Seasonal temperature variability and economic cycles *

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June 5th, 2022 ‡

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Abstract

In this paper, I examine to what extent seasonal temperature variability can explain seasonal economic cycles. To this aim, I first construct a novel dataset of seasonal temperature and seasonal GDP for a sample of 81 countries. This dataset reveals a much larger diversity of seasonal economic cycles around the world than previously reported. I then attribute these economic cycles to variation in temperature. For identification, I propose and apply a novel econometric approach that accounts for expectations and is based on seasonal differences. The results suggest that seasonal temperature has a statistically significant positive effect on seasonal GDP. The effect appears large, as seasonal temperature can explain a substantial share of the variation in seasonal GDP. Using data on GVA for different industry groups I can attribute this effect to industries that are relatively more exposed to ambient temperature. Furthermore, the results suggest that economic development makes countries more resilient to temperature fluctuations. Regarding future anthropogenic climate change, the results suggest that changes to seasonal temperatures will lead to a reallocation of economic activity from one season to another of up to several percentage points of annual GDP, pointing to a channel through which climate change will affect economic production that has so far been overlooked.

Keywords: temperature variability, seasonal cycles, macroeconomic fluctuations

JEL codes: E32, E23, Q54

*Acknowledgments: I gratefully acknowledge financial support by the UK's Economic and Social Research Council (ESRC) and support by the Grantham Research Institute on Climate Change and the Environment. For valuable comments, I am thankful to Tamma Carleton, Simon Dietz, Roger Fouquet, James Rising, Sefi Roth, Gregor Singer, Maria Waldinger, as well as participants of the 22nd IWH-CIREQ-GW Macroeconometric Workshop on Environmental Macroeconomics, the IPWSD workshop 2022 at Columbia University, the Occasional Research Workshop at UC Santa Barbara, and the LSE Environmental Economics cluster seminar. All remaining errors are my own.

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‡**If you cite this paper, please use the following reference:**
Linsenmeier, M. (2021): Seasonal temperature variability and economic cycles. Grantham Research Institute on Climate Change and the Environment Working Paper No. 374. ISSN 2515-5717 (Online).

1 Introduction

A large part of the variation of timeseries of macroeconomic variables is due to seasonality (Hylleberg et al., 1993). Understanding the causes of this seasonality has been an active area of macroeconomic research. While it has long been conjectured that some of the seasonality can be attributed to weather, research has come to the conclusion that observed quarterly variation of Gross Domestic Product (GDP) can mostly be explained by recurring shifts in preferences and technologies due to high consumption around Christmas and mid-year vacations (Beaulieu et al., 1992; Barsky and Miron, 1989; Cubadda et al., 2002; Beaulieu and Miron, 1992; Braun, 1995; Chatterjee and Ravikumar, 1992; Miron and Beaulieu, 1996; Franses, 1996). Furthermore, it has been pointed out that an important role of temperature seems to be in contradiction with similar economic cycles observed in countries in different hemispheres experiencing opposite seasons (Beaulieu et al., 1992). However, these conclusions were based on small samples of mostly OECD countries and little attention was paid to causal identification and to attribution of observed fluctuations to fundamental rather than proximate drivers. Given that anthropogenic climate change is projected to change seasonal cycles of temperature (Dwyer et al., 2012), the role of temperature for fluctuations of GDP appears to be an important question.

In this study, I empirically examine the influence of temperature on seasonal economic cycles. To do so, I construct a new dataset covering the period 1981-2020 using a global dataset of quarterly GDP covering 81 countries, a dataset on quarterly Gross Value Added (GVA) for 35 European economies, and climate reanalysis. Using information on quarterly temperature, I define seasons in a consistent way across countries in different hemispheres. For causal identification, I propose and apply a novel estimation strategy that is based on variation across countries in the differences in temperature and GDP between summer and winter.

I first use this novel dataset to identify stylised facts about quarterly fluctuations of GDP around the world. Previous studies were based on fewer economies mostly located in the Northern hemisphere and reported relatively similar cycles across countries with a primary peak of production in the fourth quarter and a trough in the first quarter. In contrast to these results, I find a large diversity of quarterly economic cycles. Of the 24 possible quarterly patterns, 15 are observed by at least one country in the sample. Economic cycles also seem to systematically differ between countries in the Northern and in the Southern hemisphere. Next I aggregate quarterly production to production in two seasons (Q1+Q4 and Q2+Q3), to which I refer as summer and winter depending on which season tends to be warmer. I find that production is larger in summer in 44 countries and larger in winter in 37 countries.

I next examine the contribution of temperature to these cycles and find that seasonal differences in temperature between summer and winter have a statistically significant positive association with seasonal differences in GDP. The estimated coefficient is robust to the inclusion of a variety of control variables, including annual mean temperature and the level of GDP per capita. The estimates are also robust to the choice between nominal and real GDP and to changing the time period from 1991-2020 to 2011-2020. Furthermore, I find similar effects if I consider the warmest and coldest quarter as summer and winter, respectively. Overall, the effect of temperature appears large, similar in size to the average observed seasonal economic cycle.

These results could be explained by several mechanisms through which temperature affects economic activity. I first use the global sample of countries and explore the role of agriculture, tourism, and international trade. I do not find evidence suggesting that any of these possible channels is important. I next use data on GVA for different industry groups for European economies and find a statistically significant effect of seasonal temperature on GVA only for industries in which production is relatively exposed to ambient temperature. At the level of industries, I can attribute this effect primarily to Construction, Industry, and Manufacturing. The results hence appear consistent with an effect of temperature on the supply side of the economy.

In the last part of the paper, I examine possible consequences of climate change. To do so, I also estimate a long differences version of the seasonal differences model. Despite the different identifying assumptions, the results are qualitatively and quantitatively similar to the results of the cross-sectional seasonal differences estimation. Specifically, I find that between 1981-2000 and 2001-2020, seasonal GDP increased relatively more if one season warmed more than the other season. This seems to be primarily due to a reallocation of economic activity between the two seasons, as I do not find evidence that seasonal warming had an effect on annual GDP.

I then combine my estimates with projections of seasonal temperature from climate models for alternative scenarios of future climate change. The results suggest that changes to the seasonal temperature cycle will cause a reallocation of economic activity across seasons of up to several percentage points of annual GDP. The results indicate a lot of variation between countries in terms of the projected reallocation. a scenario of strong climate change (RCP8.5) seasonal economic cycles are projected to increase. The magnitude of these effects is relatively uncertain, but central estimates suggest that in some countries seasonal economic cycles even double in size.

This paper contributes to prior work on seasonal economic cycles which has so far explained them primarily with recurrent shifts of preferences and technologies (Beaulieu et al., 1992; Barsky and Miron, 1989; Cubadda et al., 2002; Beaulieu and Miron, 1992; Braun, 1995; Chatterjee and Ravikumar, 1992; Miron and Beaulieu, 1996; Franses, 1996; Lumsdaine and Prasad, 2003). In contrast to this prior work, I find that some of the previously identified stylised facts can be observed only in about half of all countries because of large heterogeneity of seasonal economic cycles across countries. Furthermore, I find that the average effect of seasonal temperature is of a similar magnitude as the average seasonal economic cycle. This result does not rule out that preference and technology shocks are important channels, but points to the possibility that temperature is one fundamental driver of those shifts.

This paper also contributes to previous work on the effect of temperature on economic production. Previous work suggests a positive effect of annual mean temperature on economic production in relatively cold (and rich) and a negative effect in relatively warm (and poor) countries (Dell et al., 2012; Burke et al., 2015; Kalkuhl and Wenz, 2020). In this paper, I find evidence for an overall positive effect of seasonal temperature on seasonal production in countries with larger production in summer than in winter, but I also explain how this estimated effect is conceptually different from the effect of annual temperature on annual GDP estimated in previous studies.

The paper is structured as follows. In the next Section, I present the theoretical framework, explain the identification strategy, and describe the data used in this study. In Section 3, I first present stylised facts of seasonal economic cycles for my global sample of countries. I then discuss results obtained from my econometric estimation, before showing stylised facts and econometric results for the data on industry groups for countries in Europe. Furthermore, I combine my empirical estimates with results from climate models to quantify the order of magnitude of future possible seasonal reallocation of economic production. Conclusions are drawn in Section 5.

2 Methods

2.1 Theoretical framework

Identifying the causal effect of temperature on economic production requires an empirical framework that takes into account expectations. This is especially important for seasonal changes of temperature which are recurring every year and thus likely to be anticipated. In essence, seasonal cycles of temperature can be considered as a characteristic of the climate of a location, rather than its weather. To illustrate the challenge of causal identification in the presence of expectations and to explain the solution proposed in this paper, I start by formulating a simple conceptual model of economic production Y as a function of climate $\mathbf{C}$ and other factors $\mathbf{X}$. I follow Hsiang (2016) and assume that climate influences production through two channels: through the actually realised weather $\mathbf{c}$ and through beliefs about climate $\mathbf{b}$:

$$Y(\mathbf{C}, \mathbf{X}) = Y[\mathbf{c}(\mathbf{C}), \mathbf{b}(\mathbf{C}), \mathbf{X}] \tag{1}$$

In this framework, both climate $\mathbf{C}$ and weather $\mathbf{c}$ are charaterised by meteorological variables that describe the state of the atmosphere, such as temperature, precipitation, and humidity. The difference between the two concepts is that climate $\mathbf{C}$ refers to the (theoretical) probability distribution of these variables, while weather $\mathbf{c}$ refers to the (empirical) frequency distribution of their actually realised values. In other words, climate refers to the population of possible events, whereas weather refers to a sample drawn from that population. Weather can affect economic production directly for example through effects of precipitation on agricultural output or effects of temperature on the productivity of labour. Beliefs $\mathbf{b}$ are based on climate and affect economic production through actions of economic agents that are influenced by the expected future weather, such as the choice of production technology.

Climate and weather are specific to a location and a specific time period. Climate is typically defined for a period of 30 years, whereas weather is defined for shorter periods (hours, days, maybe a year). The term climate is commonly also used to refer to the statistics of weather of only certain parts of a year. For the purpose of this paper I use the term *seasonal climate* to refer to the climate of specific months. For example, seasonal climate can refer to the average weather of the months January, February, and March in London over the time period 1981-2010.

Given Equation 1 the marginal effect of (seasonal) climate on production can be written as

$$\frac{\partial Y(\mathbf{C})}{\partial \mathbf{C}} = \sum_{k=1}^{K} \frac{\partial Y(\mathbf{C})}{\partial \mathbf{c}_k} \frac{\mathrm{d}\mathbf{c}_k}{\mathrm{d}\mathbf{C}} + \sum_{n=1}^{N} \frac{\partial Y(\mathbf{C})}{\partial \mathbf{b}_n} \frac{\mathrm{d}\mathbf{b}_n}{\mathrm{d}\mathbf{C}} \tag{2}$$

The (marginal) effect of climate on production can hence be considered as the sum of direct effects (first term of Equation 2) and belief effects (the second term of Equation 2). For simplicity, it is assumed here that agents form their beliefs based on only climate and not weather.

2.2 Identification strategy

The decomposition of the marginal effect of climate on economic production into two channels has implications for its identification in empirical research. This identification can generally be based on variation across time or across units of observation. Depending on this choice, the two channels in Equation 2 will be captured to a greater or lesser extent by empirical estimates. Generally, variation of output across units of observations includes both direct and belief effects of climate, but cross-sectional estimates are prone to omitted variable biases. Exploiting variation of temperature and output over time at a frequency of days, months, or years removes possible biases of unobserved time-invariant effects, but is unlikely to recover belief effects of climate.

This trade-off between a plausible identification of causal effects of climate and the credible identification of both direct and beliefs effects of climate is a thread throughout the climate econometrics literature (Hsiang, 2016). For the purpose of this paper, I propose a new empirical strategy for navigating this trade-off. The strategy relies on temperature differences between two seasons of the same year. It can be considered a hybrid approach, exploiting variation across time and across units of observations for identification. In this respect, it resembles the long differences approach of panel data analysis (Hsiang, 2016). In mathematical terms, I propose to estimate an Equation:

$$Y_{i\tau_1} - Y_{i\tau_2} = \alpha_{\mathrm{SD}} + (\mathbf{c}_{i\tau_1} - \mathbf{c}_{i\tau_2})\beta_{\mathrm{SD}} + (\mathbf{x}_{i\tau_1} - \mathbf{x}_{i\tau_2})\gamma_{\mathrm{SD}} + \tilde{\mathbf{x}}_i\delta + \epsilon_i \tag{3}$$

where seasonal weather over a time period of several years is indxed by τ_1 and τ_2, with a vector of time-varying controls $\mathbf{x}$, and with a vector of season-invariant controls $\tilde{\mathbf{x}}$. The two seasons can be considered as any two time periods within a year for which both temperature and production are observed. In the empirical part of the paper, I distinguish two seasons summer and winter and use two alternative ways of assigning the four quarters of a year to these two seasons (Section 2.3).

Identification of a causal effect of seasonal climate using Equation 3 relies on a special form of the *unit homogeneity assumption*:

$$\mathrm{E}[Y_{i\tau_1} - Y_{i\tau_2} | \mathbf{c}_{\tau_1} - \mathbf{c}_{\tau_2}, \mathbf{x}_{i\tau_1} - \mathbf{x}_{i\tau_2}, \tilde{\mathbf{x}}_i] = \mathrm{E}[Y_{j\tau_1} - Y_{j\tau_2} | \mathbf{c}_{\tau_1} - \mathbf{c}_{\tau_2}, \mathbf{x}_{j\tau_1} - \mathbf{x}_{j\tau_2}, \tilde{\mathbf{x}}_j] \tag{4}$$

or, using the greek letter Δ to denote seasonal differences,

$$\mathrm{E}[\Delta Y_i | \Delta\mathbf{c}, \Delta\mathbf{x}_i, \tilde{\mathbf{x}}_i] = \mathrm{E}[\Delta Y_j | \Delta\mathbf{c}, \Delta\mathbf{x}_j, \tilde{\mathbf{x}}_j] \tag{5}$$

This assumption differs from the unit homogeneity assumption of a conventional cross-sectional regression in that it does not require that the expected *levels* of production are the same for two units of observation conditional on the level of climate and on observables, but that expected *seasonal differences* of production are the same for two units of observation conditional on the same seasonal differences in climate and conditional on observables. This means that the effect of any time-invariant variables that affect production in both seasons in the same way, such as the level of education of the workforce, cannot confound the estimated relationship.

Furthermore, the identification of both direct and belief effects of differences in the seasonal climate on differences in economic production relies on a *treatment comparability assumption*

$$\mathrm{E}[Y_i|\mathbf{c}_{\tau_1}] - \mathrm{E}[Y_i|\mathbf{c}_{\tau_2}] = \mathrm{E}[Y_i|\mathbf{C}_{\tau_1}] - \mathrm{E}[Y_i|\mathbf{C}_{\tau_2}] \tag{6}$$

This assumption is more credibly satisfied the longer the time period used to characterise seasonal weather $\mathbf{c}$.

While seasonal differences can be used to estimate the effect of any climate variable, the focus of this paper is on temperature. Temperature differences between summer and winter are primarily determined by the amplitude of the annual cycle of the intensity of the Sun's radiation at the surface and are thus larger at higher latitudes. Seasonality is also larger on land than over the oceans due to the smaller heat capacity of land surface materials than water. For the same reason, seasonal temperature differences tend to be larger in the East than in the West on large continents at mid-latitudes (North-America, Eurasia) because the wind blowing from West to East leads to more continental climate in the East.

Empirical work on the factors underlying seasonal economic cycles point to a preference shift around Christmas and a technology shifts around July and August due to vacations. To address omitted variable biases, I include seasonal differences in rainfall and annual mean temperature as control variables in all regressions. This is important because geography affects climate in several ways and previous work suggests that also annual mean temperature and rainfall affect economic production.

To explore possible channels through which seasonal temperature cycles might affect seasonal economic cycles, I examine the influence of GDP per capita, the share of agriculture of GDP, import shares, export shares, and international tourism expenses and receipts as a share of GDP. For each of these variables, I first regress that variable on seasonal temperature differences and than include it as a control variable in the main regression. Furthermore, I examine the effect of temperature on GVA for 11 industry groups for 35 European economies, which sheds further lights on the sensitivity of specific sectors and possible underlying mechanisms.

In additional robustness tests whose results are shown in the Appendix, I include additional control variables. Specifically, I use the share of the Christian population and the share of Muslim population as proxies of the consumption boom around Christmas and to control for cultural differences (including public holidays) across countries more broadly. Other controls are the latitude of a country and the average real interest rate. Furthermore, I check robustness to using either real or nominal quarterly GDP and to changing the time period from 1991-2020 to 2011-2020.

The seasonal differences approach proposed here resembles the long differences approach because both can be considered hybrid approaches that use variation over time and over space for identification (Hsiang, 2016). The interpretation of the obtained estimates is however different. An important difference between the two is that the seasonal difference estimator allows one to identify the effects of beliefs about differences between summer and winter, whereas the long differences estimator accounts for beliefs about long-term trends. In terms of the requirement of data, the seasonal differences approach requires observations at sub-annual frequency (e.g. quarters or months) of at least the treatment and the outcome variable, but it does not require observations going as far back in time as the long differences approach. Furthermore, the seasonal differences approach benefits from a larger temperature treatment at least in countries at higher latitudes for which temperature differences between summer and winter exceed gradual temperature trends by about one order of magnitude.

Estimates obtained from seasonal differences are potentially more prone to omitted variable biases than results based on long differences and are less indicative of the effects of future changes to the climate of one season or to the annual climate. However, they cannot be biased due to confounding long-term trends of unobservables that might affect long difference estimation.

The two approaches are not necessarily exclusive. In the last part of the paper I therefore combine the two approaches. This addresses some remaining concerns about omitted variable biases. Furthermore, it is more likely that the obtained estimates are indicative of the consequences of future climate change. In mathematical terms, I estimate an Equation:

$$
\begin{aligned}
(Y_{i\tau_1^B} - Y_{i\tau_2^B}) - (Y_{i\tau_1^A} - Y_{i\tau_2^A}) = \alpha_{\mathrm{LD}} &+ \Big((\mathbf{c}_{i\tau_1^B} - \mathbf{c}_{i\tau_2^B}) - (\mathbf{c}_{i\tau_1^A} - \mathbf{c}_{i\tau_2^A})\Big)\,\beta_{\mathrm{LD}} \\
&+ \Big((\mathbf{x}_{i\tau_1^B} - \mathbf{x}_{i\tau_2^B}) - (\mathbf{x}_{i\tau_1^A} - \mathbf{x}_{i\tau_2^A})\Big)\,\gamma_{\mathrm{LD}} \\
&+ ((\tilde{\mathbf{x}}_{i,B} - \tilde{\mathbf{x}}_{i,A})\,\delta_{\mathrm{LD}} + \epsilon_i \qquad (7)
\end{aligned}
$$

where A and B index two time periods, an earlier and a later time period. For example, in the main specification in the results section, $Y_{i\tau_1^A}$ is the average of log GDP of country i in winter over the time period 1981-2000, while $Y_{i\tau_1^A}$ is the same average over the period 2001-2020.

In the remainder of this paper, I will denote seasonal differences by Δ and long differences by Δ_{LD}. With this notation, Equation 7 can be written as:

$$\begin{aligned}\Delta_{LD}\Delta Y_i = \alpha_{\mathrm{LD}} &+ \Delta_{LD}\Delta \mathbf{c}_i\beta_{\mathrm{LD}} \\ &+ \Delta_{LD}\Delta \mathbf{x}_i\gamma_{\mathrm{LD}} \\ &+ \Delta_{LD}\tilde{\mathbf{x}}_i\delta_{\mathrm{LD}} + \epsilon_i \end{aligned} \tag{8}$$

This combined approach has the advantage that the estimate β_{LD} cannot be biased by any country characteristics that are either stationary or have parallel trends over time. This includes, for example, any geographical characteristics of countries which affect both seasonal differences in temperature and seasonal differences in GDP. Another advantage is that the estimates obtained from long differences are based on changes of temperature and economic production over time scales similar to those of anthropogenic climate change.

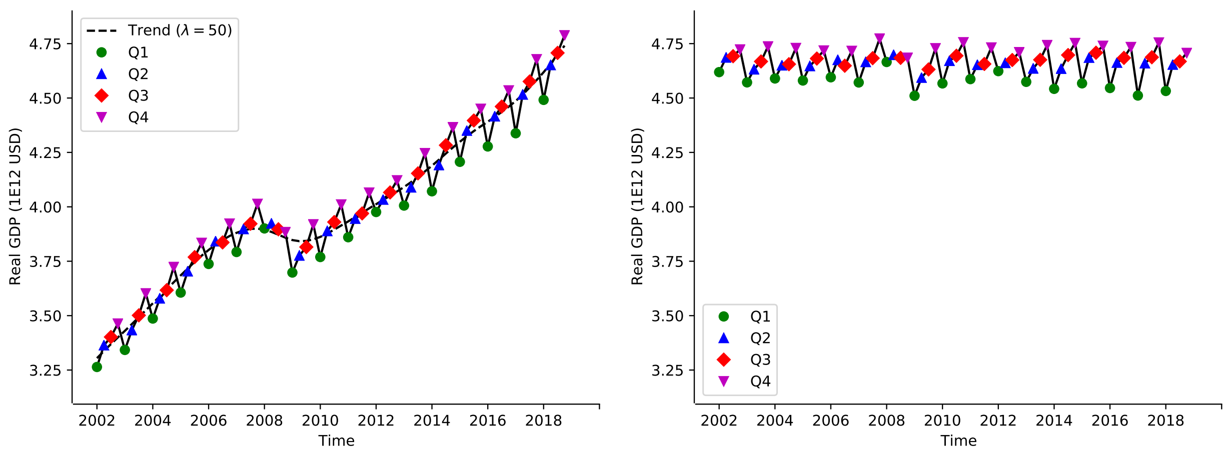
2.3 Data

I use data on quarterly Gross Domestic Product (GDP) in USD provided by the International Monetary Fund (IMF). The data covers 81 countries with different temporal coverage across countries. The data is provided in nominal and real terms and the temporal coverage differs between the two products for some countries. I restrict the data to the time period 1980-2020. The data include at least 7 years of observations for every country (the first year that data are available for Honduras is 2014 and for the Maldives 2012; for all other countries I have at least 10 years of data). In order to improve the balance of the panel data and informed by the definition of climate as an average over 30 years, I reduce the sample to the years 1991-2020 for the main estimation. As reported in the Appendix, the results are robust to using data only for the years 2011-2020. I combine this economic data with the climate reanalysis ERA5 provided by the European Center for Medium Range Weather Forecast (ECMWF). I use monthly mean temperature levels and monthly mean daily precipitation which I aggregate to quarterly frequency. The data have a spatial resolution of 0.25 degrees (approximately 25 km at the Equator) which I aggregate to the level of countries using grid-cell population from the Gridded Population of the World (GPW) dataset as weights.

I also use data on quarterly Gross Value Added (GVA) for 11 industry groups provided by EUROSTAT. The data covers 35 countries in Europe. The data cover again different time periods across countries, with all countries reporting for at least 10 years (since 2009).

To identify seasonal patterns in the timeseries, I first detrend the data. This also means that differences between nominal and real GDP are restricted to changes of prices between the seasons. In robustness tests shown in the Appendix, I find that the results are robust to using either of the two. For detrending I use a Hodrick-Prescott Filter with $\lambda = 50$. After removing deterministic trends, I add the mean value of the last year in the timeseries. The process is illustrated for timeseries of the USA in Figure 1.

Figure 1. Timeseries of quarterly real production for the USA before (left) and after detrending (right).



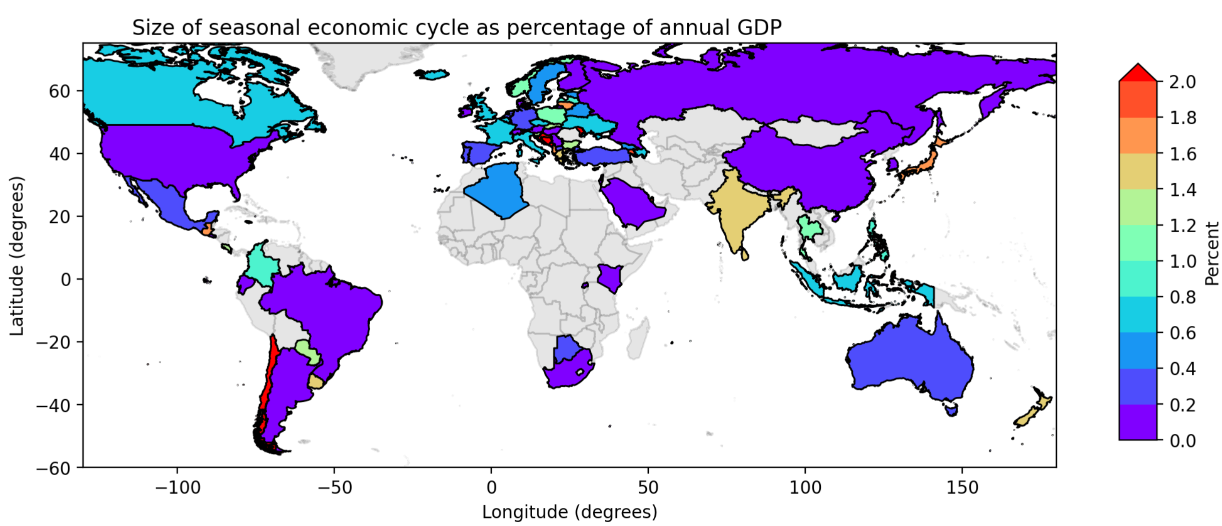
The identification strategy requires to define two seasons consistently across locations. The seasonal cycle of temperature is due to the tilt of the Earth's rotation axis and driven by the movement of the Earth around the Sun. From an Earth-centric perspective, the seasonal cycle of temperature arises from a perpetual oscillation between the time period with the maximum and the time period with the minimum of the amount of Solar radiation received at the top of the atmosphere. Except for locations close to the Equator, where variation in the distance between Earth and Sun dominates the oscillation of received Solar radiation, the time periods of minimum and maximum irradiation are around mid of December and mid of June respectively in the Northern hemisphere. In the Souther hemisphere, the pattern is the opposite.

For data with quarterly frequency a natural choice is thus to aggregate quarterly data to two time periods summer and winter. For a country in the Northern hemisphere the quarters 2 and 3 (months 4-9) can generally be considered as summer (τ_j, $j \in \{1, 2\}$) and the quarters 1 and 4 (months 1-3 and 10-12, respectively) as winter (τ_{3-j}). For countries not too close to the Equator, winter and summer defined this way will result in warmer and colder six months periods, respectively. Countries close to the Equator can experience more complex seasonal cycles with several peaks and troughs over the course of a year. For the empirical part of the paper I thus aggregate the four quarters to two seasons and then categorise the two six months periods as summer (S) and winter (W) for every country based on their average temperature. This ensures that the period referred to as summer is everywhere the warmer of the two six months periods of the year. I then use this assignment of the four quarters of a year to summer and winter to sum the detrended quarterly GDP for every country to seasonal GDP, that is GDP in summer and GDP in winter (illustrated for the USA and Brazil in Figure A1 in the Appendix).

This definition of seasons has the advantage that economic production in all four quarters of the year is taken into account. An alternative choice is considering the warmest quarter as summer and the coldest quarter as winter. Results obtained with this definition of seasons are very similar and shown as a robustness check in the Appendix.

The magnitude of the seasonal cycle, defined as the difference between GDP in summer and winter divided by the annual GDP, is shown in Figure 2. The map reveals some geographical heterogeneity but no apparent pattern associated with latitude.

Figure 2. Size of the seasonal economic cycle (difference between production in the summer half-year and in the winter half-year) as percentage of annual GDP.



For control variables I use several sources. Data on GDP per capita, land area, and the share of agriculture and manufacturing are taken from the World Development Indicator database of the World Bank. For data on trade, tourism, and interest rate I use the TC360 database of the World Bank. Information on religion is obtained from the Pew Research Center.

Projections of future climate change are taken from the CMIP6 ensemble as provided by the ECMWF. The model MPI-ESM1.2 is chosen as previous studies have shown relatively small biases for historical seasonal temperatures (Xu et al., 2021). Reassuringly, results for Europe also suggest that future warming of seasonal mean temperatures is robust across the model ensemble (Carvalho et al., 2021). I download monthly mean values for the historical period 1990-2014 and for the future periods 2041-2070 and 2071-2100. The monthly means are then used to calculate seasonal means. The seasons are defined as for the empirical analysis described above.

The analysis of future projections is based on future changes instead of future absolute values. This has the advantage that no bias correction is required, as future changes are calculated from simulations of past and future climate with the same climate model. This approach is also referred to as the delta method and very common in climate impact research. To calculate future changes I first compute mean values for both periods, 2041-2070 and 2071-2100, and then subtract the mean value of the historical period 1990-2014. All variables are aggregated from grid cells to the country level using the same population weights as for the ERA5 reanalysis data.

Descriptive statistics are shown in Table 1.

Table 1. Descriptive statistics.

Variable	Unit	Mean	Std.	Min.	Max.	No. obs.
Δ log GDP	USD 2010	-0.005	0.03	-0.17	0.04	81
Δ T	deg. C	-8.832	4.94	-18.75	-0.04	81
Δ P	mm day-1	-0.020	0.05	-0.18	0.10	81
Δ_{LD} Δ log GDP, 2001-2020 minus 1981-2000	deg. C	-0.004	0.02	-0.05	0.03	60
Δ_{LD} Δ T, 2001-2020 minus 1981-2000	deg. C	-0.074	0.39	-1.30	1.05	60
Annual mean temperature	deg. C	15.394	6.74	4.11	27.87	81
Change in Δ T for RCP4.5, 2041-2070 minus 1990-2014	deg. C	0.058	0.33	-0.98	0.69	81
Change in Δ T for RCP4.5, 2071-2100 minus 1990-2014	deg. C	0.080	0.36	-0.78	0.91	81
Change in Δ T for RCP8.5, 2041-2070 minus 1990-2014	deg. C	-0.082	0.37	-1.00	0.50	81
Change in Δ T for RCP8.5, 2071-2100 minus 1990-2014	deg. C	-0.319	0.88	-2.25	1.30	81
Share of agriculture in GDP	percent	6.131	5.88	0.07	33.54	81
Share of exports of GDP	percent	44.203	32.43	11.13	187.44	81
Share of imports of GDP	percent	46.342	28.79	12.44	165.54	81
Share of tourism receipts of GDP	percent	12.269	12.07	0.40	62.81	81
Share of tourism expenditures of GDP	percent	6.571	3.68	1.07	25.50	81
Real interest rate	percent	5.914	6.61	-21.13	41.14	77
Share of Christian population	percent	62.823	33.08	0.17	100.00	81
Share of Muslim population	percent	14.330	27.63	0.01	98.05	81
log GDP per capita	USD 2010	9.805	0.83	7.34	11.65	81
Land area	1E6 km2	11.735	2.28	5.77	16.61	81
Latitude	degrees	28.449	27.72	-41.00	65.00	81

Notes: Δ denotes seasonal differences, calculated as winter (W) minus summer (S). Δ_{LD} denotes long differences. Unless otherwise stated, statistics are based on averages over the period 1991-2020 for years in which there is quarterly GDP data for a given country.

3 Results

3.1 Stylised facts on seasonal economic cycles

Research over the last 35 years has mostly come to the conclusion that recurring shifts in preferences and technologies can explain most of the seasonal variation of economic activity (Beaulieu et al., 1992; Barsky and Miron, 1989; Cubadda et al., 2002; Beaulieu and Miron, 1992; Braun, 1995; Chatterjee and Ravikumar, 1992; Miron and Beaulieu, 1996; Franses, 1996). These shifts have been explained especially with high consumption during Christmas and vacations in June, July and August, leading to potentially very similar seasonal economic cycles across countries and industries. These conclusions were however based on small samples of countries, exclusively developed economies, and mostly located in the Northern hemisphere.

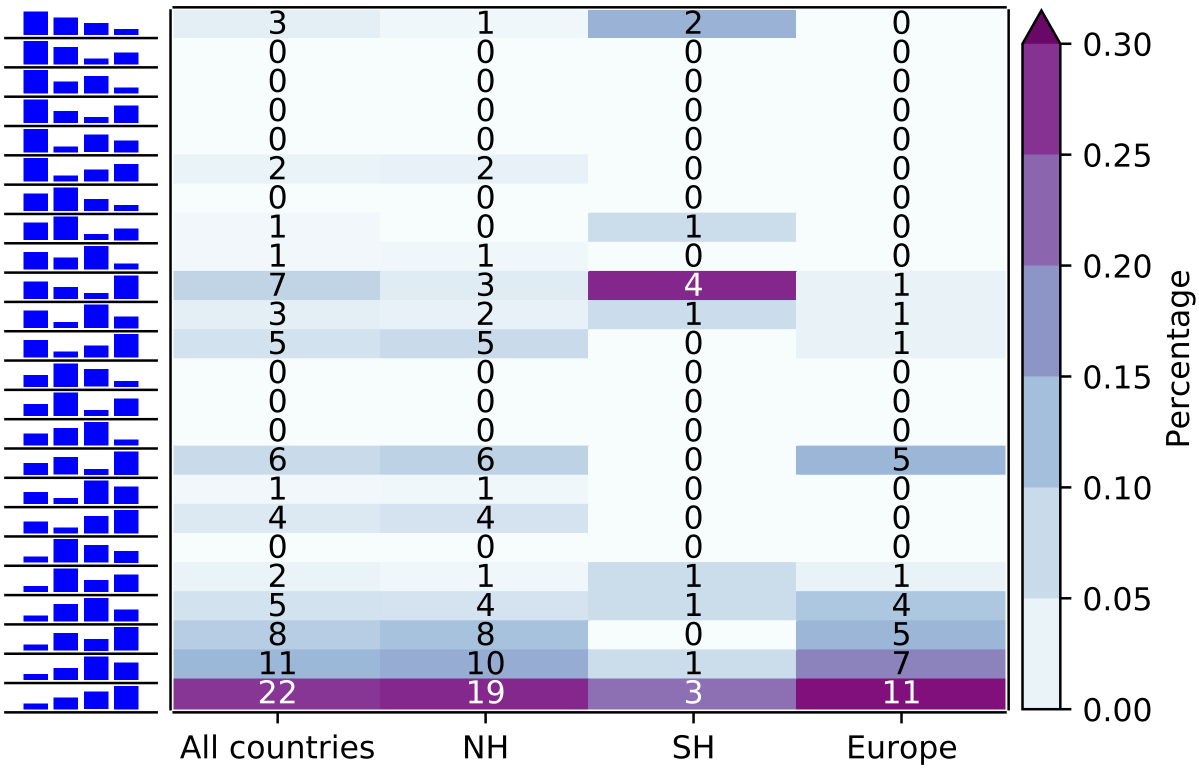
I hence first identify stylised facts about seasonal cycles in my sample of 81 economies. For every country I first regress trend-adjusted quarterly production on quarterly dummy variables. I then use the estimated coefficients of the four dummy variables to identify the pattern of the seasonal cycle. I distinguish 24 possible patterns. For example, the first of the 24 patterns corresponds to production tending to be largest in the first quarter, followed by the second, third, and fourth quarter.

Furthermore, to account for oppposite seasonal cycles of temperature, I split the sample into countries located in the Northern hemisphere (NH) and countries in the Southern hemisphere (SH). To do so, I compare the average temperature of the months 10-12 and 1-3 with the average temperature of the months 4-9. A country is then assigned to the Northern Hemisphere if the months 4-9 are warmer than the months 10-12 and 1-3.

Overall, seasonal economic cycles around the world appear quite diverse, with 15 of the 24 possible patterns being exhibited by at least one country. The most common pattern in the sample (22 of 81 countries) is a peak of production in the fourth quarter, followed by the third, second, and first quarter (Figure 3). The second most frequent pattern (11 countries) is a peak in the third quarter, followed by the fourth, second, and first quarter.

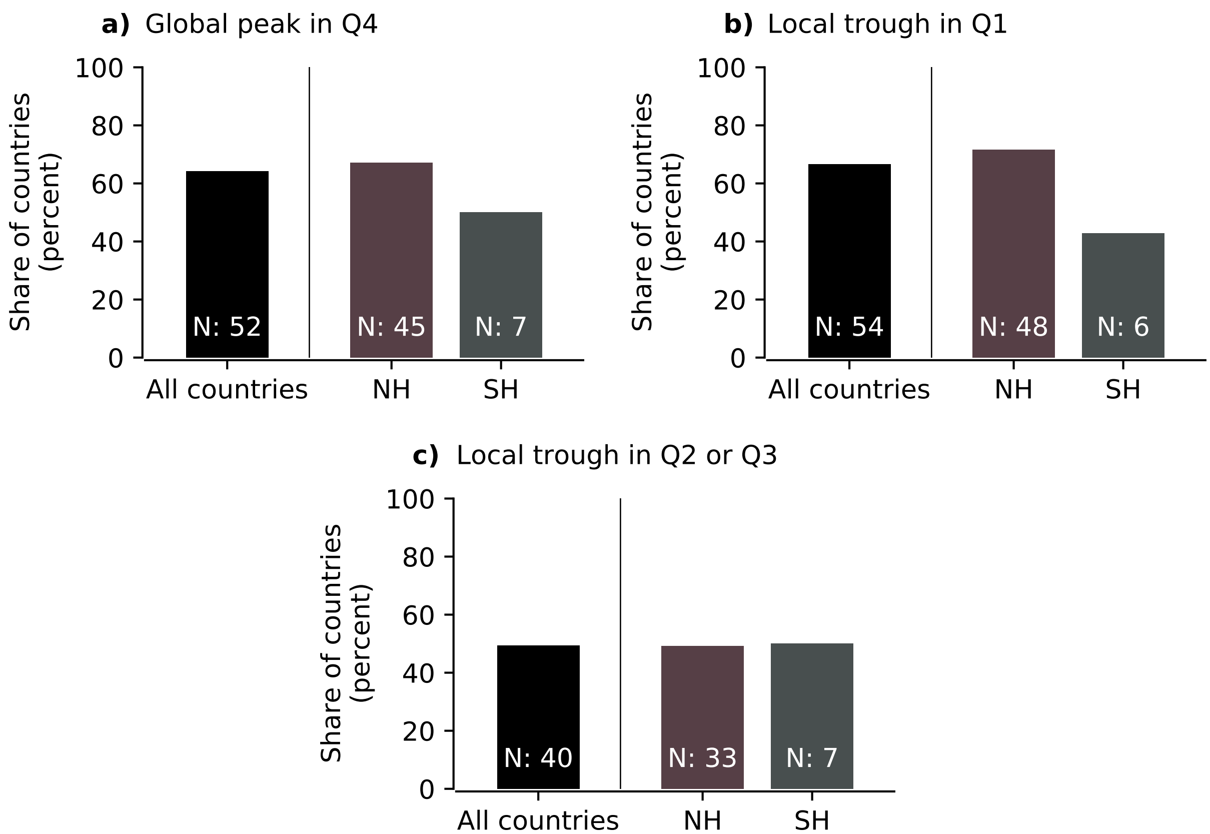
This new evidence on quarterly cycles also reveals that some stylised facts identified by previous work are not as widespread as that work might suggest. One of these facts is a peak of production in the fourth quarter, possibly due to consumption boom around Christmas (Beaulieu and Miron, 1992). I find that this is primarily a phenomenon of countries in the Northern hemisphere (Figure 4). In the full sample, about 64 % of countries (52 out of 81 countries) have the maximum production in the fourth quarter. These represent 67% of countries (45 of 67 countries) in the Northern hemisphere and 50% of countries (7 of 14 countries) in the Southern hemisphere.

Figure 3. Frequency of patterns of quarterly economic production.



Notes: Columns correspond to different samples: full sample, countries in the Northern hemisphere, countries in the Southern hemisphere, and countries in Europe. Colors indicate relative frequency based on size of corresponding sample.

Figure 4. Stylised facts identified in previous studies. Relative frequencies shown in percentages for different groups of countries.



Another stylised fact reported previously is a trough of production in the first quarter of the year, possibly due to reorganisation of production and generally economic activities at the beginning of the calendar year that result in less measurable economic output. Again I find that this can be found in countries in the Northern hemisphere (72% of countries) more frequently than among countries in the Southern hemisphere (43% of countries), but also that this fact is even in the Northern hemisphere only exhibited by about two thirds of all countries.

A third stylised fact reported previously is a slowdown of economic activity around June, July, and August, possibly due to school holidays in many countries and mid-year vacations. Such a local minimum of production in either the second or the third quarter can be found in 49% of countries in the Northern hemisphere and in 57% in the Southern hemisphere.

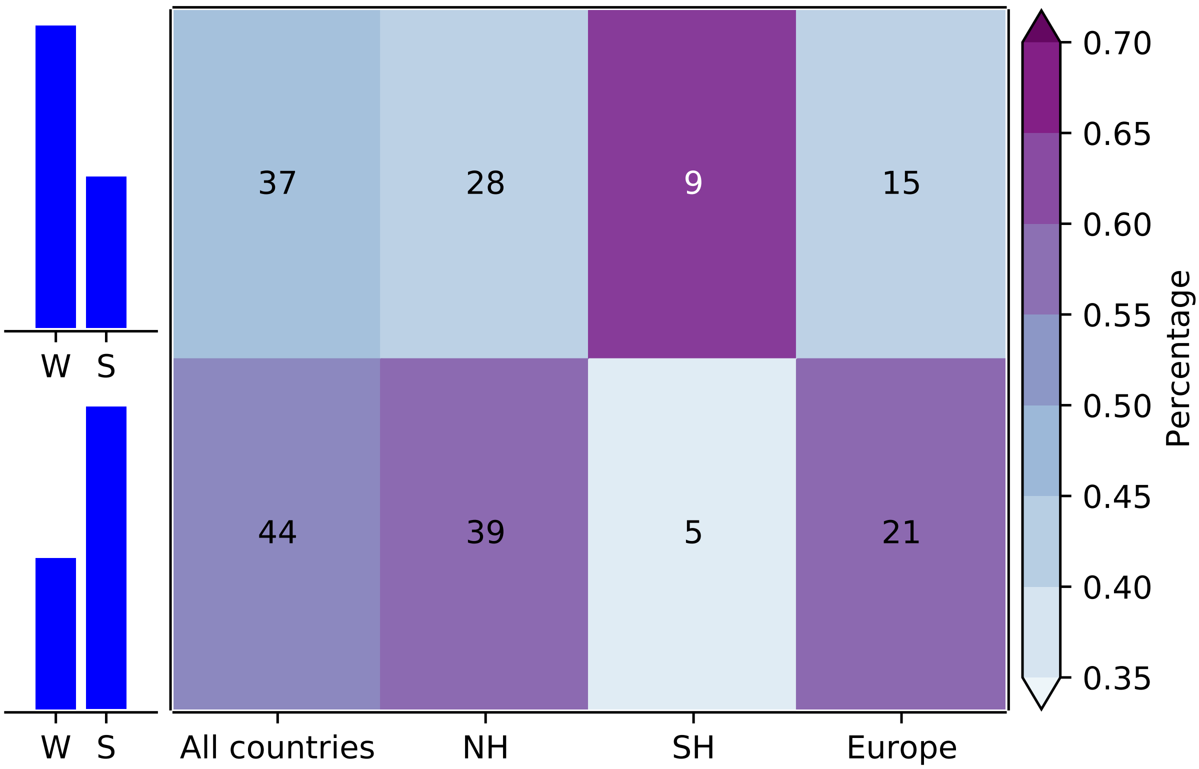
In sum, all three stylised facts about seasonal economic cycles seem to be found in only slightly more than half of all countries. Furthermore, two of these facts seem to be more frequently observed in the Northern hemisphere. One of these two, the peak of economic production in the fourth quarter, has been used to question the influence of temperature on seasonal economic cycles as countries in both hemispheres appeared to exhibit this feature in small earlier samples (Beaulieu and Miron, 1992). In contrast, the evidence of my larger sample suggests substantial differences between countries in the two hemispheres.

To reduce the dimensionality of the analysis and prepare the data for a model estimation based on seasonal differences, I next sum trend-adjusted production of the quarters 1 and 4 and 2 and 3 to semi-annual production. Based on the assignment of countries to the SH or NH, I refer to the quarters 1 and 4 as winter (summer) and to the quarters 2 and 3 as summer (winter) respectively. I refer to countries with larger production in summer as summer-peak countries and to all other countries as winter-peak countries.

In the full sample, summer-peak countries are slightly more frequent than winter-peak countries (54%, or 44 of 81 countries) (Figure 5). In the Northern hemisphere, the share of winter-peak countries is slightly larger (58%, or 39 of 67 countries). In the Southern hemisphere, countries tend to have larger production in winter than in summer (64%, or 9 of 14 countries).

Relating these findings to the cycles at quarterly frequency, in the Northern hemisphere the smaller production in winter than in summer can partly be explained with the small production in the first quarter, which seems to dominate the large production in the fourth quarter and the small production in the third or second quarter. In the Southern hemisphere, the relatively small production in summer is in line with only few countries exhibiting a peak in the fourth quarter and most countries exhibiting a local minimum of production in the second or third quarter.

Figure 5. Frequency of patterns of economic production in summer and winter.

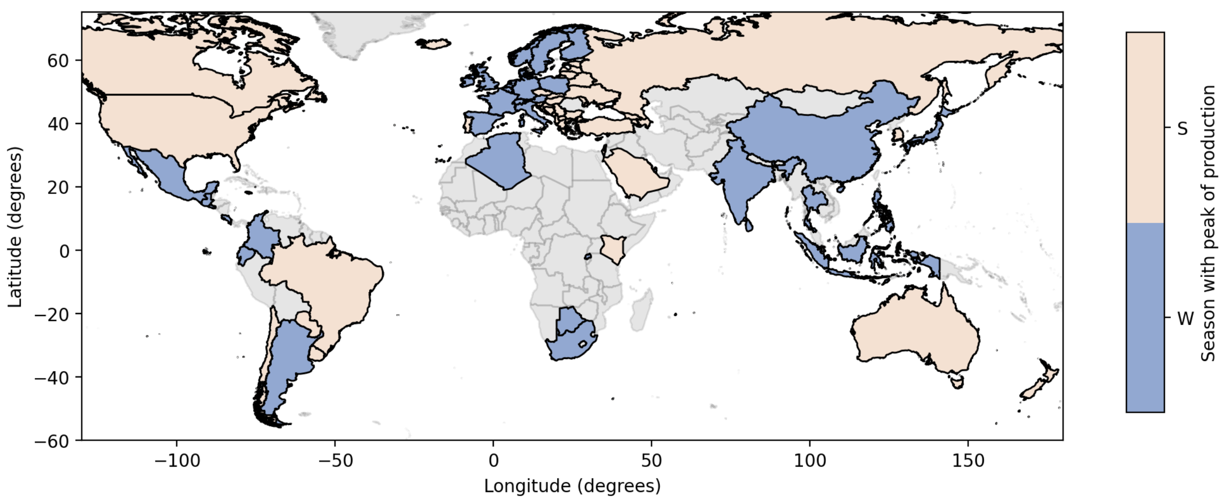


Notes: Columns correspond to different samples: full sample, countries in the Northern hemisphere, countries in the Southern hemisphere, and countries in Europe. Colors indicate relative frequency based on size of corresponding sample.

Overall, countries in the Northern hemisphere thus tend to have larger production in winter than in summer. The fact that production in winter tends to be the sum of the quarter with the maximum production and the quarter with the minimum production suggests to examine the effect of temperature not only at semi-annual but also at quarterly frequency.

The geographical distribution of summer-peak and winter-peak countries suggests some geographical clustering (Figure 6). For example, most countries in Northern and Western Europe are winter-peak countries, while most countries in Eastern Europe and the Middle East are summer-peak countries. In the Southern hemisphere, winter-peak countries are more common than summer-peak countries. There is however no clear effect of absolute latitude, with winter-peak countries being relatively frequent at relatively high and at low latitudes.

Figure 6. Geographical distribution of winter-peak (W) and summer-peak (S) countries.



I examine the balance of the two subsamples also more formally using statistical tests (Table B1 in the Appendix). I find that winter-peak countries tend to have a smaller (less positive) temperature difference between summer and winter ($p < 0.05$). They also tend to be richer ($p < 0.05$) and have a smaller share of tourism receipts of GDP ($p < 0.05$). I further quantify the contribution of different factors to the observed economic cycle, including the role of temperature, in the next Section.

3.2 The contribution of seasonal temperature variability

In order to examine the contribution of temperature to seasonal economic cycles, I regress seasonal differences in GDP on seasonal differences in temperature (Equation 3) using the data on 81 countries illustrated in the previous section. I find a significant positive association between temperature and GDP (Column 1 in Table 2). This estimate is robust to including a variety of control variables including seasonal differences in rainfall, annual mean temperature, and GDP per capita (Column 2). The results are also robust to including a large number of additional control variables, to using only data from the years 2011-2020, and to using data on nominal or real quarterly GDP (Figure E1 in the Appendix). The results are also qualitatively the same for differences between the quarters with maximum and minimum temperature (Table H1). As expected, using differences between six-months periods instead of quarters attenuates the estimated effect of temperature because in many countries the quarter with the maximum and the quarter with the minimum GDP fall within the same six-months period.

I next study heterogeneity in the effect of seasonal temperature. Including interaction terms in the model, I find that the effect of temperature is smaller in countries with higher level of GDP capita and turns negative for countries with a GDP per capita higher than about 36.000 USD (Column 3). I do not find evidence that other control variables in the model moderate the effect of seasonal temperature (Column 5).

The magnitude of the estimated effect of temperature is large. The sample mean of the seasonal difference in temperatures of about 8.8 degree Celsius (Table 1) is associated with a seasonal difference in GDP of about 1.2 percent. This effect is of the same order of magnitude as the sample mean of the seasonal difference in GDP, which is about 0.5 percent (Table 1). The effect seems not to be driven by outliers and there is no apparent difference in the magnitude of the effect between countries in the Northern and in the Southern hemisphere (Figure C1 in the Appendix). Temperature thus appears to be an important factor contributing to the larger production in summer than in winter that is observed in many countries (Figure 6).

To study possible mechanisms, I examine the role of agriculture, international trade, GDP per capita, and tourism. I first regress variables such as the share of agriculture of GDP, import shares, GDP per capita, and the share of international tourism expenses of GDP on the seasonal difference on temperature. I do not find and significant associations (Table D1 in the Appendix). This suggests that these sectors are not the primary channels through wich seasonal temperature cycles affect economies. As an additional test, I also include those variables as additional explanatory variables in my main specification (as possibly "bad controls") and find that my main estimates barely change (Figure E1 in the Appendix). In sum, the results suggest that other channels are primarily responsible for the estimated effect.

Table 2. Results of regressions using a global sample of GDP of 81 countries.

Dependent variable:	Δ *log GDP*			
Column:	1	2	3	4
ΔT	0.0018***	0.0014**	0.0105**	0.0135**
	(0.0004)	(0.0007)	(0.0050)	(0.0062)
ΔT · log GDP pc			-0.0010*	-0.0009*
			(0.0005)	(0.0005)
ΔT · Annual mean temperature				-0.0000
				(0.0001)
ΔT · log Landarea				-0.0003
				(0.0002)
Δ Precipitation		-0.1817**	-0.1787**	-0.1802*
		(0.0849)	(0.0835)	(0.0906)
Annual mean temperature		0.0004	0.0005	0.0004
		(0.0005)	(0.0004)	(0.0010)
log GDP pc		0.0107***	0.0031	0.0029
		(0.0036)	(0.0058)	(0.0053)
log Landarea		0.0024**	0.0020*	-0.0000
		(0.0010)	(0.0011)	(0.0018)
R2	0.10	0.34	0.36	0.37
R2 adj.	0.09	0.29	0.30	0.30
N	81	81	81	81

Notes: Sample period is 1991-2020. Seasonal differences Δ *calculated as winter minus summer. Significance as follows:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3.3 Effects by industry groups for European economies

The results in the previous section suggest that temperature has a positive effect on production in some countries and no effect or a negative effect in others. In this section, I explore to what extent this finding can be explained by differences in sectoral composition. To this aim, I use data on gross value added (GVA) by industry group for 35 countries in Europe. Focusing on Europe has the advantage that reporting quality is probably more homogeneous across countries than for the global sample and that also the climate and especially seasonal temperature cycles are more similar. Furthermore, EUROSTAT provides to my knowledge the most comprehensive homogeneous database of quarterly production by industry group.

Reassuringly, I find a similar significantly positive effect of seasonal temperature on seasonal GDP as for the global sample, with about twice the magnitude. I next estimate the seasonal differences model in Equation 3 for each of the industry groups. I follow previous literature and group industries according to whether labour is relatively more or less exposed to outdoor temperature (Behrer and Park, 2019; Acevedo et al., 2020). I accordingly classify agriculture, construction, manufacturing, and other industries as relatively exposed. I find a significantly positive effect of seasonal differences in temperature on seasonal differences in GVA for total GVA and for GVA in exposed industries. For all other, non-exposed industries I find an insignificantly positive effect (Table 3). I conduct the same exercise at the level of individual industries and find that the positive coefficients for all exposed industries can be explained primarily with positive coefficients for Construction and other Industry, and possibly also Manufacturing, but not Agriculture (Table F1 in the Appendix).

Table 3. Results of regressions using a sample of GVA by industry groups of 35 European economies.

Dependent variable:	Δ *log GDP*		
Industries:	All	Exposed	Non-Exposed
Column:	1	2	3
ΔT	0.0037**	0.0071**	0.0014
	(0.0018)	(0.0033)	(0.0016)
Δ Precipitation	-0.0807	-0.3897	0.1322
	(0.1565)	(0.3410)	(0.1485)
Annual mean temperature	-0.0022*	0.0001	-0.0027**
	(0.0012)	(0.0024)	(0.0011)
log GDP pc	0.0179*	0.0339*	0.0082
	(0.0088)	(0.0175)	(0.0075)
log Landarea	0.0052***	0.0078**	0.0040***
	(0.0016)	(0.0029)	(0.0014)
R2	0.54	0.49	0.32
R2 adj.	0.46	0.40	0.21
N	35	35	35

Notes: Seasonal differences Δ calculated as winter minus summer. Exposed industries: Agriculture, Construction, Manufacturing, other Industry. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In sum, the results suggest that exposure to ambient temperature in economic production is an important moderator, pointing to effects of temperature on the supply side of economies as a possible mechanisms.

3.4 Results from long differences

These results obtained from seasonal differences estimation are based on cross-sectional variation in seasonal differences and therefore have two caveats. The first is that there is still a risk of omitted variable biases from omitted but important country characteristics. These could include geographical characteristics that influence both seasonal temperature variability and seasonal economic cycles. The second caveat is that the results are not necessarily indicative of the effects of changes over time to seasonal temperature variability in a specific country, as discussed in Section 2.

To overcome these limitations, I also estimate a model based on long differences of seasonal differences. Because of limited data availability at the quarterly frequency, I use the two time periods 1981-2000 and 2001-2020. This reduces the sample to 60 countries for which GDP data from the earlier period is available. For all these countries, both winters and summers became warmer between the two time periods. In about half of all countries winters warmed more strongly than summers (Figure I1 in the Appendix).

The results are qualitatively similar to the results obtained from cross-sectional variation in seasonal differences (Table 4). Specifically, I find that seasonal temperature has a positive effect on seasonal GDP which becomes smaller and even negative for richer countries. The magnitude of the effect is larger. Furthermore, as for the cross-sectional estimates, seasonal rainfall has a negative effect on seasonal GDP. These results are robust to including trends in annual mean temperature and annual total precipitation (Column 5) and similar for countries for which winters warmed more than summers and countries with opposite trends (Column 6).

The magnitude of the effect estimated from long differences is larger than the magnitude of the effect estimated from the cross-section 1991-2020. This difference can primarily be explained with the different samples that are used in the two estimations due to a lack of data for the earlier period for some countries (Table G1 in the Appendix). Once the differences between the two samples are taken into account, the coefficients have a similar magnitude. For example, for a country with a GDP per capita of about 22,000 USD, which corresponds to the mean value of the larger sample, the estimated coefficients are 0.011 and 0.015 log points of GDP per degree Celsius based on the cross-sectional and the long differences estimation respectively.

Table 4. Results of regressions with long differences using a global sample of GDP of 60 countries.

Dependent variable:	$\Delta_{\mathrm{LD}}\ \Delta$ *log GDP*					
Column:	1	2	3	4	5	6
$\Delta_{\mathrm{LD}}\Delta T$	0.0059	0.0058	0.1053**	0.0821*	0.1075**	0.1177***
	(0.0065)	(0.0063)	(0.0405)	(0.0469)	(0.0440)	(0.0421)
$\Delta_{\mathrm{LD}}\Delta T \cdot$ log GDP pc			-0.0105**	-0.0091**	-0.0106**	-0.0121***
			(0.0040)	(0.0043)	(0.0043)	(0.0042)
$\Delta_{\mathrm{LD}}\Delta T \cdot$ Annual mean temperature				0.0009		
				(0.0008)		
$\Delta_{\mathrm{LD}}\Delta T \cdot (\Delta_{\mathrm{LD}}\Delta T > 0)$						0.0099
						(0.0124)
$\Delta_{\mathrm{LD}}\Delta$ Precipitation		-0.1122***	-0.1595***	-0.1259***	-0.1826***	-0.1918***
		(0.0337)	(0.0338)	(0.0358)	(0.0378)	(0.0434)
Annual mean temperature				0.0006**		
				(0.0003)		
log GDP pc			0.0088***	0.0100***	0.0105***	0.0109***
			(0.0024)	(0.0021)	(0.0026)	(0.0026)
Δ_{LD} Annual mean temperature					-0.0094	-0.0087
					(0.0065)	(0.0066)
Δ_{LD} Precipitation					0.1148	0.0822
					(0.1645)	(0.1675)
$(\Delta_{\mathrm{LD}}\Delta T > 0)$						0.0009
						(0.0048)
R2	0.02	0.13	0.36	0.41	0.39	0.40
R2 adj.	0.00	0.10	0.32	0.35	0.32	0.30
N	60	60	60	60	60	60

Notes: Long differences Δ_{LD} *calculated by subtracting mean over 1981-2000 from mean over 2001-2020. Seasonal differences* Δ *calculated as winter minus summer. For the purpose of the analysis, annual mean temperature and log GDP per capita (the 5th and 6th variable in this table, respectively) are considered as time-invariant variables. Their average values over 1991-2020 are included as a moderator variable in the same way as in the cross-sectional regression (Table 2). Significance as follows:* $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

These results suggest that if one season warmed more than another between 1981-2000 and 2001-2020, it also witnessed a relatively stronger growth in GDP. IIn additional analysis, I do not find evidence for significant effects of changes in seasonal temperatures on changes in annual GDP (Table 4 in the Appendix), suggesting that the results in Table 4 are primarily driven by a reallocation of economic activity instead of an effect of temperature on economic production in only one of the two seasons.

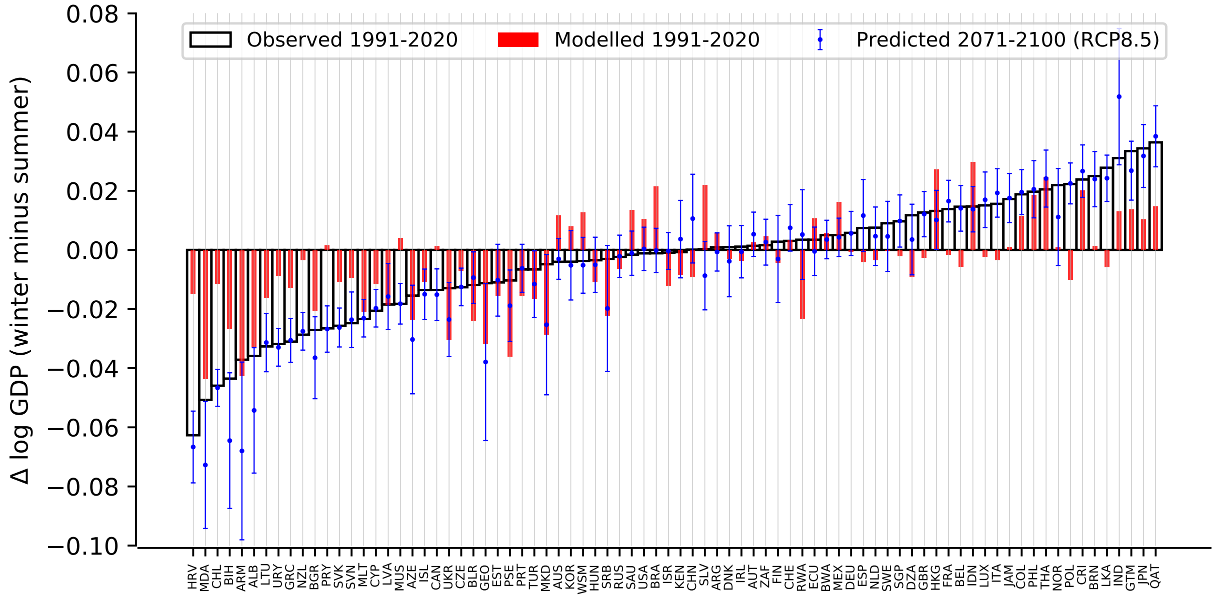
3.5 Scenarios of future climate change

These results suggest that economic production will be reallocated between winter and summer if under future climate change one season warms more strongly than the other. Such changes are indeed projected by global climate models. In a few countries, winters are projected to warm more quickly than summers because of reductions in snow cover in winter and accelerated warming due to the snow-albedo feedback (Carvalho et al., 2021). In most other countries outside the tropics, summers are projected to warm more quickly than winters because of increased dryness in summer and thus less surface humidity that can reduce the projected warming through latent heat transfer (Byrne, 2021). The following analysis aims to quantify the approximate order of magnitude of possible reallocations of economic acitivity across the seasons due to these changes.

To this aim, I combine climate model projections with the empirically estimated effect of seasonal differences in temperature on seasonal economic production from the long difference estimation with interaction term (Column 5 in Table 4). I first focus on the RCP8.5 scenario and the time period 2071-2100. I find that for some countries, production will shift more towards summer and for other countries towards winter (Figure 7). The magnitude of the projected changes varies greatly among countries, depending on their GDP per capita levels and projected changes to seasonal temperatures, and can be up to several percentage points of annual GDP large.

Reallocation of economic production between the seasons can increase or decrease seasonal economic cycles. For the RCP8.5 scenario, more countries experience a reallocation towards summer than towards winter, and the effect is particularly large, with a long tail, for countries that have their peak of production in summer (Figure 7 and Figure L1 in the Appendix). On average, sasonal economic cycles are projected to increase, This average effect masks however substantial heterogeneity across countries (Figure 7 and Figure M1 in the Appendix). These results are for the far future and a scenario of strong climate change (RCP8.5). The projected changes are qualitatively similar for an earlier period (2041-2070) and an alternative scenario (RCP4.5) (Figure L1 in the Appendix).

Figure 7. Projections of Δ GDP by country for the global sample.



Notes: The plot shows the projected changes of Δ log GDP for individual countries for the RCP8.5 scenario based on the results from the long difference estimation. Seasonal differences Δ calculated as winter minus summer. Positive values mean that for the given scenario GDP will be reallocated from summer to winter.

4 Conclusions

In this paper I study the effect of seasonal temperature on seasonal economic production. For causal identification I propose a novel econometric approach using variation of differences between seasons across countries. This seasonal differences estimator is applied to a global sample of 81 countries using quarterly data on GDP and climate reanalysis. The results suggest that differences in temperature between summer and winter can explain a major part of the observed differences in GDP between summer and winter. This finding is in contrast to previous work which concluded that temperature plays at most a minor role for seasonal cycles of GDP. This discrepancy can partly be explained with limited evidence available at the time of earlier studies, inappropriate methods to infer causality that neglected expectations, and possibly a focus on proximate (technology shocks, preference shocks) rather than fundamental drivers of economic fluctuations.

The analysis also reveals a large diversity of seasonal economic cycles and systematic differences between countries in the Northern and in the Southern hemisphere. Given that previous work focused on small subsets of countries, this global heterogeneity can potentially explain some of the differences from earlier studies. Furthermore, I find that in the majority of countries economic activity is larger in summer than in winter. Somewhat consistent with this finding, my results suggest an overall positive association between seasonal temperature and seasonal economic production.

This effect of seasonal temperature is both significant and large. On average it is of the same magnitude as observed differences in seasonal GDP. To address concerns about causal inference from cross-sectional variation, I conduct extensive robustness tests with a wide range of control variables, including seasonal differences in rainfall, annual mean temperature, GDP per capita levels, religious composition, geographical size of a country, latitude, and variables related to the sectoral composition of an economy, international trade, and international tourism. The results are also robust to considering the quarter with maximum and minimum temperature as summer and winter respectively and to shortening the time period to 2011-2020. Regarding possible mechanisms, results on the industry level for a subsample of European countries points to an important role of industries that are relatively exposed to ambient temperature, including Construction, Industry, and Manufacturing.

Regarding future climate change, the results suggest that economic activity will be reallocated between the seasons. However, the results do not allow conclusions about the extent to which annual GDP will be affected by future changes to annual mean temperature. That question has been the focus of a large body of prior literature which tends to agree that an increase in annual mean temperature has a negative effect on GDP in very warm countries and a possibly positive effect in relatively cold countries (Dell et al. (2012); Burke et al. (2015); Acevedo Mejia et al. (2018); Colacito et al. (2019), among others).

To quantify the possible seasonal reallocation of economic production under future climate change, I combine empirical estimates obtained from a long differences specification of the model with the projections of climate models. The results point to substantial future changes to seasonal economic cycles, which are projected to more than double in some countries by 2071-2100 for the scenario RCP8.5. For the time period 2041-2070 and for the scenario RCP4.5, the results suggest a reallocation of economic production of up to one percentage point of seasonal GDP.

The results overall suggest that temperature should be taken into account in seasonal forecasts of economic production. While this is already the case in some countries (see e.g. Bundesbank (2012, 2014)), the results point to an influence of weather on seasonal economic cycles across a wide range of socio-economic and climatic contexts. Given that climate change will increase seasonal economic cycles in some countries, the results also suggest a future increase in demand for fiscal, monetary, and structural policies that help to smoothen quarterly fluctuations of production and employment. Furthermore, my results suggest that economic development can make economies generally more resilient to the influence of seasonal temperature variability, pointing to possible adaptation.

The quarterly GDP data used in this paper cover 81 countries around the world representing all continents and a large range of socioeconomic contexts and climates. The analysis of heterogeneity suggests that the effect of seasonal temperature on seasonal GDP decreases with the level of GDP per capita of a country, but this pattern is based on relatively few economies in Africa, demanding caution when extrapolating from the global sample to other countries.

The results also point to a new avenue of macroeconomic research on the fundamental drivers of fluctuations of GDP, employment, and prices accounting for the deterministic and the stochastic part of temperature variability. The evidence presented here suggests that temperature affects production through productivity shocks, but does not exclude that part of the estimated effects is also due to seasonal shifts in preferences. Disentangling the two with a structural model appears to be one promising research perspective. Furthermore, the analysis revealed that some countries have largest production in winter and others in summer. Future research could examine to what extent these opposite patterns can be explained with economic specialisation and trade.

Previous research has found negative effects of seasonal temperature variability on economic activity (Linsenmeier, 2021). The results in this paper corroborate an influence of seasonal temperature variability on economic production. Furthermore, the results suggest that larger seasonal variability is associated with larger seasonal differences in GDP. While previous research has found that fluctuations of GDP between years have a negative effect on GDP (Ramey and Ramey, 1994), this possible mechanism has not been studied in the context of quarterly or seasonal fluctuations and seems to deserve the attention of future research. Given that future climate change is projected to change seasonal temperature differences, this points to yet another channel through which climate change will affect economic production in the future.

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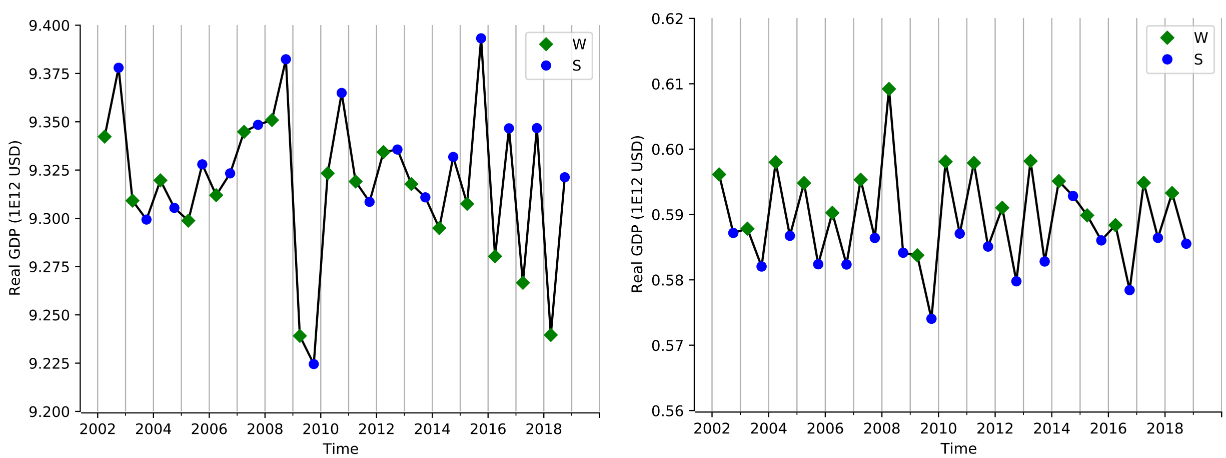
A Detrending of time series

Figure A1. Timeseries of seasonal production: winter (W) and summer (S) for the USA (left) and Brazil (right).



Notes: Note that there is no clear ordering of summer and winter within a calendar year. The order chosen here for visualisation (winter, summer) is arbitrary and does not affect any of the results.

B Summer peak vs winter peak countries

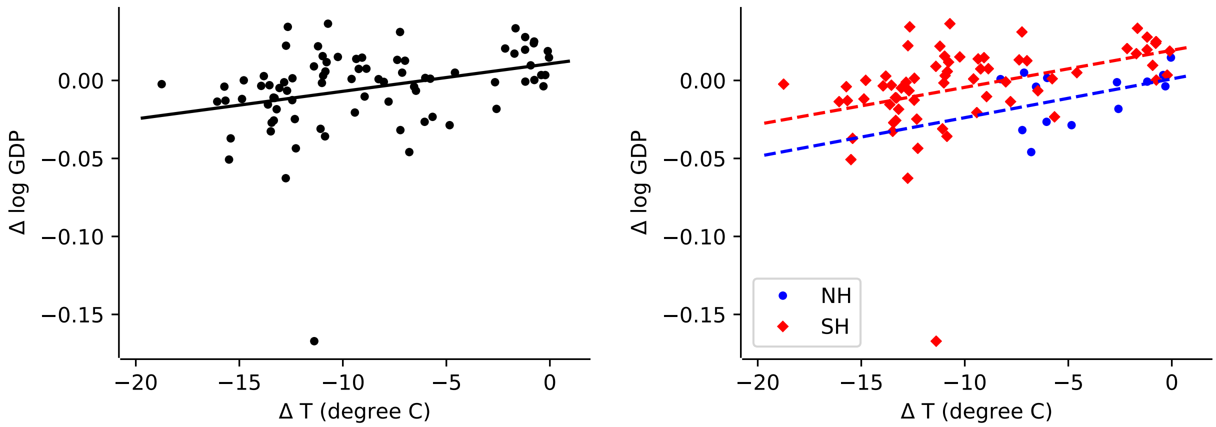
Table B1. Results of balancing tests for summer-peak and winter-peak countries.

Peak of temperature in:		W		S		
Variable	Unit	Mean	Std.	Mean	Std.	p-value
Δ log GDP	USD 2010	0.01	0.01	-0.01	0.03	0.000
Δ T	deg. C	-7.03	4.59	-9.84	4.88	0.011
Δ P	mm day-1	-0.03	0.05	-0.02	0.06	0.315
Annual mean temperature	deg. C	16.38	7.08	14.63	6.23	0.260
Share of agriculture in GDP	percent	4.81	5.33	7.04	6.05	0.090
Share of manufacturing of GDP	percent	14.75	4.90	14.36	6.12	0.762
Share of exports of GDP	percent	44.58	37.11	44.71	29.94	0.987
Share of imports of GDP	percent	42.31	31.25	50.41	27.72	0.239
Share of tourism receipts of GDP	percent	9.18	11.07	14.95	12.62	0.036
Share of tourism expenditures of GDP	percent	6.52	2.41	6.32	3.95	0.778
Real interest rate	percent	7.33	8.02	4.56	5.15	0.096
Share of Christian population	percent	64.04	32.18	63.48	32.95	0.940
Share of Muslim population	percent	11.82	24.36	13.74	27.22	0.745
log GDP per capita	USD 2010	10.02	0.85	9.61	0.73	0.030
Land area	1E6 km2	11.96	2.19	11.48	2.28	0.358
Latitude	degrees	22.15	31.34	32.51	24.82	0.120
Latitude, absolute value	degrees	32.36	20.22	38.01	14.79	0.177

Notes: There are 43 summer-peak countries (S) and 34 winter-peak countries in the sample. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C Descriptive evidence on statistical associations

Figure C1. Scatter plot of seasonal differences of temperature and log GDP.



Notes: Colors indicate split of sample into countries in the Northern hemisphere (NH) and Southern hemisphere (SH).

D Estimation results to explore alternative channels

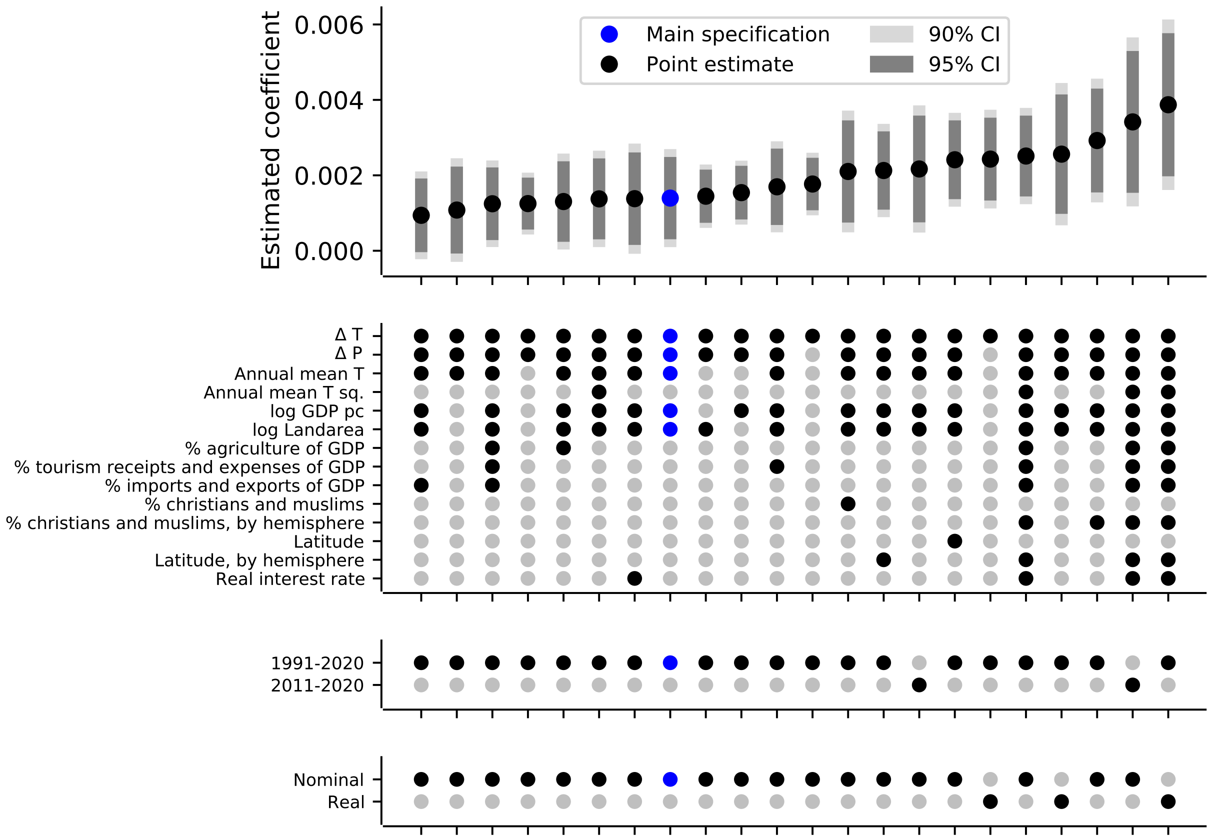
Table D1. Results of regressions to explore possible channels through with temperature variability might affect seasonal economic cycles.

Dependent variable:	log GDP pc	% agriculture	% imports	% exports	% tourism exp.	% tourism rec.
Column:	1	2	3	4	5	6
ΔT	-0.0152	0.0945	-0.7797	-0.5687	-0.1271	0.0798
	(0.0383)	(0.1254)	(0.6696)	(0.7321)	(0.1459)	(0.2524)
Δ Precipitation	2.0623	21.0396**	-102.0344*	-133.4057**	16.5967*	59.0979**
	(2.2562)	(9.8009)	(57.8043)	(60.5778)	(9.7562)	(28.9485)
Annual mean temperature	-0.0187	0.0189	-0.1567	0.0130	0.1399	0.2440
	(0.0275)	(0.0821)	(0.6110)	(0.6476)	(0.1297)	(0.1736)
log GDP pc		-5.9706***	5.1230	16.1331***	0.5443	-5.4378***
		(0.6544)	(3.5792)	(4.1690)	(0.6466)	(1.4660)
log Landarea	-0.0362	0.2422	-9.6960***	-8.7134***	0.0582	-1.8469***
	(0.0436)	(0.1663)	(1.3761)	(1.5763)	(0.1698)	(0.6243)
R2	0.10	0.73	0.59	0.56	0.09	0.33
R2 adj.	0.05	0.71	0.57	0.53	0.03	0.29
N	81	81	81	81	81	81

Notes: Percentages of total GDP. Exp. = expenditures, rec. = receipts. Seasonal differences Δ *calculated as winter minus summer. Significance as follows:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

E Specification chart

Figure E1. Specification chart.



Notes: The figure shows the central estimates and 95% and 90% confidence intervals of the estimated effect of ΔT on Δ log GDP for models with different explanatory variables (top panel), different underlying data (central panel), and different time periods (bottom panel).

F Results by industry group

Table F1. Results of regressions using a sample of GVA by industry groups of 35 European economies.

Variable	TOTAL	A	B-E	C	F	G-I	J	K	L	M-N	O-Q	R-U
ΔT	0.0037^{**}	-0.0010	0.0063	0.0034	0.0072	0.0062	-0.0038	0.0008	0.0009	-0.0062^{**}	-0.0002	0.0008
	(0.0018)	(0.0204)	(0.0039)	(0.0032)	(0.0046)	(0.0043)	(0.0023)	(0.0033)	(0.0015)	(0.0027)	(0.0028)	(0.0035)
Δ Precipitation	-0.0807	0.4764	0.0677	-0.0718	-0.1152	-0.0157	0.5887^{***}	-0.6512	0.3325	0.6309^{**}	0.0927	0.3128
	(0.1565)	(1.4129)	(0.2710)	(0.2555)	(0.7347)	(0.4187)	(0.1942)	(0.3949)	(0.2040)	(0.2302)	(0.3072)	(0.4650)
Annual mean temperature	-0.0022^{*}	0.0068	-0.0051^{**}	0.0004	0.0050	-0.0061^{**}	-0.0028	0.0033	-0.0023	0.0010	-0.0028	-0.0019
	(0.0012)	(0.0127)	(0.0022)	(0.0022)	(0.0050)	(0.0028)	(0.0017)	(0.0034)	(0.0016)	(0.0016)	(0.0029)	(0.0030)
log GDP pc	0.0179^{*}	0.1668^{**}	0.0052	0.0294^{*}	0.0190	0.0193	0.0220^{***}	-0.0141	-0.0033	0.0399^{***}	-0.0169	-0.0153
	(0.0088)	(0.0794)	(0.0137)	(0.0152)	(0.0247)	(0.0182)	(0.0070)	(0.0128)	(0.0064)	(0.0105)	(0.0166)	(0.0173)
log Landarea	0.0052^{***}	0.0070	0.0076^{***}	0.0094^{***}	0.0052	0.0076^{*}	0.0037^{**}	0.0040	-0.0037	0.0067^{***}	0.0025	0.0012
	(0.0016)	(0.0180)	(0.0026)	(0.0026)	(0.0051)	(0.0038)	(0.0015)	(0.0035)	(0.0023)	(0.0019)	(0.0034)	(0.0044)
R2	0.54	0.19	0.41	0.42	0.22	0.31	0.40	0.12	0.15	0.46	0.12	0.06
R2 adj.	0.46	0.05	0.31	0.32	0.08	0.19	0.30	-0.03	-0.00	0.37	-0.04	-0.11
N	35	35	35	35	35	35	35	35	35	35	35	35

Notes: Seasonal differences Δ calculated as winter minus summer. A: Agriculture, forestry and fishing, B-E: Industry (except construction), C: Manufacturing, F: Construction, G-I: Wholesale and retail trade, transport, accommo., J: Information and communication, K: Financial and insurance activities, L: Real estate activities, M-N: Professional, scientific and technical activit., O-Q: Public administration, defence, education, hum., R-U: Arts, entertainment and recreation; other serv. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

G Estimation results for different samples

Table G1. Results of regressions using the global samples of GDP of countries that are used for the cross-sectional and the long differences estimation.

Dependent variable:	Δ *log GDP*	
Sample used for:	Cross-section	Long differences
Column:	1	2
ΔT	0.0105**	0.0061
	(0.0050)	(0.0057)
$\Delta T \cdot$ log GDP pc	-0.0010*	-0.0005
	(0.0005)	(0.0006)
Δ Precipitation	-0.1787**	-0.1365***
	(0.0835)	(0.0401)
Annual mean temperature	0.0005	-0.0000
	(0.0004)	(0.0005)
log GDP pc	0.0031	0.0077
	(0.0058)	(0.0069)
log Landarea	0.0020*	0.0018*
	(0.0011)	(0.0009)
R2	0.36	0.40
R2 adj.	0.30	0.34
N	81	60

Notes: Sample of cross-sectional regression is the same as in Table 2. Sample of long differences estimation is the same as in Table 4. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

H Robustness check with seasons based on quarters

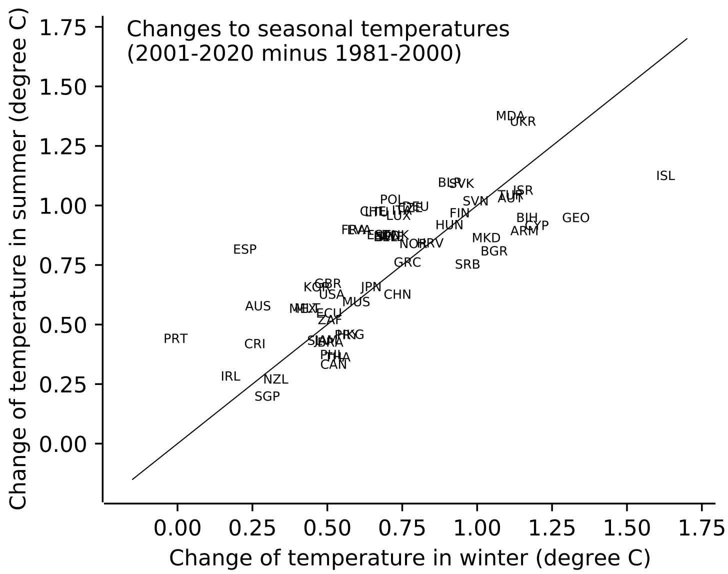
Table H1. Results of regressions using a global sample of GDP of countries using differences between quarter with maximum and mimnimum temperature for identification.

Dependent variable:	Δ *log GDP*		
Column:	1	2	3
ΔT	0.0042***	0.0045***	0.0237***
	(0.0008)	(0.0009)	(0.0077)
$\Delta T \cdot$ log GDP pc			-0.0021***
			(0.0008)
Δ Precipitation		-0.2406*	-0.2256*
		(0.1364)	(0.1351)
Annual mean temperature		-0.0003	-0.0005
		(0.0007)	(0.0007)
log GDP pc		-0.0218***	0.0003
		(0.0076)	(0.0074)
log Landarea		-0.0056**	-0.0048**
		(0.0022)	(0.0021)
R2	0.23	0.43	0.47
R2 adj.	0.23	0.40	0.43
N	81	81	81

Notes: Time period is 1991-2020. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

I Past climate trends

Figure I1. Change in seasonal temperatures between 1981-2000 and 2001-2020 for winter and summer months.



J Estimation results by season

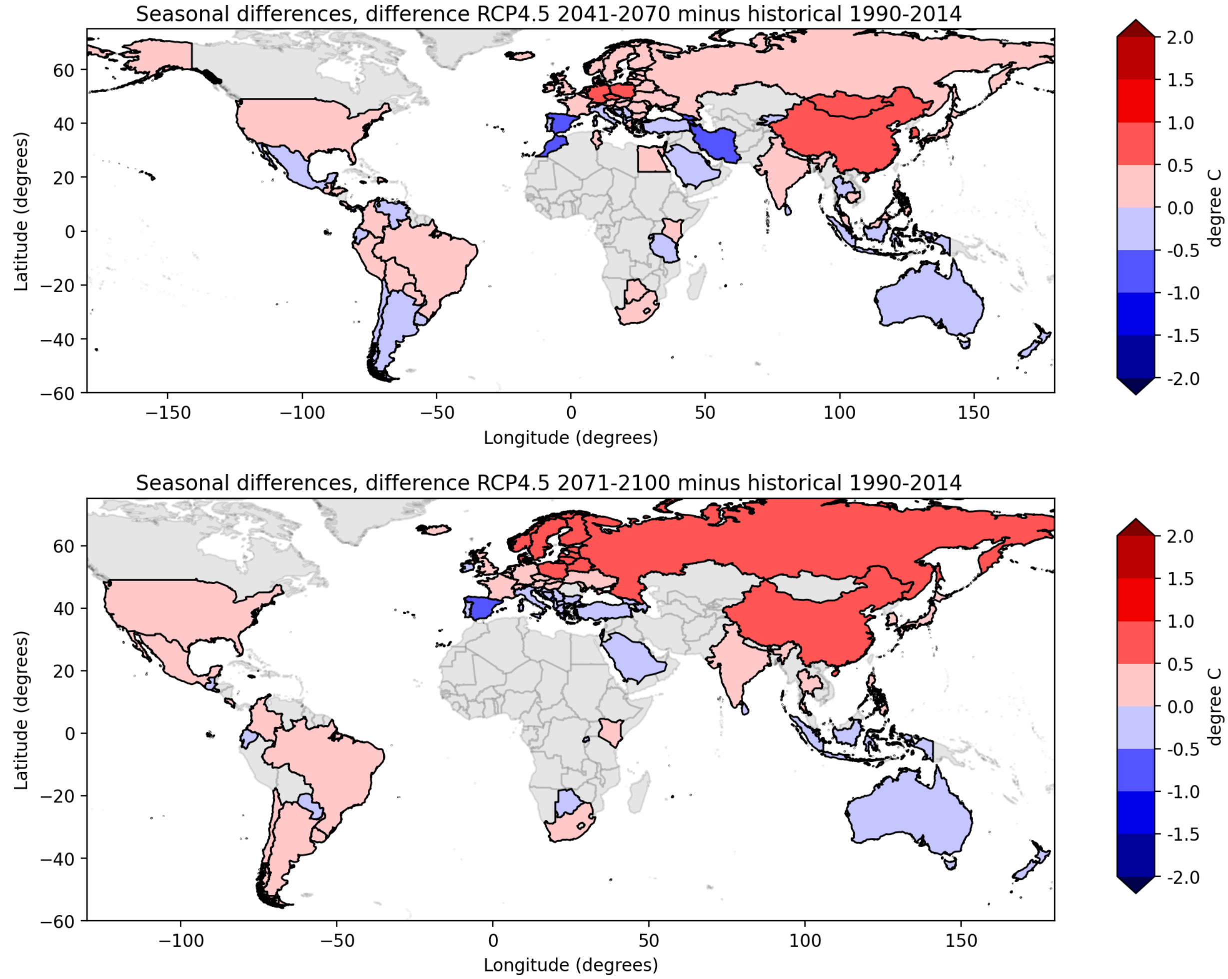
Table J1. Results of regressions using a global sample of GDP of 60 countries, by season.

Dependent variable:	Δ_{LD} *log GDP*	
Column:	1	2
Δ_{LD} Temperature in summer	-0.0005	0.0161
	(0.0007)	(0.0110)
Δ_{LD} Temperature in winter	0.0003	-0.0082
	(0.0004)	(0.0053)
Δ_{LD}Temperature in summer · log GDP pc		-0.0016
		(0.0011)
Δ_{LD}Temperature in winter · log GDP pc		0.0008
		(0.0005)
Δ_{LD}Precipitation in summer	-0.0213	-0.0017
	(0.0228)	(0.0140)
Δ_{LD} Precipitation in winter	-0.0312	-0.0384
	(0.0332)	(0.0259)
log GDP pc		0.2352
		(0.1724)
R2	0.05	0.14
R2 adj.	-0.02	0.03
N	60	60

Notes: Long differences Δ_{LD} calculated by subtracting mean over 1981-2000 from mean over 2001-2020. Seasonal differences Δ calculated as winter minus summer. Significance as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

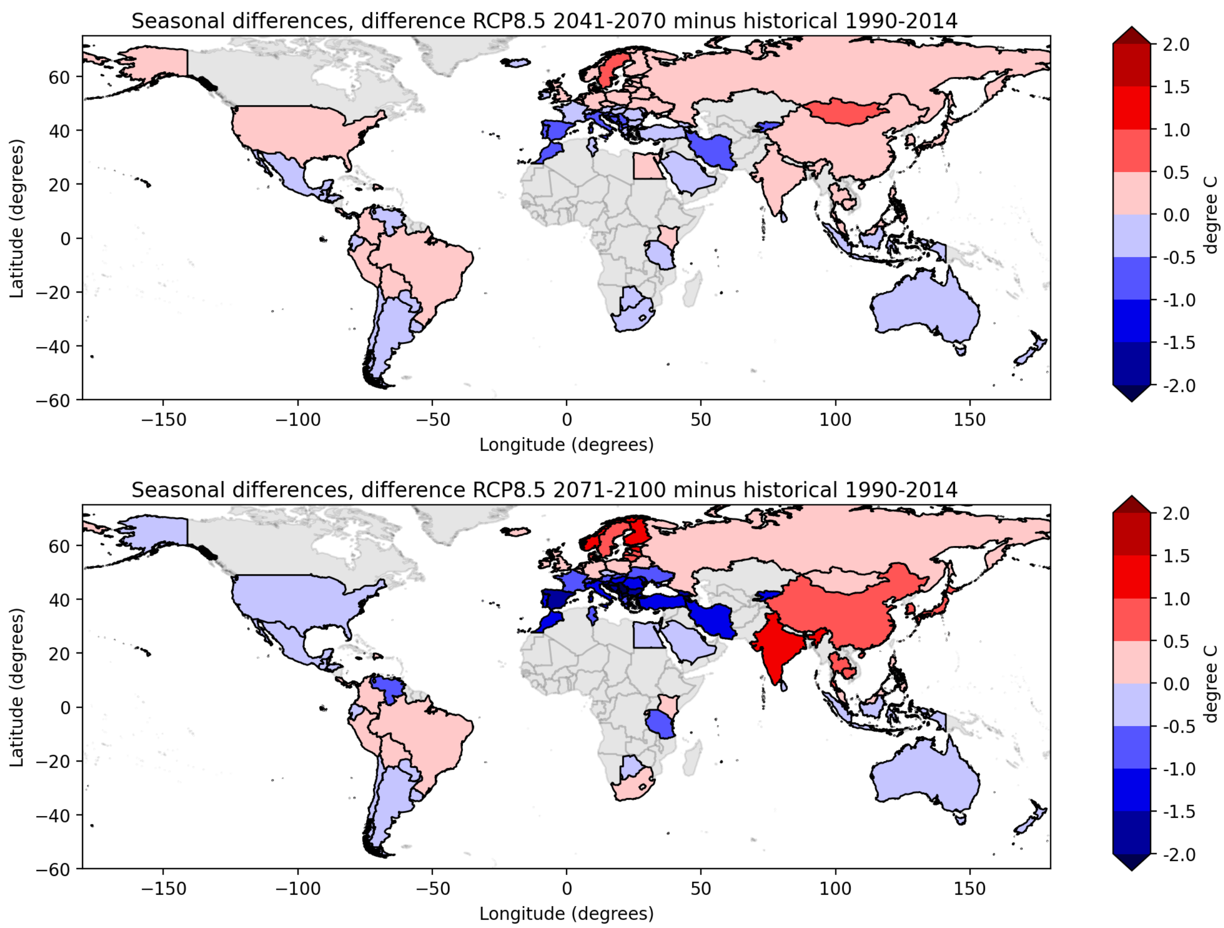
K Climate projections

Figure K1. Future projections of ΔT for RCP4.5 for 2041-2070 and 2071-2100.



Notes: Seasonal differences calculated as winter minus summer. Positive values mean that temperature in winter is projected to increase more than temperature in summer.

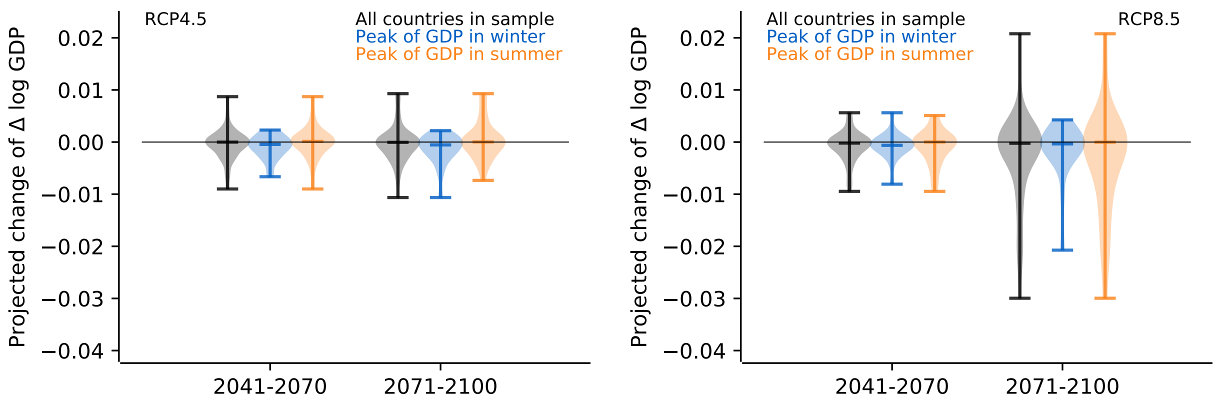
Figure K2. Future projections of ΔT for RCP8.5 for 2041-2070 and 2071-2100.



Notes: Seasonal differences calculated as winter minus summer. Positive values mean that temperature in winter is projected to increase more than temperature in summer.

L Projected changes to seasonal economic cycles for RCP4.5 and RCP8.5

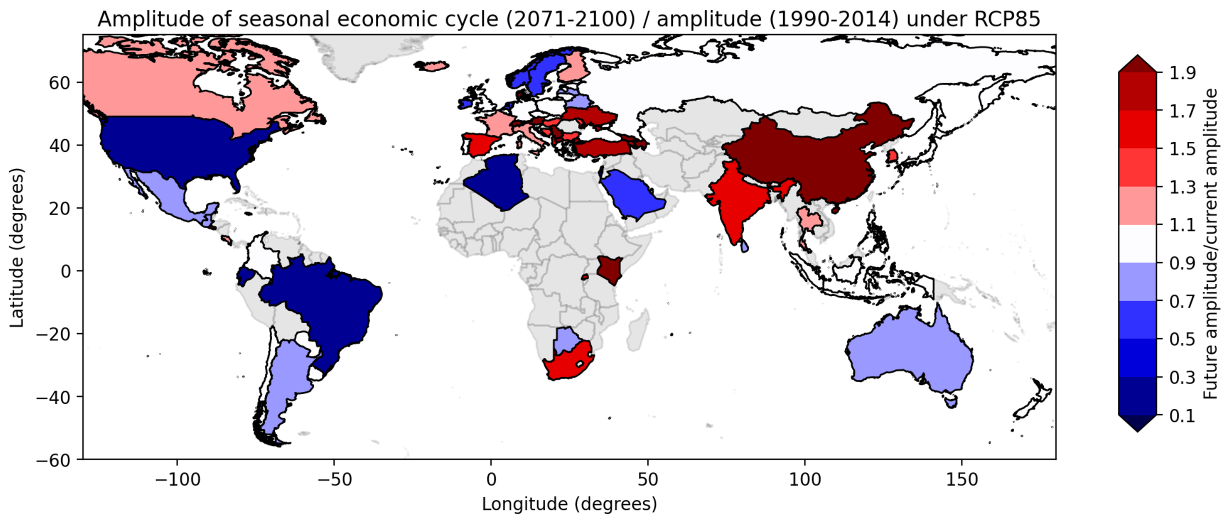
Figure L1. Projections of Δ GDP for two alternative scenarios of future climate change for the global sample.



Notes: The plot shows the distribution of the projected changes of Δ log GDP for individual countries in the vertical direction (violinplots) based on the results from the long-difference estimation. . Horizontal bars indicate the maximum, median, and minimum values. Seasonal differences Δ calculated as winter minus summer. Positive values mean that for the given scenario GDP will be reallocated from summer to winter.

M Map of projected changes to seasonal economic cycles

Figure M1. Map of projections of Δ GDP for the RCP8.5 scenario of future climate change for the global sample.



Notes: The map shows the distribution of the projected changes of Δ log GDP for the RCP 8.5 scenarios based on the results from the long-difference estimation. Seasonal differences Δ calculated as winter minus summer. Positive values mean that for the given scenario GDP will be reallocated from summer to winter.