not include zero).

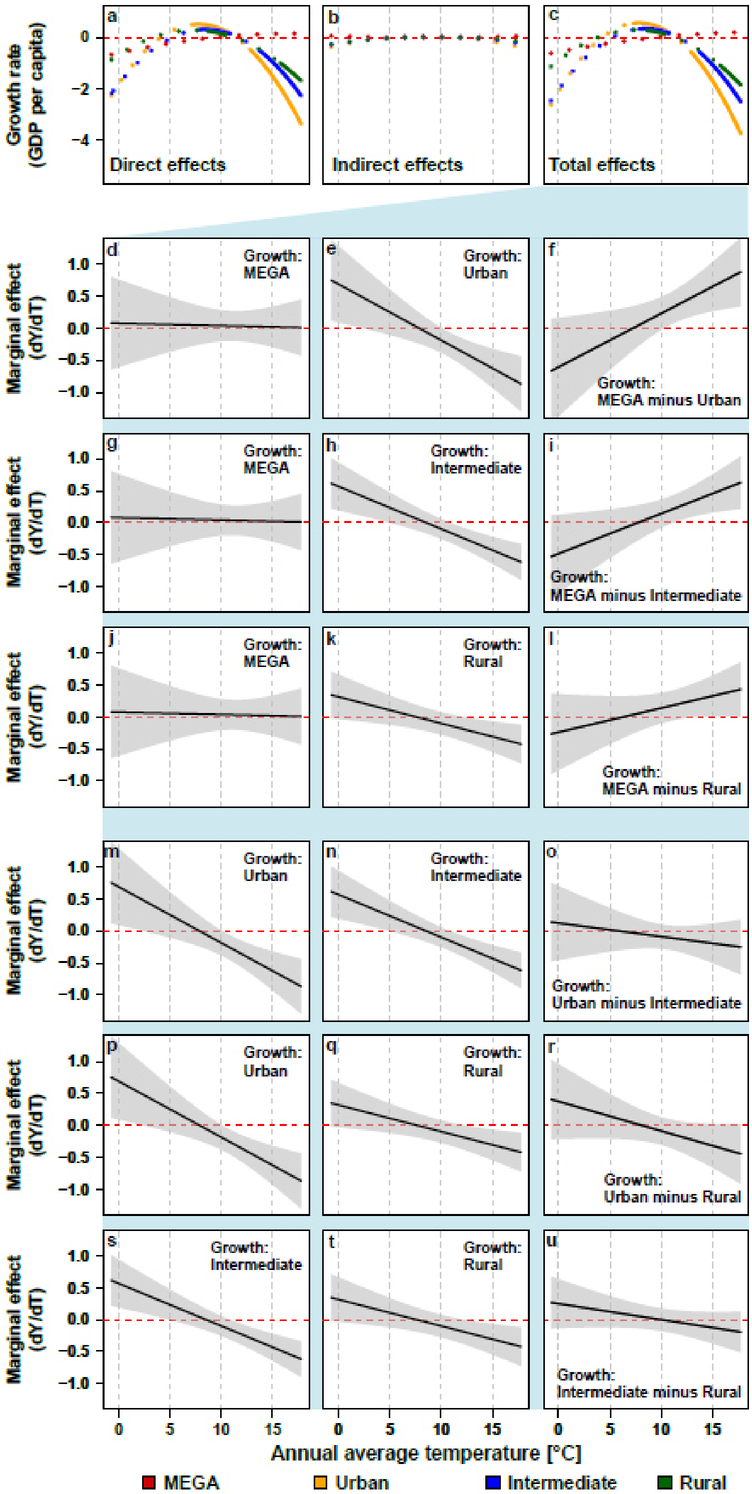

Figure D.4: Heterogenous effects of yearly average (YA) temperature on regional economic growth.

a-c) Relationship (direct, indirect, and total effects) between annual average temperature and regional growth of GDP per capita divided according to region types (Table D.4: (1)). Solid lines indicate a statistically significant relationship at 10% level or lower. Dotted lines indicate a non-significant relationship.

d-u) Comparison of marginal effects (black lines) between region types calculated on basis of total spatial effects of non-linear response functions depicted in c) with 90% credible intervals (grey). Third column shows the estimated difference between marginal effects of the first column and second column with 90% credible interval (grey) to test whether marginal effects are the same for different region types at different annual average temperatures. Rows 2-4 highlight the pairwise comparison of MEGA regions with the remaining regions types, while rows 5-7 display pairwise comparisons of marginal effects between non-MEGA regions.

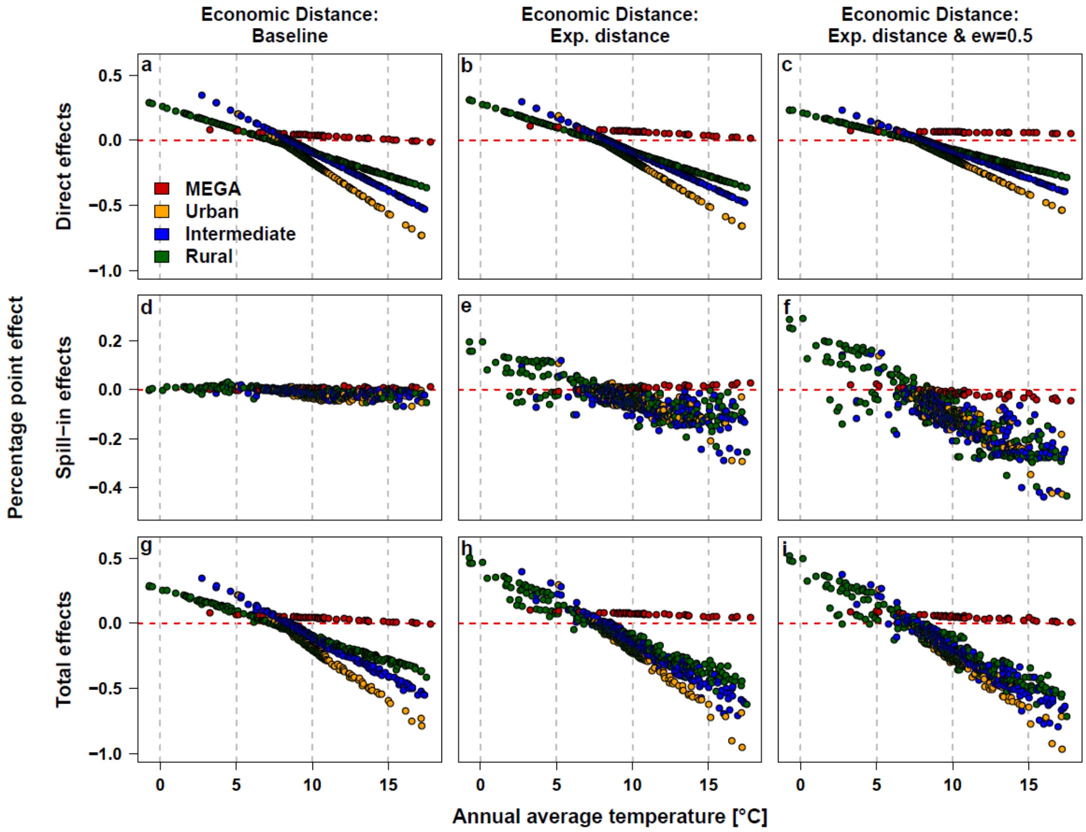

Figure D.5: Percentage point effect of uniform 1 °C warming with alternative specifications of the "Economic Distance" dependency structure.

Direct, spill-in, and total percentage point effect of uniform 1 °C warming at different baseline temperature levels for alternative computation methods of the "Economic Distance" spatial weights. Left column: baseline specification (Table D.4: (1)), central column: exponential distance decay function to model the distance penalty (Table D.4: (2)), right column: as in central column but down-weighting the influence of economic mass in the dependency structure (Table D.4: (3)). Note the different y axis scale for spill-in effects in the middle row of the plot.

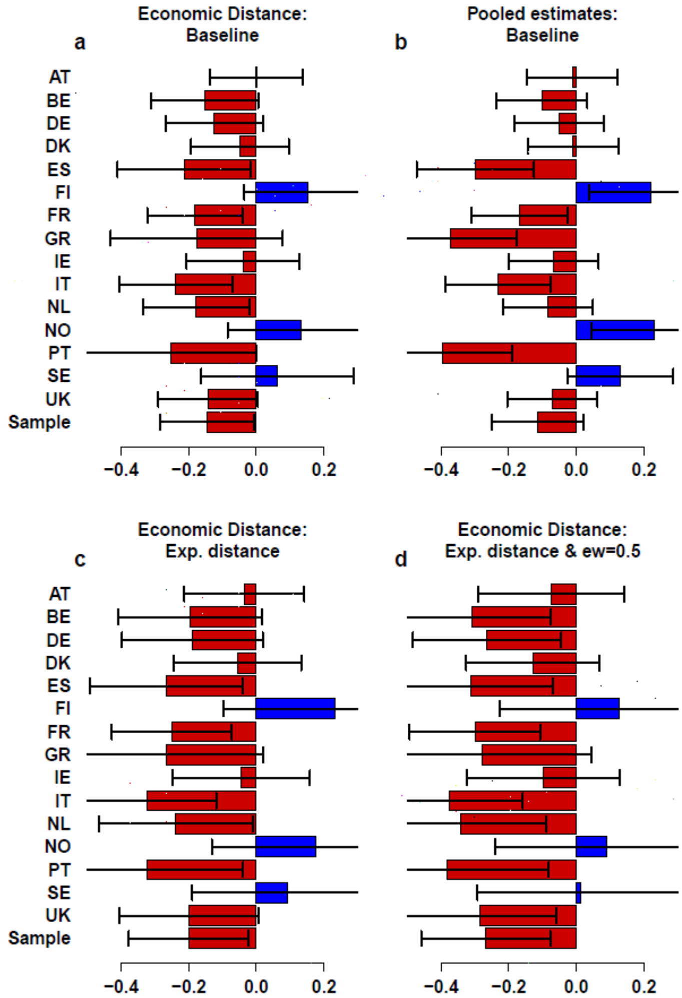

Figure D.6: Aggregated national percentage point effect of uniform 1 °C warming for alternative specifications of the "Economic Distance" dependency structure using the spatial regime model and the pooled model.

Aggregated effects on national growth rates derived from the baseline spatial regime model with alternative "Economic Distance" weights specifications and from the baseline pooled model, whereby regional growth effects are weighted by region´s annual average fraction of national (sample) GDP. Whiskers show 90% credible intervals.

a) Spatial regime model with heterogenous coefficients for region types using baseline "Economic Distance" weights (see Figure 3e and Table D.4: (1)).

b) Pooled model using baseline "Economic Distance" weights (see Figure 3e and Table D.1: (2)).

c) Spatial regime model using exponential distance decay function in the calculation of "Economic Distance" weights (Table D.4: (2)).

d) Spatial regime model using exponential distance decay function and down-weighting the influence of economic mass in the calculation of "Economic Distance" weights (Table D.4: (3)).

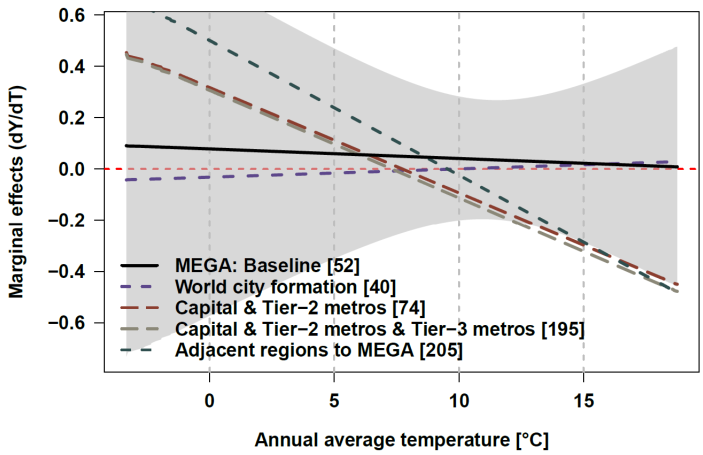

Figure D.7: Alternative definitions for top-tier city regions: robustness checks (YA).

Point estimate for marginal effect of temperature on regional growth for different annual average temperatures. Alternative MEGA definitions: Baseline (black line) with corresponding 90% credible interval (grey), World city formation: NUTS-3 regions that host a city that shows evidence of world city transformation as defined by Beaverstock et al. (1999) (dashed purple line), core regions of capital regions and Tier-2 metropolitan regions following the regional typology of Dijstkra (dashed brown line), core regions of metropolitan regions (capital regions, Tier-2 metros, and Tier-3 metros) following the regional typology of Dijstkra (2009) (dashed darkgrey line), and surrounding regions of baseline MEGA definition using the Queen (common border) weighting scheme to determine adjacent regions (dotdashed darkgreen line). Depicted marginal effects are based on total spatial effects. Number of regions for each classification in square brackets.

Table D.5: Regression estimates for region type subsamples (WSD)

WSD		(1) Baseline: ED	 Impacts	(2) ED: exp. Dist.	 Impacts	(3) ED: exp. Dist. & ew=0.5	 Impacts
MEGA (ME)	WSD: Temp.	0.1683 (0.3683)	0.1681 -0.0087 0.1594	0.1256 (0.3928)	0.1252 -0.0121 0.1131	0.0401 (0.3808)	0.0403 0.0171 0.0574
	WSD: Temp. sq.	0.3552 ** (0.1451)	0.3548 ** -0.0096 0.3452 **	0.3689 ** (0.1525)	0.3678 ** -0.0118 0.3560 **	0.3496 ** (0.1456)	0.3531 ** 0.0267 0.3798 **
	WSD: Temp. cu.	-0.0172 (0.0810)	-0.0171 -0.0028 -0.0199	0.0184 (0.0838)	0.0183 -0.0040 0.0143	0.0258 (0.0849)	0.0261 0.0090 0.0350
	WSD: Temp. qu.	-0.0484 (0.0404)	-0.0483 0.0027 -0.0456	-0.0606 (0.0436)	-0.0604 0.0034 -0.0570	-0.0593 (0.0420)	-0.0599 -0.0077 -0.0675
	WSD: Temp. * $\bar{T}_i$	-0.0260 (0.0281)	-0.0260 0.0020 -0.0240	-0.0253 (0.0301)	-0.0252 0.0028 -0.0224	-0.0169 (0.0288)	-0.0171 -0.0053 -0.0224
Urban (PU)	WSD: Temp.	0.0840 (0.2661)	0.0841 0.0338 0.1180	0.0811 (0.2488)	0.0818 0.0710 0.1528	-0.0078 (0.2384	-0.0079 0.0273 0.0193
	WSD: Temp. sq.	0.2836 *** (0.1026)	0.2841 *** 0.0716 *** 0.3557 ***	0.2451 ** (0.0981)	0.2471 ** 0.1515 *** 0.3986 ***	0.2353 ** (0.0926)	0.2395 ** 0.0363 *** 0.4779 ***
	WSD: Temp. cu.	0.1022 ** (0.0459)	0.1024 ** 0.0201 ** 0.1225 **	0.0961 ** (0.0439)	0.0968 ** 0.0490 ** 0.1458 **	0.0826 ** (0.0419)	0.0841 ** 0.0742 ** 0.1583 **
	WSD: Temp. qu.	-0.0799 *** (0.0269)	-0.0801 *** -0.0192 *** -0.0992 ***	-0.0673 *** (0.0260)	-0.0679 *** -0.0404 *** -0.1083 ***	-0.0611 ** (0.0254)	-0.0622 ** -0.0621 *** -0.1243 ***
	WSD: Temp. * $\bar{T}_i$	-0.0565 *** (0.0218)	-0.0820 *** -0.0127 *** -0.0693 ***	-0.0529 *** (0.0205)	-0.0534 ** -0.0283 *** -0.0817 ***	-0.0408 ** (0.0196)	-0.0415 ** -0.0360 ** -0.0775 **
Interm. (IN)	WSD: Temp.	0.1155 (0.1816)	0.1157 0.0451 0.1608	0.0758 (0.1754)	0.0764 0.1055 0.1820	0.0100 (0.1636)	0.0102 0.0869 0.0971
	WSD: Temp. sq.	0.1533 * (0.0867)	0.1536 * 0.0590 *** 0.2126 **	0.1109 (0.0837)	0.1118 0.1340 *** 0.2458 ***	0.0792 (0.0781)	0.0808 0.2126 *** 0.2934 **
	WSD: Temp. cu.	0.0907 ** (0.0393)	0.0908 ** 0.0157 * 0.1066 **	0.0852 ** (0.0372)	0.0859 ** 0.0424 ** 0.1282 ***	0.0764 ** (0.0362)	0.0779 ** 0.0677 ** 0.1456 **
	WSD: Temp. qu.	-0.0732 *** (0.0230)	-0.0733 *** -0.0163 *** -0.0896 ***	-0.0598 *** (0.0224)	-0.0603 *** -0.0373 *** -0.0976 ***	-0.0512 ** (0.0214)	-0.0522 ** -0.0588 *** -0.1109 ***
	WSD: Temp. * $\bar{T}_i$	-0.0354 ** (0.0139)	-0.0355 ** -0.0113 *** -0.0468 ***	-0.0302 ** (0.0141)	-0.0305 ** -0.0277 *** -0.0581 ***	-0.0206 (0.0125)	-0.0210 -0.0363 *** -0.0573 ***
Rural (PR)	WSD: Temp.	0.4809 *** (0.1765)	0.4822 *** 0.0739 * 0.5561 ***	0.5163 *** (0.0186)	0.5211 *** 0.1493 * 0.6704 ***	0.4366 *** (0.1556)	0.4473 *** 0.1971 0.6444 **
	WSD: Temp. sq.	0.0496 (0.1041)	0.0497 0.0518 ** 0.1016 ***	0.0132 (0.0999)	0.0134 0.0915 ** 0.1048	-0.0033 (0.0928	-0.0034 0.1591 ** 0.1557 **
	WSD: Temp. cu.	-0.0208 (0.0407	-0.0208 0.0105 -0.0103	-0.0272 (0.0385)	-0.0275 0.0234 -0.0041	-0.0206 (0.0359	-0.0211 0.0450 0.0239
	WSD: Temp. qu.	-0.0073 (0.0261)	-0.0074 -0.0139 ** -0.0213	0.0021 (0.0249)	0.0021 -0.0250 ** -0.0229	0.0038 (0.0234)	0.0039 -0.0444 ** -0.0405
	WSD: Temp. * $\bar{T}_i$	-0.0406 *** 0.0133	-0.0407 *** -0.0118 *** -0.0525 ***	-0.0421 *** (0.0127)	-0.0425 *** -0.0239 *** -0.0664 ***	-0.0341 *** (0.0117)	-0.0350 *** -0.0361 *** -0.071 ***
	Rho: MEGA	-0.0394 (0.0491)		-0.0465 (0.0413)		0.0901 ** (0.0459)	
	Rho: Urban	0.2270 *** (0.0256)		0.4320 *** (0.0246)		0.5693 *** (0.0222)	
	Rho: Interm.	0.2191 *** (0.0259)		0.4548 *** (0.0229)		0.6101 *** (0.0201)	
	Rho: Rural	0.2430 *** (0.0339)		0.4102 *** (0.0306)		0.6106 *** (0.0213)	
	Lambda	0.4440 *** (0.0082)		0.3667 *** (0.0084)		0.2457 *** (0.0100)	
Observations R squared		29,574 0.378		29,574 0.375		29,574 0.381	

Notes: Analogous to Table D.4 but using Weighted Standardized Deviations (WSD) of temperature instead of yearly average (YA) temperature as weather indicator.

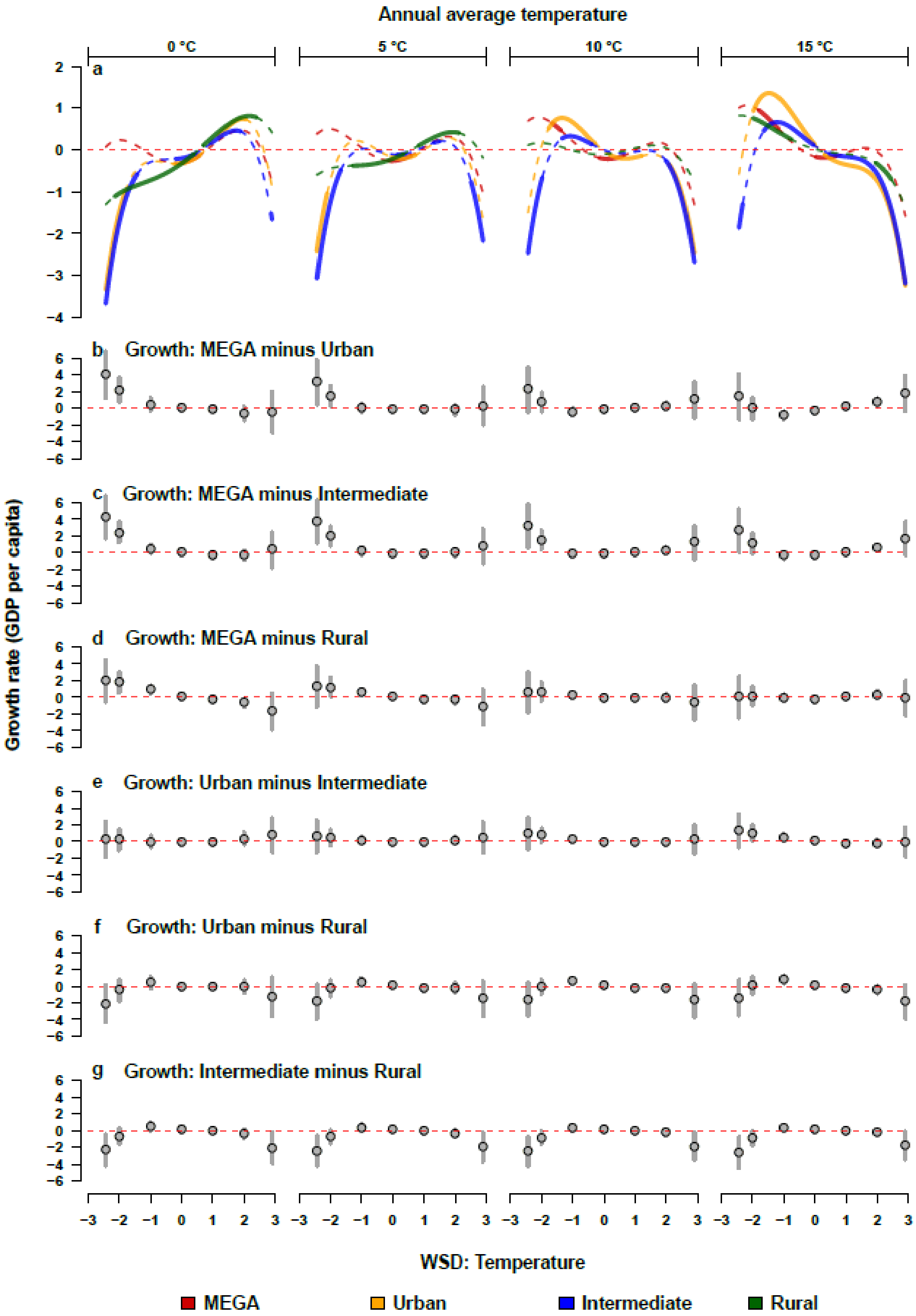

Figure D.8: Heterogenous effects of WSD temperature on regional economic growth.
a) Non-linear relationship between WSD of temperature and regional growth of GDP per capita at selected baseline temperature levels differentiated by region type (see Table D.5). Solid lines indicate a statistically significant relationship at 10% level or lower, while non-solid lines indicate an insignificant relationship.
b-g) Comparison of predicted growth effects between region types at selected magnitudes of temperature deviation calculated on basis of total spatial effects. Each panel shows the difference in predicted effects between the corresponding region pair (points) with 90% credible intervals (grey bars).

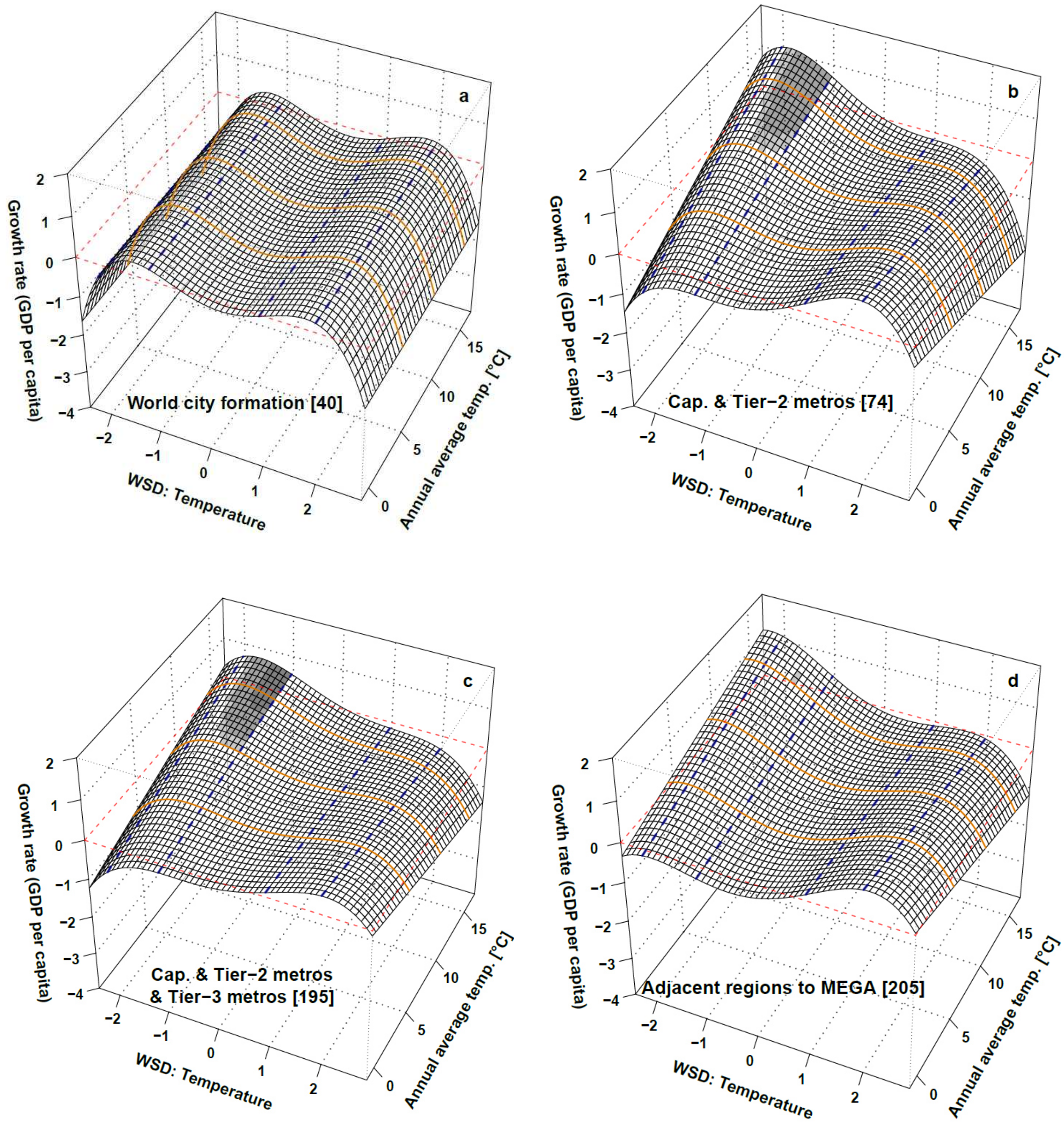

Figure D.9: Alternative definitions top-tier city regions: robustness checks (WSD).
Relationship between WSD of temperature and regional growth of GDP per capita moderated by regional climatic conditions (annual average temperature) distinguished by alternative MEGA definitions. The WSD is expressed in standard deviations (σ). Black grid lines in 3D plot show response functions depending on values of annual average temperature calculated on basis of total spatial effects (sum of direct effects and spill-in effects). White areas in response grid indicate non-significant relationships and grey shaded areas indicate statistically significant relationships at 10% significance level or lower (darker shade represents higher probability that the posterior distribution does not contain zero). Blue dashed lines mark WSD axis tick values for thresholds of moderate and severe anomalies. Depicted marginal effects are based on total spatial effects. Number of regions in square brackets.

a) World city formation: NUTS-3 regions that host a city that shows evidence of world city transformation as defined by Beaverstock et al. (1999).

b) Core regions of capital regions and Tier-2 metropolitan regions following the regional typology of Dijstkra (2009).

c) Core regions of metropolitan regions (capital regions, Tier-2 metros, and Tier-3 metros) following the regional typology of Dijstkra (2009).

d) Surrounding regions of baseline MEGA definition using the Queen (common border) weighting scheme to determine adjacent regions.

Table D.6: Regression estimates for components of output growth (YA)

YA	SARAR (ED,Q)							
	(1)		(2)		(3)		(4)	
	Agriculture	Impacts	Industry	Impacts	Services	Impacts	Non-market	Impacts
Temp.	1.3134 ** (0.6619)	1.3134 ** 0.1061 1.4195 **	0.3768 (0.2806)	0.3777 0.1365 0.5142	0.1272 (0.1914)	0.1272 0.0123 0.1395	0.0175 (0.1838)	0.0176 0.0117 0.0293
Temp. sq.	-0.0723 ** (0.0284)	-0.0723 ** -0.0058 ** -0.0782 **	-0.0260 ** (0.0120)	-0.0261 ** -0.0094 ** -0.0355 **	-0.0052 (0.0085)	-0.0052 -0.0005 -0.0057	-0.0031 (0.0083)	-0.0031 -0.0021 -0.0052
Rho	0.0749 *** (0.0214)		0.2673 *** (0.0751)		0.0871 *** (0.0157)		0.4026 *** (0.0120)	
Lambda	0.6931 *** (0.0059)		0.4004 *** (0.0012)		0.4916 *** (0.0008)		0.4365 *** (0.0023)	
Observations	29,574		29,574		29,574		29,574	
R squared	0.486		0.299		0.281		0.287	
Optimum	9.1		7.3		12.2		2.8	

Notes: Estimation results of baseline SARAR model for pooled sample to model the relationship between yearly averages (YA) of temperature and growth of sectoral output. All models include precipitation controls, region fixed effects, year fixed effects separated for Scandinavian regions and remaining regions, and errors clustered by regions. Dependent variables are growth rates of inflation-adjusted Gross Value Added (GVA) for the respective sector: (1) agriculture, (2) industry, (3) services, (4) non-market. Impacts show spatial impacts for each covariate: direct impact (first row), indirect impact (second row) and total impact (third row). Optimum is the estimated temperature optimum of the non-linear response function (calculation based on total impacts). Temperature is measured in °C. Coefficients are derived by the mean of posterior distribution and standard deviation of posterior in parentheses. Statistical significance level: 1% ***, 5% **, 10% * (*** 99%, ** 95%, * 90% credible interval for parameter does not include zero).

Table D.7: Regression estimates for components of output growth (WSD)

WSD	SARAR (ED,Q)							
	(1)		(2)		(3)		(4)	
	Agriculture	Impacts	Industry	Impacts	Services	Impacts	Non-market	Impacts
WSD: Temp.	1.2243 ** (0.6188)	1.2245 ** 0.0878 * 1.3123 **	-0.2714 (0.2608)	-0.2720 -0.0976 -0.3696	0.1848 (0.1891)	0.1848 0.0153 0.2002	0.1889 (0.1714)	0.1899 0.1280 0.3179
WSD: Temp. sq.	-1.1204 *** (0.3036)	-1.1206 *** 0.0816 ** -1.2022 ***	0.2819 ** (0.1187)	0.2826 ** 0.1010 ** 0.3836 **	0.1342 (0.0866)	0.1342 0.0112 0.1455	0.1803 ** (0.0798)	0.1813 ** 0.1223 ** 0.3036 **
WSD: Temp. cu.	0.0600 (0.1229)	0.0601 0.0045 0.0646	0.1644 *** (0.0559)	0.1648 *** 0.0590 *** 0.2238 ***	-0.0435 (0.0378)	-0.0435 -0.0036 -0.0471	-0.0322 (0.0330)	-0.0323 -0.0217 -0.0541
WSD: Temp. qu.	0.0437 (0.0721)	0.0437 0.0032 0.0469	-0.1097 *** (0.0323)	-0.1099 *** -0.0393 *** -0.1493 ***	0.0014 (0.0223)	0.0014 1.00E-04 0.0015	-0.0034 (0.0197)	-0.0135 -0.0091 -0.0227
WSD: Temp. * $\overline{T}_i$	-0.0820 * (0.0481)	-0.0820 * -0.0059 -0.0879 *	-0.0274 (0.0196)	-0.0275 -0.0098 -0.0373	-0.0192 (0.0143)	-0.0192 -0.0016 -0.0208	-0.0192 (0.0136)	-0.0193 -0.0130 -0.0323
Rho	0.0674 *** (0.0194)		0.2645 *** (0.0170)		0.0764 *** (0.0210)		0.4060 *** (0.0132)	
Lambda	0.6955 *** (0.0063)		0.3992 *** (0.0079)		0.4975 *** (0.0080)		0.4316 *** (0.0079)	
Observations	29,574		29,574		29,574		29,574	
R squared	0.486		0.299		0.281		0.287	

Notes: Analogous to Table D.6 but using Weighted Standardized Deviations (WSD) of temperature instead of yearly average (YA) temperature as weather indicator.

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