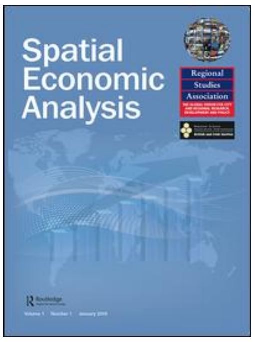

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Sharing the burden: quantifying climate change spillovers in the European Union under the Paris Agreement

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SPATIAL ECONOMIC ANALYSIS
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ABSTRACT

Climate change has emerged as a growing threat to the European economy, whose economic losses are relevant for global growth. Rising temperatures and worsening extreme events are expected to affect climate-vulnerable sectors. Due to the economic integration within the European Union (EU), these impacts will likely have spillover effects and feedback loops to and from other regions. This study uses spatial econometrics to account for the interdependencies between the subnational EU regions to estimate the future impacts of changes in temperature on sectoral labour productivity under the Paris Agreement. The study confirms the presence of spatial spillover effects of climate change, and finds that observations at the economy-wide level of a non-linear, concave and single-peaked relationship between temperature and productivity do not always hold true at the sectoral level.

KEYWORDS

spatial econometrics, labour productivity, subnational analysis, climate change, sectoral analysis, European Union

HISTORY Received 17 March 2019; in revised form 3 March 2021

INTRODUCTION

The European Union is an economic powerhouse contributing 20.7% of the global economy, and has been increasingly important for innovation, growth and international trade.[1] However, it remains at risk of climate change impacts. Observed trends and future projections show regional differences in temperature and precipitation changes (e.g., precipitation is expected to increase in Northern Europe but expected to decrease in the South), as well as frequency and intensity of

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climate extremes in Europe. These changes will have large implications for human health through increases in heatwaves and the spread of infectious diseases; and can greatly affect sectors such as agriculture, forestry, energy, transport and tourism (Kovats et al., 2014).[2]

Based on existing studies, the reduction in overall output associated with the increase in mean temperature is non-linear, concave and single-peaked (Burke et al., 2015; Dell et al., 2014; Heal & Park, 2013). Global estimates from Burke et al. (2015) show that productivity peaks at an annual average temperature of 13°C, and sharply declining at higher temperatures. The International Monetary Fund (IMF) (2017) follows the methodologies of Burke et al. (2015) and arrives at similar conclusions of optimal temperatures around 13–15°C; and estimates a degree deviation from 22°C for the median emerging economy by 0.9 percentage points, and a degree deviation from 25°C for the median low-income country by 1.2 percentage points. Among the three main economic sectors, the outputs of agriculture and industry sectors are most affected by rising temperatures, and only the services sector seems to be protected from weather and climatic shocks (Burke et al., 2015; Dell et al., 2012; IMF, 2017).

While rising temperatures are seen to be detrimental to most economic activity, specifically for outdoor workers as discussed in the impacts on labour productivity, there may still be positive impacts on some sectors. For instance, some crops that prosper in warmer conditions and summer tourism could benefit from this change (Bosello et al., 2012; Grillakis et al., 2016). Barrios & Ibáñez (2015) estimate a modest annual increase of 0.32% of gross domestic product (GDP) for Northern Europe, while Southern Europe could experience a reduction by 0.45% of GDP per year given current climate conditions. Economic projections of climate change impacts in the EU plus UK amount to a total household welfare loss of €175 billion, or 1.38%, under a 3°C warming scenario, of which the impacts from human mortality are the largest. Restricting global warming to 1.5 and 2.0°C lowers the impacts to €42 and €83 billion, respectively (Szewczyk et al., 2020).

Climate-related economic risks are not only determined by the magnitude of the biophysical hazard and the exposure to these hazards, but also by vulnerability, which is both multidimensional, sector and area-specific (Field et al., 2015). That is, the overall impact is determined by how the biophysical impacts are channelled into the different economic activities, and the resilience and sensitivity of each factor of production,[3] which depend on human and physical capital capacities to adapt, anticipate and absorb changes. Due to vulnerabilities in multiple sectors (i.e., tourism, agriculture, forestry, infrastructure, energy and population health), Southern Europe is expected to be affected more than any other region (Kovats et al., 2014).

The increase in temperatures is likely to operate through four impact channels: lower agricultural output, reduction in labour productivity, reduced capital formation and poorer health. The impact of rising temperatures to capital accumulation is most pronounced in the medium term for investment, estimated to decline by 6% and have a lag of seven years (IMF, 2017). On the other hand, heat (or cold) also affect human health, behaviour and decisions (Heal & Park, 2013), which have substantial implications on labour as a factor of production in two aspect: labour supply and labour productivity.

Labour supply is directly reduced through lasting damages to health due to heat exhaustion, heat stroke or even death (Bouchama & Knochel, 2002; Schulte et al., 2016; Schulte & Chun, 2009; United Nations Development Programme (UNDP), 2016). Rising temperatures also raise infant mortality by 0.12 percentage points (IMF, 2017); and mortality due to cardiovascular and respiratory diseases that result in much higher rates than natural causes (Baccini et al., 2008).

The reduction in labour productivity has been associated with the natural trade-off between spending time to avoid health risks and the time to engage in economic activity (Dell et al., 2014; UNDP, 2016). Temperature shocks that are unmitigated through adequate thermoregulatory infrastructure, such as air-conditioning, cause poor countries to remain poor due to productivity losses from an already heat-stressed workforce (Heal & Park, 2013). Research on occupational health risk from increasing temperatures using changes in ambient temperature point to the reduction in labour productivity in higher temperatures as a result of natural human responses to avoid damages to health, for example, workers slow down, take more breaks to rehydrate and cool down (Kjellstrom et al., 2009a, 2009b; Parsons, 2014); or in cases of severe temperature increases, excessive body temperature and dehydration can cause not only slower working but also workers making more mistakes and having increased accidental injuries (Bouchama & Knochel, 2002; Schulte et al., 2016; Schulte & Chun, 2009). Sahu et al. (2013) estimate that for the agriculture sector, where there is minimal protection from outside temperatures, hourly labour reduces its productivity when ambient temperature increases from 26 to 31°C.[4] Heat stress from prolonged exposure to high temperatures also diminishes cognitive performance (Martin et al., 2019). This impact makes rising temperatures relevant not only for heavy mechanical outdoor work but also for indoor work that requires heavy analytical thinking (e.g., the finance sector).

Although there is the possibility of physiological acclimatization, this form of adaptation takes one to two weeks of exposure to develop, therefore negative impacts are likely to happen in the event of a sudden large deviation of temperature from normal, particularly during heatwaves. Economic sectors vulnerable to increasing temperatures are those whose work environment cannot be fully controlled, such as agriculture, manufacturing, construction and other industrial work, tourism, and transport, as well as industries that require heavy physical exertions such as heavy and manual labour (UNDP, 2016).

A large assumption in many econometric methods in estimating climate change impacts is that the variables used are independent and identically distributed (iid), which does not always hold true in the real world. Particularly in the case of the single-market economy of the EU, where spatial interdependence is very likely, an impact on one region can have spillover effects and feedback loops to and from another region.

This paper considers the possibility of direct climate impacts and spillovers within the EU by using a spatial panel regression at the NUTS-2 level[5] to estimate the historical, economy-wide and sectoral impacts of climate change. To compute the impacts of future warming, we use policy-relevant climate projections from several regional climate models (RCMs) that reflect levels of mitigation action from the Paris Agreement targets of 1.5 and 2°C. Three key findings of this paper contribute to the existing knowledge on climate impact estimation: first, the results confirm the non-linear relationship between temperature and productivity; however, this finding does not hold true for all sectors; second, the calculated optimal temperature is also sector-specific; and finally, the omission of spatial interdependence in econometric modelling would lead to biased estimates, at least in the case of the EU, given the significance of our spatially lagged dependent and independent variables that provide evidence of spatial spillovers.

The following sections discusses the data used, detail the empirical framework, present the results and, finally, conclude and discuss the realizations and implications of the results.

DATA

Economic data

The dependent variable used in this analysis is the estimate of labour productivity, computed as the sectoral gross value-added (GVA) at basic prices[6] per economically active person aged 15–74 years[7] from 2000 to 2015 sourced from EUROSTAT (European Commission, 2020). It needs to be noted that the NUTS-2 regions of France are missing from 2000 to 2014. We have estimated the values of France's GVA by taking the mean share of the subnational regions to total France in 2015 and 2016 by economic sector, and applying these shares to the total GVA of France at the country level (NUTS-0). After doing this, we arrive at a balanced panel of 268 subnational regions from the EU-27[8] plus the UK.

Following the value-added approach or the supply-side approach in calculating overall economic production, we define the sectors as (1) agriculture, which consists of agriculture (crops), forestry and fishing; (2) industry, which consists of mining, manufacturing and utilities (electricity, water, gas); (3) construction; and (4) services, which consists of wholesale and retail trade; transport; accommodation and food service activities; information and communication; financial and insurance activities; real estate activities; professional, scientific and technical activities; administrative and support service activities, and public administration and defence; compulsory social security; education; human health and social work activities; arts, entertainment and recreation; repair of household goods; and other services.

Climate data

GLDAS

Our historical climatic data comes from the Global Land Assimilation System (GLDAS v2.1) (Rodell et al., 2004), a gridded, reanalysis climatic dataset, with $0.25^\circ \times 0.25^\circ$ spatial and 3-hourly temporal resolution. We utilize the gridded 3-hourly data and compute the various aggregated indicators at the subnational level (NUTS-2).

GCM-RCM

We use three regional climate models (RCMs) from the Euro-CORDEX initiative Jacob et al. (2014) with 0.11° horizontal resolution (12.5 km) forced with three global climate models (GCMs) (EUR-11). We considered two criteria for the selection of climate models: (1) the RCMs should be driven by different GCMs; and (2) the RCMs should be developed by different institutions. In the absence of a representative concentration pathway (RCP) corresponding to the Paris Agreement targets,[9] we use a time-slicing approach to determine the time period when global warming thresholds are crossed. The GCM-RCM combination used to project the future climate at these thresholds refers to RCP8.5,[10] which covers a wider range of warming levels compared with the more optimistic RCPs. To define a period of warming of global mean temperature rise of the above-mentioned thresholds, we follow Vautard et al. (2014) and Schleussner et al. (2016) where each threshold period is defined as the time when the 21-year global mean temperature reaches at a particular threshold compared with the pre-industrial period of 1850–1900. We use the observed warming (HADCRUT4) as the reference period (1985–2005), and then add the projected warming from a GCM in order to reach a specific threshold.

The GCM-RCM matrix used in this study, along with the time period when RCP 8.5 reaches 1.5 and 2.0°C thresholds, are summarized in Table 1. Table 2 provides the summary statistics of the historical data; while Figure 1 provides the projected mean and maximum temperatures under the baseline, 1.5 and 2.0°C scenarios .

EMPIRICAL FRAMEWORK

The analysis focuses on the relationship between temperature and labour productivity at the EU subnational level. A balanced panel is used, consisting of 268 spatial entities and 16 years, totalling 4288 observations for each variable used.

Table 1. Global climate models (GCMs)–regional climate models (RCMs) ensemble members used in this paper.

Driving GCMs	RCM	1.5°C	2.0°C
MPI-ESM-LR	CSC-REMO2009	2019–39	2033–53
MOHC-HadGEM2-ES	SMHI-RCA4	2009–29	2022–42
ICHEC-EC-EARTH	KNMI-RACMO22E	2017–37	2033–53

Table 2. Summary statistics.

Statistic[a]	Mean	SD	Minimum	Pctl(25)	Pctl(75)	Maximum
Dependent variable[b]						
Agriculture	1003.2	809.5	−446.0[f]	416.0	1403.1	4959.6
Industry	9051.3	5122.6	522.2	4981.3	12,329.5	46,669.9
Construction	2733.9	1325.7	115.2	1887.7	3572.6	10,588.4
Manufacturing	7368.9	4540.2	380.9	3707.3	10,208.5	44,487.2
Services	32,464.7	22,487.1	1049.5	21,410.9	39,703.9	355,402.5
Total economy	45,220.6	25,465.1	2112.5	31,058.4	55,972.1	370,198.0
Independent variable						
Precipitation	2.500	0.638	0.404	2.081	2.852	7.128
Maximum temperature	14.247	3.515	1.594	12.380	16.038	31.892
Mean temperature	10.165	3.147	−1.649	8.641	11.324	26.133
Temperature deviation[c]	0.075	0.540	−2.921	−0.204	0.429	2.541
WBGT[d]	9.530	1.930	2.544	8.601	10.222	20.035
WSDI[e]	10.498	17.308	0	0	14	346

Notes: [a]$N = 4288$.
[b]Sectoral labour productivity defined as the sectoral gross value-added (GVA) per active population.
[c]Deviation of temperature to the short-run rolling average.
[d]Wet bulb globe temperature.
[e]Warm spell duration index, defined as the annual count of days with at least six consecutive days when maximum temperature > 90th percentile.
[f]The negative labour productivity calculation is due to a negative recorded GVA for agriculture in Småland and the islands (SE21) in 2005 of €−184.76 million. Since a negative labour productivity is illogical, we have converted this negative entry into a value close to zero in the analysis.

The empirical analysis takes a two-step approach: first, we estimate the historical relationship between climatic stressors and sectoral productivity, and we then apply these estimates with climate projections under different global warming thresholds: 1.5 and 2°C.

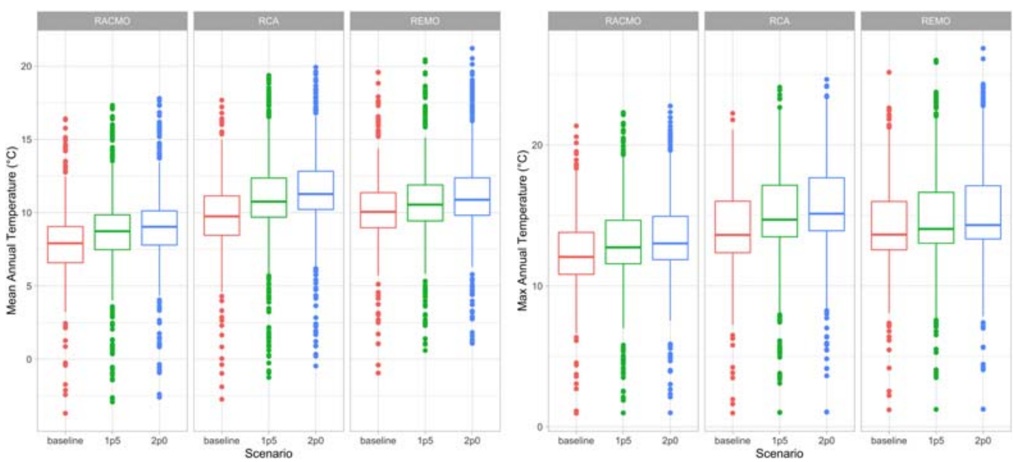

Figure 1. Mean and maximum temperature projections.
Note: Projected mean annual temperature (left) and maximum temperature (right) by the climate model and global warming scenario: baseline, 1.5°C (1p5) and 2.0°C (2p0).

Historical impact

Non-linear panel regression

We consider a non-linear, econometric panel regression (Burke et al., 2015; Hsiang, 2016), controlling for various climatic stressors and socioeconomic variables, as specified in equation (1):

$$y_{its} = \alpha + \beta X_{it} + \mu_i + \gamma_t + \epsilon_{it} \tag{1}$$

where y_{its} is the natural logarithm of labour productivity in region i in a given year t for sector s; X is a vector of independent variables influencing sectoral labour productivity including mean annual temperature, total annual precipitation and its second-degree polynomial, the short-run temperature shock computed as the difference of the mean temperature from a rolling average of four periods prior,[11] the warm spell duration index (WSDI) calculated as the annual count of days with at least six consecutive days when the daily maximum is greater than the 90th percentile (Mistry, 2019), and the maximum annual temperature defined as the maximum near surface air temperature. We also include region (α_i) and year (γ_t) specific fixed effects.

Given the existing findings on the non-linear and inverse 'U'-shaped relationship of economic performance and local temperatures, we expect the linear term of temperature to be positive and the second-degree polynomial of temperature to be negative. Precipitation affects the returns in sectors such as agriculture and is known to influence aggregate economic output as well. The WSDI is a long-term climatic stressor that captures the heterogeneous impact of extreme heat-related events on labour productivity.

As a robustness check, we also consider wet bulb globe temperature (WBGT), instead of mean annual temperature, which is a commonly used heat-stress index when looking into occupational health (International Labour Office (ILO), 2019; Mistry, 2020).

Spatial econometrics

Given the possibility of spatial interdependence in a close-knitted economy such as the EU, we transform equation (1) into a spatial lag of y model, particularly the spatial Durbin model (SDM), which includes a linear combination of neighbouring region values for both the dependent and independent variables. We utilize a row-normalized spatial weight matrix to define neighbouring regions within 250 km based on the greatest Euclidean distance. The spatial dependence between NUTS-2 regions decays as distance between them increases, while the diagonal elements of the matrix are zero to signify that a region is not a neighbour of itself. By incorporating the spatial weights, we run a SDM with fixed effects of the form:

$$y_N = \alpha\iota_N + \rho W_N y_N + X_N\beta + W_N X_N \delta + \mu + \gamma_t + \epsilon_N \tag{2}$$

where y is the $N \times 1$ vector of dependent variable; X is a $N \times k$ matrix of explanatory variables with the corresponding $k \times 1$ parameter vector β; W_N is a non-stochastic $N \times N$ spatial weights matrix; ρ and δ are the spatially lagged parameters of the dependent and independent variables, respectively; μ and γ represent the region and year fixed effects; and ϵ_N is assumed to be normally distributed and adheres to the Gauss Markov assumptions ($\epsilon_N \sim iid(0, \sigma_\epsilon^2 I_N)$) (LeSage & Pace, 2014; Millo & Piras, 2012).

Isolating the dependent variable on the left-hand side of the equation, we arrive at equation (3), which implies a non-linear relationship in SDM between the dependent and independent variable, such that $(I_N - \rho W_N)^{-1}$ can be expressed as an infinite sequence

$I_N + \rho W + \rho^2 W^2 + \rho^3 W^3 \ldots$, and so on:

$$y_N = (I_N - \rho W_N)^{-1}(\alpha\iota_N + X_N\beta + W_N X_N\delta + \mu + \gamma_t + \epsilon_N) \tag{3}$$

The non-linearity in the relationship implies that the resulting coefficients α, β and δ cannot be interpreted directly as a partial derivative as in the non-spatial linear regression, but would need additional calculations (LeSage & Pace, 2014). We refer to these calculations as the marginal effects that represent an $N \times N$ matrix of partial derivatives, as shown in equation (4):

$$\frac{\partial y}{\partial x_k} = (I_N - \rho W_N)^{-1}(I_N\beta_r + W_N\delta) \tag{4}$$

A matrix representation of the partial derivatives is given by equation (5) Elhorst (2014):

$$\left[\frac{\partial y}{\partial x_{1k}} \cdot \frac{\partial y}{\partial x_{Nk}}\right] = (I_N - \rho W_N)^{-1}\begin{bmatrix} \beta_k & w_{12}\delta_k & \cdot & w_{1N}\delta_k \\ w_{21}\delta_k & \beta_k & \cdot & w_{2N}\delta_k \\ w_{N1}\delta_k & w_{N2}\delta_k & \cdot & \beta_k \end{bmatrix} \tag{5}$$

A scalar representation of the marginal effects consists of the direct effects, referring to the mean of the main diagonal elements which show the impact of the kth explanatory variable of region i to itself; the indirect effects, referring to the off-diagonal elements, wherein the mean of the sum of the off-diagonal elements from each row represents a scalar measure of the cumulative indirect effects or spatial spillovers (LeSage & Pace, 2014).

Impact projections

In order to estimate the future sectoral, subnational economic risk on labour productivity, we combine our econometric estimates with gridded climate data from three RCMs under various global warming scenarios using the Delta method (Gleick, 1986; Mistry et al., 2017). The projections capture uncertainties around mitigation action and warming trajectories through a range bounded by two mitigation scenarios consistent with the Paris Agreement – a low-warming scenario of 1.5°C and 0.5° increment to 2.0°C. Given the focus on temperature in this study, we apply the changes in temperature under the two warming scenarios to the matrix of marginal effects on labour productivity with respect to mean and maximum temperatures, assuming all other variables remain constant.

EMPIRICAL RESULTS

Historical impacts

Our regression results based on equation (1) (see Table A1 in Appendix A in the supplemental data online) confirm the non-linearity and concave relationship between the mean annual temperature and total labour productivity, as well as precipitation. This observation is not consistent with all the subsectors. For instance, the agriculture sector responds linearly and positively to increases in mean annual temperature and deviations to the short-run mean, but is the most negatively affected sector as maximum temperatures increase. Precipitation and WSDI show no significant impacts to labour productivity in agriculture, which could be attributed to a well-established irrigation system within the EU (European Parliament, 2019). In terms of productivity in the industry sector, precipitation shows significant non-linear, concave impacts, which suggest that both the lack of and excessive amounts of rainfall lead to a suboptimal level of production. Similar to the total economy, the construction sector also shows a non-linear and concave relationship between mean temperature and productivity. The services sector show a linear and positive relationship between mean temperature and productivity, as well as precipitation and productivity, but negatively to the extreme

Table 3. Regression results: spatial Durbin model (SDM).

	Total economy	Agriculture	Industry (excluding cons)	Construction	Services
Spatial lag (ρ)	0.497***	0.066**	0.474***	0.482***	0.518***
	(0.021)	(0.029)	(0.021)	(0.021)	(0.020)
Mean Temp.	0.024**	0.081	0.030**	0.082***	0.019*
	(0.011)	(0.050)	(0.015)	(0.020)	(0.011)
Mean Temp. sq.	−0.001*	−0.002	−0.000	−0.005***	−0.000
	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)
Precipitation	0.074***	0.154	0.107***	0.016	0.070***
	(0.021)	(0.101)	(0.029)	(0.041)	(0.021)
Precipitation sq.	−0.008**	−0.025	−0.013**	−0.001	−0.007*
	(0.003)	(0.018)	(0.005)	(0.007)	(0.004)
Temp. Dev.	0.088***	0.085***	0.106***	0.150***	0.080***
	(0.006)	(0.028)	(0.008)	(0.011)	(0.006)
WSDI	−0.001***	−0.000	−0.001***	−0.002***	−0.001***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Max Temp.	−0.016***	−0.059**	−0.031***	−0.020**	−0.015***
	(0.005)	(0.024)	(0.007)	(0.010)	(0.005)
W_Mean Temp.	0.022	0.165	−0.031	0.206***	0.007
	(0.030)	(0.137)	(0.040)	(0.056)	(0.029)
W_Mean Temp.	0.001	−0.003	0.002	−0.002	0.001
sq.	(0.001)	(0.006)	(0.002)	(0.002)	(0.001)
W_Precipitation	0.039	−0.209	0.145	0.142	0.017
	(0.069)	(0.314)	(0.092)	(0.128)	(0.066)
W_Precipitation	−0.007	0.039	−0.024	−0.029	−0.003
sq.	(0.013)	(0.060)	(0.017)	(0.024)	(0.013)
W_Temp. Dev.	−0.024*	−0.026	−0.021	−0.051**	−0.027**
	(0.013)	(0.061)	(0.018)	(0.025)	(0.013)
W_WSDI	−0.001*	−0.001	−0.001***	−0.001	−0.001**
	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)
W_Max Temp.	−0.000	−0.064	0.034**	−0.116***	0.009
	(0.012)	(0.056)	(0.016)	(0.023)	(0.012)

Notes: WSDI, warm spell duration index.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

heat indices. All sectors indicate that temperature deviations from the short-run mean have positive impacts; however, extreme indices – WSDI (except for agriculture) and maximum temperature – result in negative impacts.

While these results show significant impacts, our likelihood ratio (LR) tests (see Table A3 in Appendix A in the supplemental data online) show that spatial autocorrelation exists, in which case the estimates of equation (1), derived using ordinary least squares (OLS), are biased.[12] We now refer to the results of the SDM in Table 3, where we see the same patterns of observation as the non-spatial regression results (see Table A1 in Appendix A in the supplemental data online); but with a different magnitude of impact due to the inclusion of spatially lagged dependent and independent variables. Our results show significant positive coefficients for the spatial lag of the dependent variables (ρ) for all sectors, suggesting that increases in productivity in one region has a positive effect on that in other regions. Similarly, negative impacts in one region would also result in negative spillovers. The coefficients of the spatially lagged independent variables (δ) show mixed results: WSDI (total economy, industry and service) and maximum temperature (industry and construction) show an additional negative impact to a region's productivity due to increases in neighbouring regions; while short-run temperature deviations in neighbouring countries (total economy, construction and service) partially offset the positive temperature deviation in a particular region. These results show that, depending on the sector and the climate stressor, the total impact to productivity would depend on the direct impacts to the region, and the indirect impacts from neighbouring regions, which would not always have the same direction of change.

Marginal effects

In order to interpret the findings in Table 3 correctly, we now refer to Table 4, which provides the summary measures of the direct, indirect and total effects.

The marginal direct impacts show the same observed patterns as in the coefficients in Table 3. Similar to the non-spatial panel regression, the results also suggest a similar pattern in that gradual changes in mean temperature have positive impacts, but worsening extreme temperatures have a very significant, negative effect.

The indirect impacts, however, provide additional insights into the sensitivity of the sector to its neighbours' productivity. Based on our results, we find that the impacts to the agriculture sector are mainly coming from direct impacts to the region, and not from spatial spillover effects. This is, however, different for the other sectors, where we find that the spillover effects are only slightly lower than the direct effects, suggesting that total impacts are also largely driven by losses (or gains) in the neighbouring regions. This finding is supported by intra-EU trade statistics, where manufactured goods are significantly more heavily traded than primary goods. In 2019, trade in manufactured goods are four times as much as primary goods, with some member states having much larger values (i.e., Czechia and Slovakia had more than 10 times as much, while Estonia, Lithuania and Latvia had less than twice as much) (European Commission, 2020).

The findings and this study, however, are limited to within the EU-28 countries, and do not exclude the possibility of having spatial spillover effects from climate change from outside the EU in the agriculture sector. The EU is, in fact, a net importer of primary goods, with imports mainly coming from Russia (19%) and the United States (7%) (European Commission, 2019). Expanding the study outside the member states would, therefore, likely produce significant indirect effects from climate change.

Sensitivity analysis

Weights matrix

We test different distance thresholds (50, 150, and 250 KM) for the spatial weight matrix to control for spatial dependence across the climatic and productivity variables. Our results show minimal changes in the parameters. We choose the distance threshold of 250 KM based on the Akaike information criterion (AIC) statistic, where the AIC for this regression was the lowest for all the sectors.

WBGT

In addition, we conducted an alternative specification of the regression equation, replacing the mean annual temperature with WBGT. The results indicate the same direction of

Table 4. Summary estimates of the direct, indirect and total effects.

	Total economy	Agriculture	Industry (excluding cons)	Construction	Services
Direct effects					
Mean Temp.	0.025**	0.082*	0.032**	0.085***	0.020*
	(0.012)	(0.046)	(0.014)	(0.021)	(0.011)
Mean Temp.	−0.001*	−0.003	−0.0003	−0.005***	−0.0003
sq.	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)
Precipitation	0.077***	0.154	0.111***	0.017	0.073***
	(0.022)	(0.102)	(0.033)	(0.040)	(0.022)
Precipitation	−0.008**	−0.025	−0.013**	−0.001	−0.007*
sq.	(0.004)	(0.018)	(0.006)	(0.007)	(0.004)
Temp. Dev.	0.092***	0.085***	0.110***	0.157***	0.084***
	(0.006)	(0.027)	(0.008)	(0.025)	(0.006)
WSDI	−0.001***	−0.0003	−0.001***	−0.002***	−0.001***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Max Temp.	−0.018***	−0.059**	−0.032***	−0.021*	−0.016***
	(0.005)	(0.021)	(0.007)	(0.010)	(0.005)
Indirect effects					
Mean Temp.	0.023**	0.006	0.026**	0.073***	0.020*
	(0.010)	(0.005)	(0.012)	(0.019)	(0.011)
Mean Temp.	−0.001*	−0.0002	−0.0003	−0.004***	−0.0003
sq.	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Precipitation	0.070***	0.01	0.092**	0.015	0.071***
	(0.020)	(0.009)	(0.029)	(0.035)	(0.023)
Precipitation	−0.008**	−0.002	−0.011**	−0.001	−0.007*
sq.	(0.004)	(0.002)	(0.005)	(0.006)	(0.004)
Temp. Dev.	0.083***	0.006	0.091***	0.134***	0.082***
	(0.009)	(0.004)	(0.011)	(0.016)	(0.009)
WSDI	−0.001***	−0.00002	−0.001***	−0.002***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Max Temp.	−0.016***	−0.004	−0.027***	−0.018*	−0.015***
	(0.005)	(0.003)	(0.006)	(0.009)	(0.005)
Total effects					
Mean Temp.	0.048**	0.088*	0.058**	0.158***	0.040*
	(0.021)	(0.050)	(0.026)	(0.039)	(0.022)
Mean Temp.	−0.001*	−0.003	−0.001	−0.009***	−0.001
sq.	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Precipitation	0.147***	0.165	0.203***	0.032	0.144***
	(0.042)	(0.109)	(0.061)	(0.075)	(0.044)

(*Continued*)

Table 4. Continued.

	Total economy	Agriculture	Industry (excluding cons)	Construction	Services
Precipitation	−0.016**	−0.026**	−0.024	−0.003	−0.015*
sq.	(0.007)	(0.019)	(0.011)	(0.014)	(0.008)
Temp. Dev.	0.176***	0.091***	0.201***	0.291***	0.166***
	(0.015)	(0.030)	(0.018)	(0.027)	(0.014)
WSDI	−0.002***	−0.0003	−0.002***	−0.004***	−0.002***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Max Temp.	−0.033***	−0.064***	−0.059***	−0.038*	−0.031***
	(0.010)	(0.023)	(0.014)	(0.019)	(0.011)

Notes: WSDI, warm spell duration index.
$*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

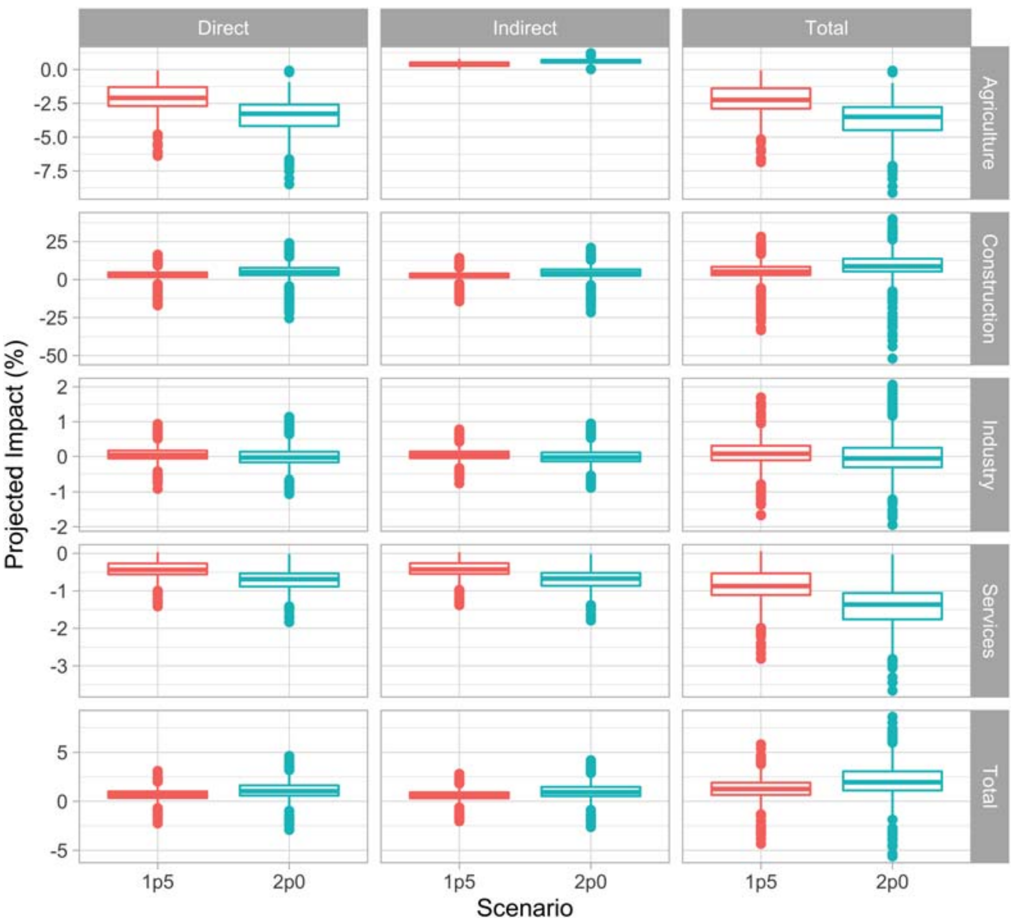

Figure 2. Projected impacts from mean and maximum temperatures.
Note: Projected impacts of mean and maximum temperatures by economic sector and type of marginal effect: direct, indirect and total effect.

relationship between the dependent and independent variables, with little change in the estimated optimal conditions, when applicable (see Table A2 in Appendix A in the supplemental data online).

Impact projections

The projected changes in mean and maximum temperatures, applied to the marginal impacts estimated, show losses in the agriculture and services sectors, and mixed results for the industry and construction sectors. Losses worsen as global warming estimates increase by 0.5° from 1.5 to 2.0°C, while gains under the former scenario increase with the latter. The estimates of the median total productivity show gains in the EU; however, the range of impacts show that there are also regions that are losing and gaining.

The largest direct losses in the subsectors are estimated in the subnational regions of northern Sweden and Finland, particularly in the Middle and Upper Norrland, West Finland, and the north and east Finland. Gains are expected for regions in Portugal (Alentejo, Algarve, Centro) and Spain (Extremadura, Castile-La Mancha, Madrid).

The direct impacts to the Upper Norrland and the north and east Finland are, however, partially and slightly offset by the gains in indirect impacts. Regions that are likely to have indirect gains in agriculture are western Austria (Vorarlberg, Tyrol, Salzburg) and north-east Italy (South Tyrol); indirect gains in industry, construction, and services are regions in Portugal and Spain.

The direct impact on agriculture shows that even under the 1.5°C scenario, all regions are expected to incur losses, which lead to an overall loss in total impacts. The services sector shows a similar pattern as the agriculture sector; however, indirect gains in this sector do not offset the direct gains, but rather increase the losses, leading to a greater total impact (Figure 2).

CONCLUSIONS

The estimation of climate impacts provides the key evidence to strengthening both mitigation and adaptation actions. In order to guide climate policy more accurately, our results suggest that one consider carefully where the impacts are originating, which implies looking into two main factors: first, the response of the economic sector to changes in climate – both gradual changes and sudden, extreme shocks; and second, the spatial origin of the climate shocks. In a highly interconnected economy as in the EU, it is logical to provide additional support to regions that are most affected by climate change, as these neighbouring impacts spread to other regions and could cause indirect changes, particularly for extreme heat events.

The results suggest that gradual warming may benefit the EU, however; this benefit may result in a net loss if extreme heat events worsen. Furthermore, the impacts are particular only to specific parts of a country and differ across economic sectors, which support the need for further study at the subnational and sectoral levels. Even at the most optimistic scenario of 1.5°C warming, losses are expected for the agriculture and services sectors, but these losses are still lower compared with a 2.0°C scenario, suggesting that even 0.5°C warming matters to the EU economy.

The results also imply the importance of economic structures and, consequently, future structural changes in determining the overall productivity impact due to climate change.

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NOTES

[1] IMF World Economic Outlook, October 2018.
[2] The health, agriculture, energy supply and tourism sectors are also noted by the European Commission as sectors at risk of increasing temperatures (European Commission).
[3] Labour, capital and technology.
[4] International Organization for Standardization (ISO) international standard (No. 7243, 1989) recommends regular rest periods when wet-bulb globe temperature (WBGT) > 26°C (UNDP, 2016).
[5] Nomenclature of Territorial Units for Statistics level 2.
[6] Labelled as nama_10r_3gva in the source database.
[7] Labelled as lfst_r_lfp2act in the source database. Due to many missing observations in terms of the number of employed in NUTS-2 regions (i.e., France and Poland) and in terms of hours worked (i.e., France, Hungary, Poland and Romania), we have opted to use economically active persons.
[8] Austria, Belgium, Bulgaria, Croatia, Republic of Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain and Sweden.
[9] The 1.5°C pathway can be closely approximated by RCP 1.9; however, bias-corrected data were not yet available at the time of publication.
[10] Referring to radiative forcing that reaches > 8.5 W m^{-2} by 2100 and continues to rise for some time. Source: https://www.ipcc-data.org/guidelines/pages/glossary/glossary_r.html.
[11] The length of the rolling average is arbitrary and guided by the observable length of a business cycle in EU regions.
[12] Baring the regression specifications run on the agriculture sector, LR test results reject the OLS in favour of the SDM.

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