Seasonal temperature variability and economic cycles *

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Abstract

In this paper, we examine to what extent seasonal temperature variability can explain seasonal economic cycles. To this aim, we 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. We then attribute these economic cycles to variation in temperature. For identification, we 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 we 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 seasonal 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 similar in size to current seasonal economic cycles, pointing to a channel through which climate change will affect economic production that has so far been overlooked.

Keywords: seasonal cycle, temperature variability, climate change

JEL codes: E32, E23, Q54

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1 Introduction

A large part of the variation of time-series 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, we empirically examine the influence of temperature on seasonal economic cycles. To do so, we 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, we define seasons in a consistent way across countries in different hemispheres. For causal identification, we 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. We discuss in details the underlying assumptions and conduct a large number of robustness checks, including a combination of seasonal differences and long differences.

We 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, we 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. We then aggregate quarterly production to production in two seasons (Q1+Q4 and Q2+Q3), to which we refer as summer and winter depending on which season tends to be warmer. We find that production is larger in summer in 44 countries and larger in winter in 37 countries.

We next examine the contribution of temperature to economic 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, we find similar effects if we 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 can potentially be explained by several mechanisms through which temperature affects economic activity. To investigate some of these mechanisms, we 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, we 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. We also explore the role of other channels, including agriculture, tourism, religion, and international trade but we do not find evidence suggesting that any of these specific channels is important.

In the last part of the paper, we examine possible consequences of climate change. To do so, we first 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 estimation based on seasonal differences alone. Specifically, we find that between 1981-2000 and 2001-2020, seasonal GDP increased relatively more in seasons that warmed more. This seems to be primarily due to a reallocation of economic activity between the two seasons, as we do not find evidence that seasonal warming had an effect on annual GDP. We then combine our estimates with projections of seasonal temperature from climate models for a scenario of intermediate climate change (RCP4.5). The results suggest that future seasonal warming will cause a reallocation of economic activity across seasons with substantial variation across countries. On average seasonal economic cycles are projected to increase. The magnitude of these effects is substantial as our estimates suggest that in some countries seasonal economic cycles are projected to 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, we 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, we 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. These insights have important implications for any analysis of seasonality in economic timeseries and the future study of business cycles (e.g. Wen (2002)) and are potentially relevant for fiscal and monetary policy that aims to smoothen fluctuations in the economy (see e.g. Liu (2000)).

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). Furthermore, previous research has reported negative effects of temperature variability on economic production (Kotz et al., 2022; Linsenmeier, 2021). In this paper, we find evidence for an overall positive effect of seasonal temperature on seasonal production, but we also explain how this estimated effect is conceptually different from the effect of annual temperature on annual GDP estimated in previous studies. Our results therefore point to a way in which climate change will affect economies that has so far been overlooked. Given our finding that economic development makes countries more resilient to economic fluctuations from temperature, our results are particularly relevant for relatively poor economies.

The paper is structured as follows. In the next Section, we present the theoretical framework, explain the identification strategy, and describe the data used in this study. In Section 3, we first present stylised facts of seasonal economic cycles for our global sample of countries. We then discuss results obtained from our econometric estimation, before showing stylised facts and econometric results for the data on industry groups for countries in Europe. Furthermore, we combine our 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, we start by formulating a simple conceptual model of economic production Y as a function of climate $\mathbf{C}$ and other factors $\mathbf{X}$. We 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 we 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).

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, we propose a new empirical strategy for navigating this trade-off. The strategy relies on temperature differences between two seasons of the same year. Wet 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, we 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, we 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. However, biases can still arise from country characteristics that are correlated with both seasonal differences in temperature and seasonal differences in GDP. To address such concerns, we include a variety of control variables related to for example geography, religion, trade openness, and sectoral composition including tourism and agriculture and examine the robustness of the estimates.

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 essentially requires that expectations about seasonal climate are formed based on the observed seasonal weather $\mathbf{c}$. The assumption is more credibly satisfied the longer the time period used to characterise seasonal weather. In the main specification, we use a 30 year period which is the common choice to characterise climate.

In the last part of the paper we combine seasonal differences with long-differences. In mathematical terms, we estimate an Equation:

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

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 $Y_{i\tau_1^B}$ is the same average over the period 2001-2020.

Denoting seasonal differences by Δ and long differences by Δ_{LD} 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 recent changes of temperature and economic production which are likely more indicative of any effects of future anthropogenic climate change.

2.3 Data

The main data are timeseries of quarterly Gross Domestic Product (GDP) in USD provided by the International Monetary Fund (IMF). The data include 81 countries with different temporal coverage. The data are provided in nominal and real terms and the temporal coverage differs between the two products for some countries. We restrict the data to the time period 1980-2020. The data include at least 7 years of observations for every country (the first year in which data are available for Honduras is 2014 and for the Maldives 2012; for all other countries we 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, we reduce the sample to the years 1991-2020 for the main estimation. The results are robust to using data only for the years 2011-2020 (Figure C1 Appendix). We combine this economic data with the climate reanalysis ERA5 provided by the European Center for Medium Range Weather Forecast (ECMWF). We use monthly mean temperature levels and monthly mean daily precipitation which we aggregate to quarterly frequency. The data have a spatial resolution of 0.25 degrees (approximately 25 km at the Equator) which we aggregate to the level of countries using grid-cell population from the Gridded Population of the World

(GPW) dataset as weights.

We also use data on quarterly Gross Value Added (GVA) for 11 industry groups provided by EUROSTAT. The data cover 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 time-series, we 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, we find that the results are robust to using either of the two (Figure C1 Appendix). For detrending we use a Hodrick-Prescott Filter with $\lambda = 50$. This filter has received criticism regarding its use in timeseries econometrics (Hamilton, 2018), but these issues are of minor concern here because the filter is only used to subtract a gradual trend. The detrended data are then averaged over time and identification is obtained from cross-sectional variation. After applying the filter and removing deterministic trends, we add the mean value of the last year in the time-series (Appendix Figure A3).

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 Southern 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 we 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. We 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 Appendix). 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.

For control variables we 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 we 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). We 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 we 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.

The magnitude of the seasonal cycle, defined as the difference between GDP in summer and winter divided by the annual GDP, reveals some geographical heterogeneity but no apparent pattern associated with latitude, suggesting that it is determined by several factors (Appendix Figure A2). 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
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

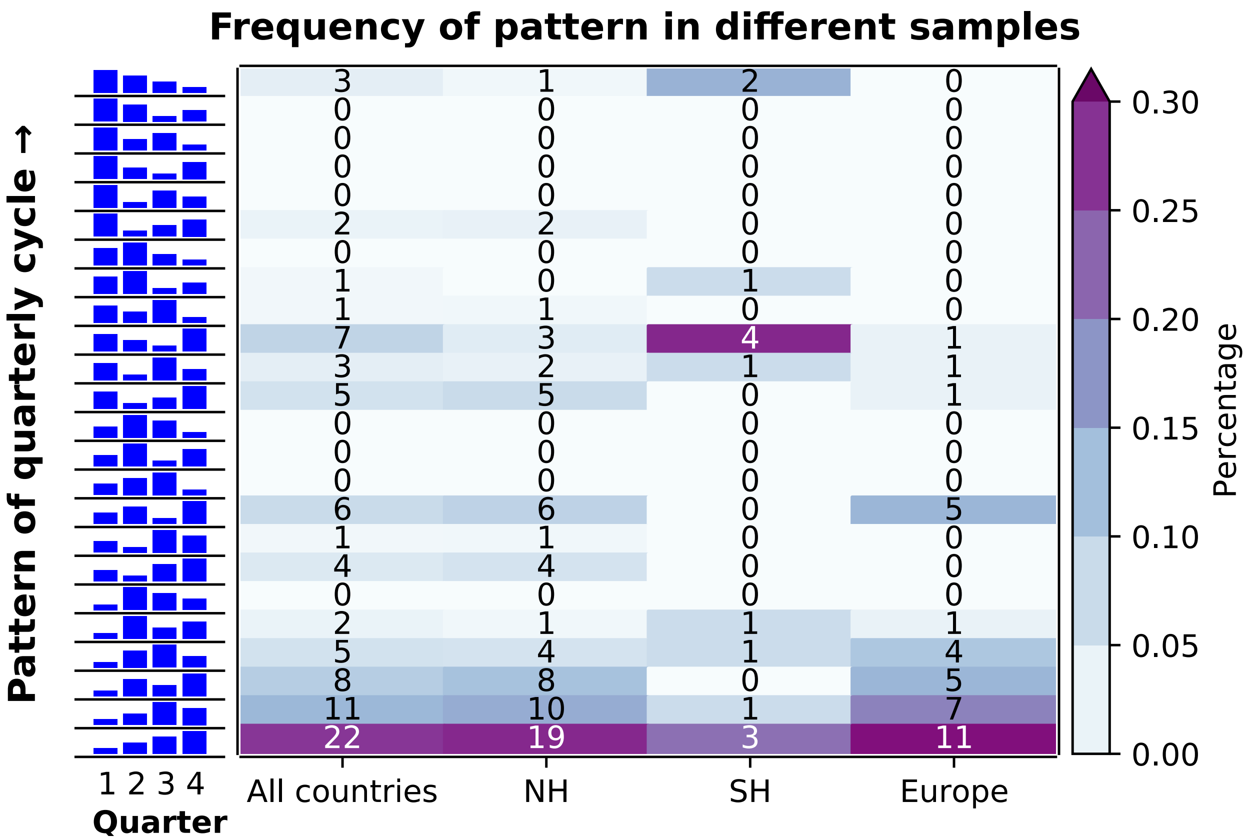
3.1 Stylised facts on seasonal economic cycles

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. We hence first identify stylised facts about seasonal cycles based on our larger and more representative sample of 81 economies. Overall, seasonal economic cycles around the world appear quite diverse, with 15 of the 24 possible patterns being exhibited by at least one country (Figure 1).

Our more comprehensive evidence suggests 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 a consumption boom around Christmas (Beaulieu and Miron, 1992). In our sample, the most common pattern (22 of 81 countries) indeed exhibits a peak of production in the fourth quarter, followed by the third, second, and first quarter (Figure 1). However, already the second most frequent pattern (11 countries) features the peak of production in the third quarter, followed by the fourth, second, and first quarter. Overall, we find that the peak in the fourth quarter is primarily a phenomenon of countries in the Northern hemisphere (Figure 2). 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.

Another 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 (Figure 2). A third 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 we 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

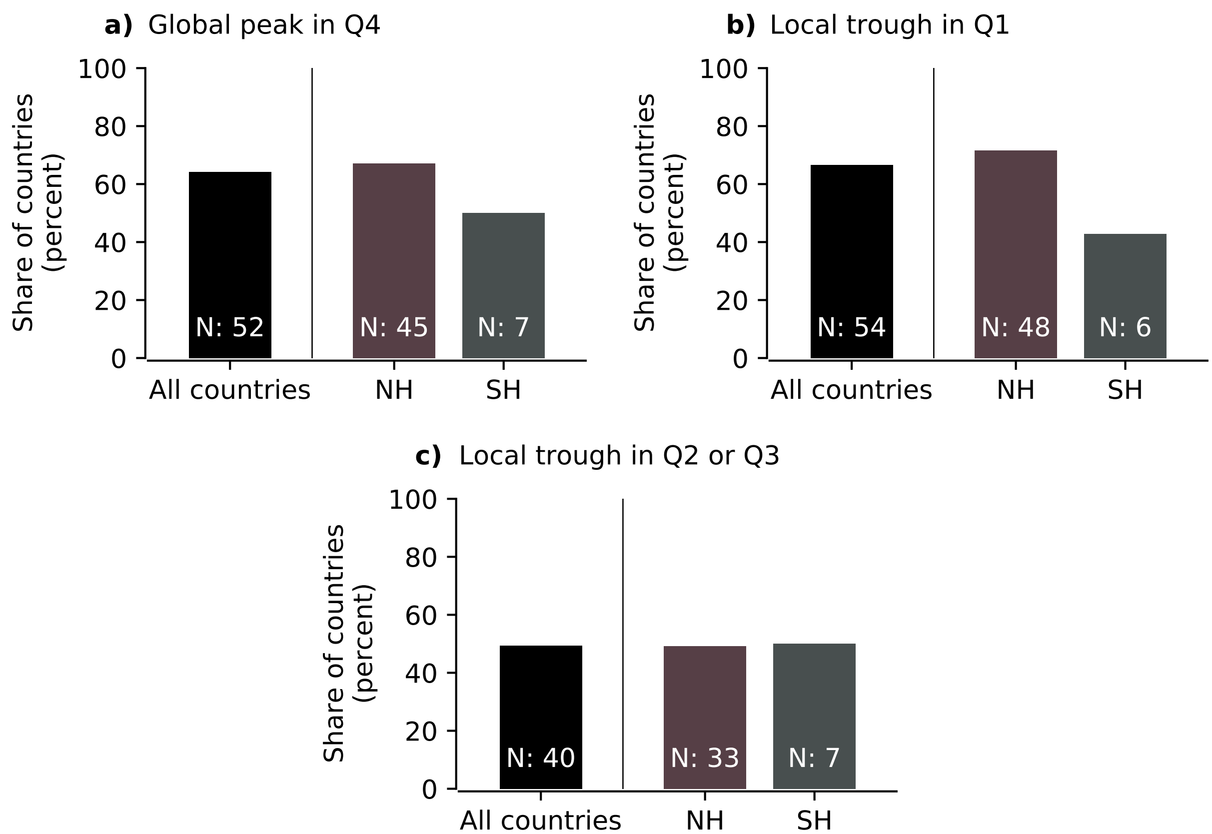
Figure 1. Quarterly cycles of GDP.



Notes: The figure shows the frequency of the 24 possible patterns of quarterly GDP among the countries in the sample. Every row corresponds to one pattern, which is shown with the blue bars on the left. The number in each cell is the number of countries that exhibit the corresponding pattern. Columns correspond to different samples of countries: full sample, countries in the Northern hemisphere, countries in the Southern hemisphere, and countries in Europe. Colors indicate relative frequency based on the size of the corresponding sample.

also that this fact is even in the Northern hemisphere only exhibited by about two thirds of all countries (Figure 2).

Figure 2. Stylised facts identified by previous studies and their frequency among the 81 countries in the sample.



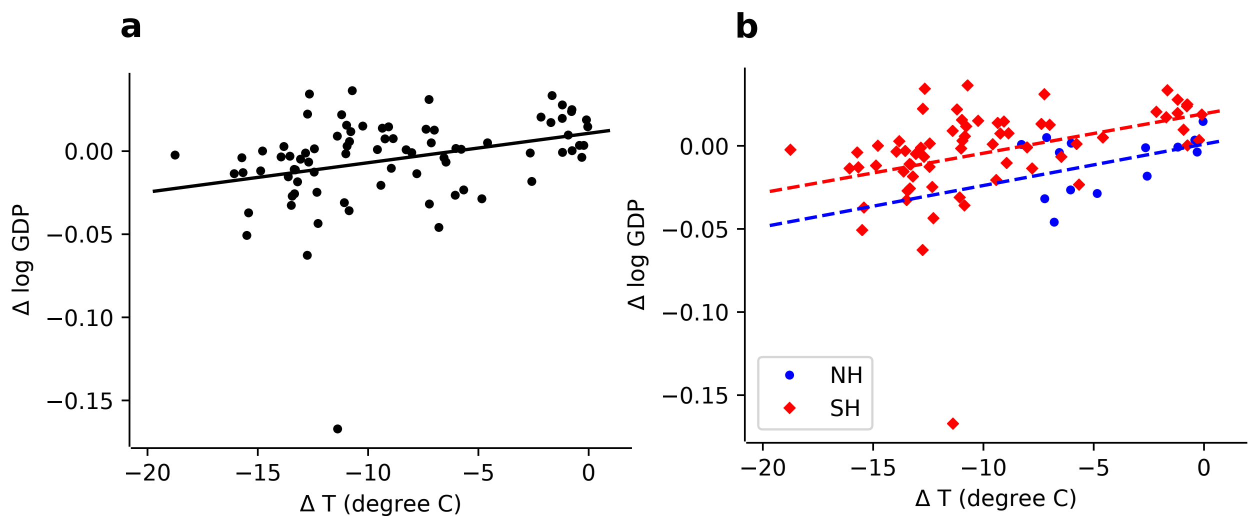
Notes: Relative frequencies shown in percentages for different groups of countries.

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 our larger sample suggests substantial differences between countries in the two hemispheres.

3.2 The contribution of seasonal temperature variability

In order to examine the contribution of temperature to seasonal economic cycles, we calculate seasonal GDP by summing economic production Q1+Q4 and Q2+Q3 and considering summer and winter as the warmer and the colder of these two six-months period (Section 2.3). We then take seasonal differences by subtracting GDP and temperature in winter from their values in summer. The results for our sample of 81 countries suggest that countries with larger seasonal differences in temperature also tend to have larger seasonal differences in GDP (Figure 3a). Overall, the relationship is positive suggesting that higher temperatures in summer tend to increase GDP in that period (relative to winter). This descriptive evidence is almost identical for countries in the Northern Hemisphere and in the Southern Hemisphere, despite those groups of countries having summer at opposite times of the calendar year (Figure 3b). We consider this insight reassuring because it reduces the plausibility that calendar effects (e.g. Christmas, slow down at beginning of year, mid-year vacations) confound the relationship.

Figure 3. Statistical association between seasonal differences in temperature and seasonal differences in log GDP.



Notes: Seasonal differences Δ calculated as winter minus summer. Colors indicate split of sample into countries in the Northern hemisphere (NH) and Southern hemisphere (SH).

To examine the relationship between seasonal temperature and seasonal GDP in more details, we next regress seasonal differences in GDP on seasonal differences in temperature (Equation 3). We 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 the inclusion of 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 C1 Appendix). We also observe that the results are very similar for differences between the quarters with maximum and minimum temperature (Columns 4-6). 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.

We next study heterogeneity in the effect of seasonal temperature. Including interaction terms in the model, we 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). We do not find evidence that other control variables in the model including annual mean temperature moderate the effect of seasonal temperature (not shown).

Table 2. Results of regressions using a global sample of GDP of 81 countries based on seasonal differences.

Dependent variable:	*Δ log GDP*								
Seasons defined by:	Q1+Q4, Q2+Q3			Q_{max}, Q_{min}			Q1+Q4, Q2+Q3		
Sample:	Global						Europe		
Sectors:	All						All	Exposed	Non-Exposed
Column:	1	2	3	4	5	6	7	8	9
ΔT	0.0018***	0.0014**	0.0105**	0.0042***	0.0045***	0.0237***	0.0037**	0.0071**	0.0014
	(0.0004)	(0.0007)	(0.0050)	(0.0008)	(0.0009)	(0.0077)	(0.0018)	(0.0033)	(0.0016)
$\Delta T \cdot$ log GDP pc			-0.0010*			-0.0021***			
			(0.0005)			(0.0008)			
Δ Precipitation		-0.1817**	-0.1787**		-0.2406*	-0.2256*	-0.0807	-0.3897	0.1322
		(0.0849)	(0.0835)		(0.1364)	(0.1351)	(0.1565)	(0.3410)	(0.1485)
Annual mean temperature		0.0004	0.0005		-0.0003	-0.0005	-0.0022*	0.0001	-0.0027**
		(0.0005)	(0.0004)		(0.0007)	(0.0007)	(0.0012)	(0.0024)	(0.0011)
log GDP pc		0.0107***	0.0031		-0.0218***	0.0003	0.0179*	0.0339*	0.0082
		(0.0036)	(0.0058)		(0.0076)	(0.0074)	(0.0088)	(0.0175)	(0.0075)
log Landarea		0.0024**	0.0020*		-0.0056**	-0.0048**	0.0052***	0.0078**	0.0040***
		(0.0010)	(0.0011)		(0.0022)	(0.0021)	(0.0016)	(0.0029)	(0.0014)
R2	0.10	0.34	0.36	0.23	0.43	0.47	0.54	0.49	0.32
R2 adj.	0.09	0.29	0.30	0.23	0.40	0.43	0.46	0.40	0.21
N	81	81	81	81	81	81	35	35	35

Notes: Sample period is 1991-2020. The symbols Q_{max}, Q_{min} *refer quarters with maximum and minimum mean temperature, respectively. Exposed industries: Agriculture, Construction, Manufacturing, other Industry. Seasonal differences Δ calculated as winter minus summer. Significance as follows:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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 3b). Temperature thus appears to be an important factor contributing to seasonal economic cycles.

These results obtained from seasonal differences estimation are based on cross-sectional variation in seasonal differences and therefore have two caveats. The first caveat is the residual risk of biases from omitted but relevant 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 future changes to economic cycles under climate change because the underlying mechanisms might not be relevant anymore.

To overcome these limitations, we also estimate a model based on long differences of seasonal differences. Because of limited data availability at the quarterly frequency, we 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 are 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 F1 Appendix).

The results are qualitatively similar to the results obtained from cross-sectional variation in seasonal differences (Table 3). Specifically, we 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 again large. 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 E1 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 3. Results of regressions using a global sample of GDP of 60 countries based on long differences of seasonal differences.

Dependent variable:	$\Delta_{\text{LD}}\ \Delta$ *log GDP*					
Column:	1	2	3	4	5	6
$\Delta_{\text{LD}}\Delta T$	0.0059	0.0058	0.1053**	0.0821*	0.1075**	0.1177***
	(0.0065)	(0.0063)	(0.0405)	(0.0469)	(0.0440)	(0.0421)
$\Delta_{\text{LD}}\Delta T \cdot$ log GDP pc			-0.0105**	-0.0091**	-0.0106**	-0.0121***
			(0.0040)	(0.0043)	(0.0043)	(0.0042)
$\Delta_{\text{LD}}\Delta T \cdot$ Annual mean temperature				0.0009		
				(0.0008)		
$\Delta_{\text{LD}}\Delta T \cdot (\Delta_{\text{LD}}\Delta T > 0)$						0.0099
						(0.0124)
$\Delta_{\text{LD}}\Delta$ 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)
$(\Delta_{\text{LD}}\Delta T > 0)$						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. Seasons defined by Q1+Q4, Q2+Q3. 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. In additional analysis, we do not find evidence for significant effects of changes in seasonal temperatures on changes in annual GDP (Table 3 Appendix), suggesting that the results in Table 3 are primarily driven by a reallocation of economic activity between summer and winter and not due to temperature increasing or decreasing economic production in only one of the two seasons.

3.3 Mechanisms

The results in the previous section suggest that seasonal temperature is statistically associated with seasonal economic production. In this section, we explore possible mechanisms. We first examine the role of sectoral composition. To do so, we 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 our knowledge the most comprehensive homogeneous database of quarterly production by industry group.

Reassuringly, we find a similar significantly positive effect of seasonal temperature on seasonal GDP as for the global sample, with about twice the magnitude (Column 7 in Table 2). We next 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). We accordingly classify agriculture, construction, manufacturing, and other industries as relatively exposed. We 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 we find an insignificantly positive effect (Table 2 Columns 8-9). We 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 D1 Appendix).

To study specific mechanisms in more detail, we also examine the role of agriculture, international trade, GDP per capita, and tourism. We 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. We do not find and significant associations (Table B1 Appendix). This suggests that these sectors are not the primary channels through wich seasonal temperature cycles affect economies. As an additional test, we also include those variables as additional explanatory variables in our main specification (as possibly "bad controls") and find that our main estimates barely change (Figure C1

Appendix). In sum, the results suggest that other channels are primarily responsible for the estimated effect. 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 plausible mechanisms.

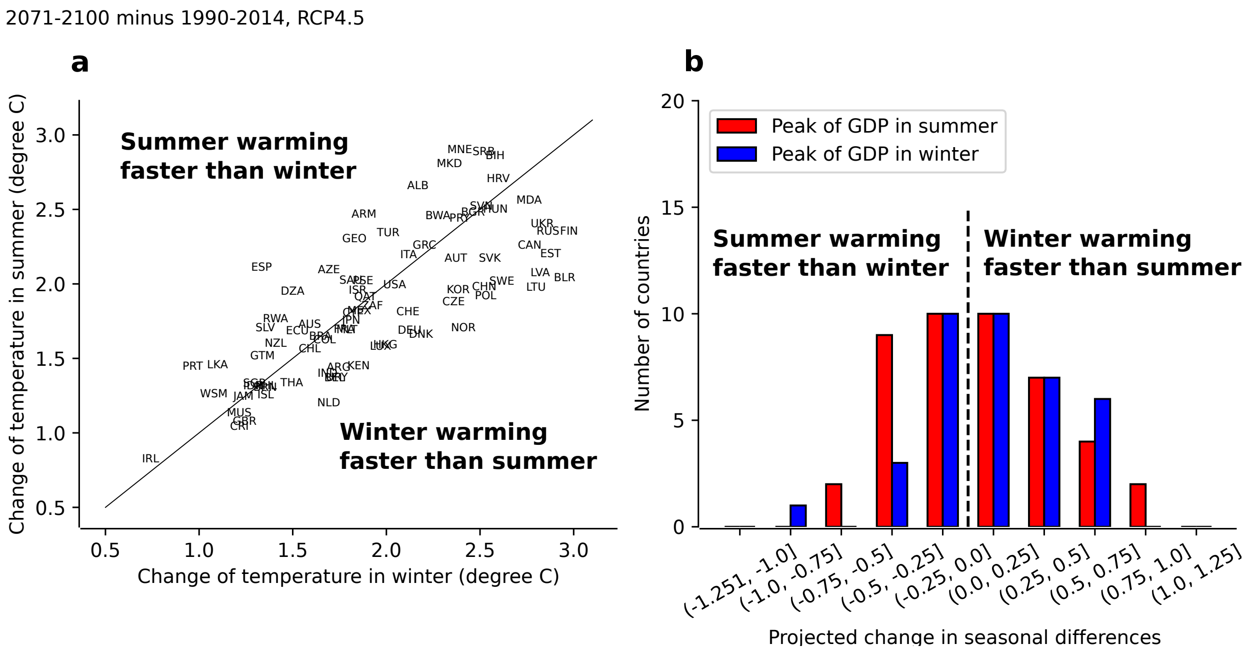
3.4 Scenarios of future climate change

Our results from the long differences estimation suggest that economic production will tend to be reallocated between winter and summer if one season warms more strongly than the other. In this section, we combine this insight with future scenarios of seasonal warming under anthropogenic climate change. Prior literature suggest that in many 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 other countries, 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 the transfer of latent heat from the surface to the atmosphere (Byrne, 2021).

To examine prospective future changes to seasonal economic cycles, we combine climate model projections with our empirical estimates from the long difference estimation. We focus on the "middle of the road" RCP4.5 scenario and the time period 2071-2100. In this scenario, in all but one countries, both summers and winters will warm by more than 1 degree Celsius (Figure 4a). In about half of all countries, winters will warm faster than summers (Figure 4a). The opposite pattern, faster warming in summers than in winters, is primarily observed in clusters of countries in the Mediterranean and Pacific regions (Figure F2 Appendix). These patterns of future warming are similar to observed trends of seasonal warming over the past 40 years (Figure F1 Appendix).

Our estimates suggest that economic production will shift towards the season that warms faster. This will result in an increase of the seasonal economic cycle if economic production is already larger in that season and a decrease otherwise. Overall, our results suggest that in countries in which GDP currently peaks in winter, winters tend to warm faster than summers (Figure 4b). Similarly, countries with a peak of production in summer tend to experience faster warming in summer. On average, seasonal economic cycles are therefore projected to increase. The magnitude of the projected changes varies greatly among countries. Based on our empirical estimate of 0.58 percent of seasonal GDP per degree C (Column 2 in Table 3), projected reallocations of economic production amount to about 0.1-0.5 percent of seasonal GDP.

Figure 4. 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 RCP4.5 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 Conclusion

In this paper we study the effect of seasonal temperature on seasonal economic production. For causal identification we propose a novel econometric approach that uses variation of differences between seasons across countries. We then apply this seasonal differences estimator to a global sample of 81 countries using quarterly data on GDP and climate reanalysis. The results suggest that seasonal temperature variability can explain a major part of the observed seasonal cycles of GDP. 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.

Our 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, we find that in the majority of countries economic activity is larger in summer than in winter. Somewhat consistent with this finding, our results suggest an overall positive association between seasonal temperature and seasonal economic production.

The effect of seasonal temperature on seasonal GDP is both statistically significant and large. On average the effect size is of the same magnitude as the sample mean of the observed differences in seasonal GDP. To address concerns about causal inference from cross-sectional variation, we 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. Reassuringly, we also find very similar results when we combine our seasonal differences with long differences.

We explore possible mechanisms with an analysis on the industry level for a subsample of European countries. The results point to an important role of industries that are relatively exposed to ambient temperature, including Construction, Industry, and Manufacturing. We do not find any evidence that agriculture, tourism, religion, or trade play a major role.

To quantify the possible seasonal reallocation of economic production under future climate change, we combine our empirical estimates with projections of a climate model. We find that on average, seasonal economic cycles are projected to increase. The magnitude of the projected reallocation of economic activity between the seasons is up to 0.5 percent of seasonal GDP by 2071-2100 for the "middle of the road" scenario RCP4.5. This corresponds to the approximate current size of the seasonal economic cycle in many countries.

Our 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 (Liu, 2000), which in the US have been shown to be only partly offset by existing policies and result in large drops in household income (Coglianese and Price, 2020). Furthermore, our results suggest that economic development can make economies more resilient to temperature fluctuations, pointing to additional benefits of development for climate change adaptation.

Our analysis is limited in certain ways. 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. However, the sample includes relatively few economies in Africa, demanding caution when extrapolating from our results to specific 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 cannot rule out 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. The results also suggest to examine the importance of temperature variability for business cycles possibly re-examining prior conclusions about calendar effects (see e.g. Wen (2002) and Price and Wasserman (2022)).

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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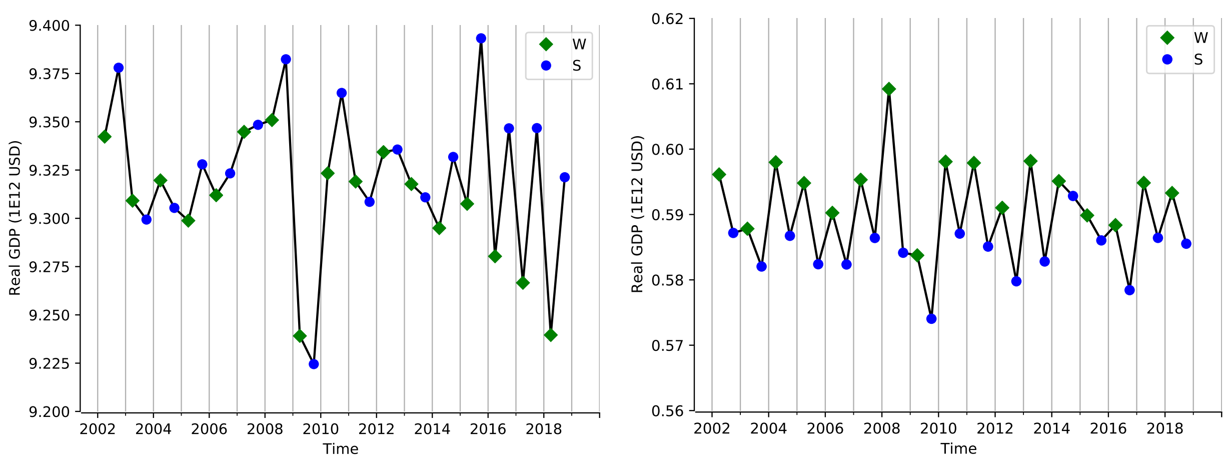
A Detrending of time-series and descriptive statistics

Figure A1. Time-series 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.

Figure A2. 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.

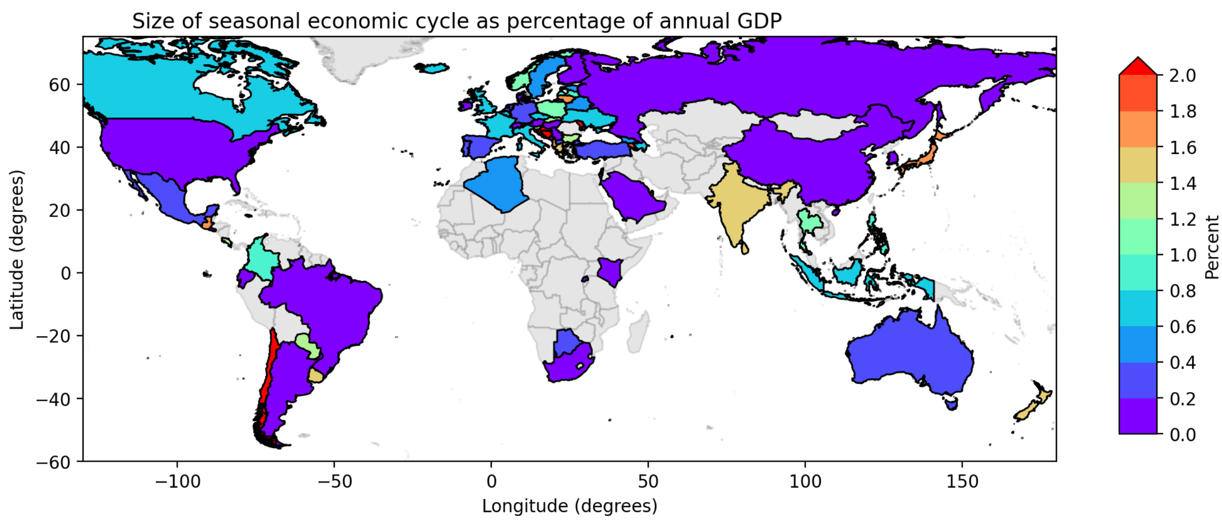
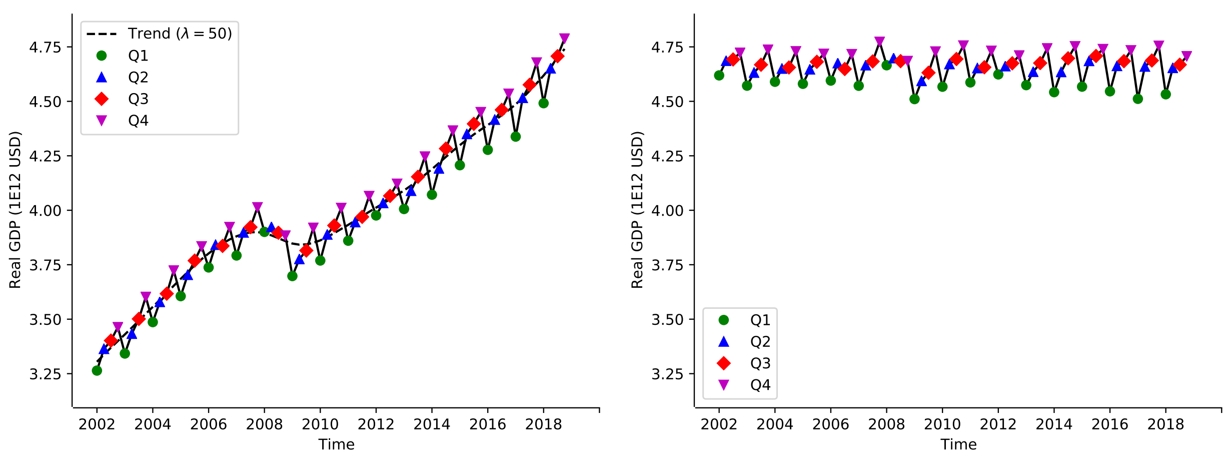


Figure A3. Time-series of quarterly real production for the USA before (left) and after detrending (right).



B Estimation results to explore alternative channels

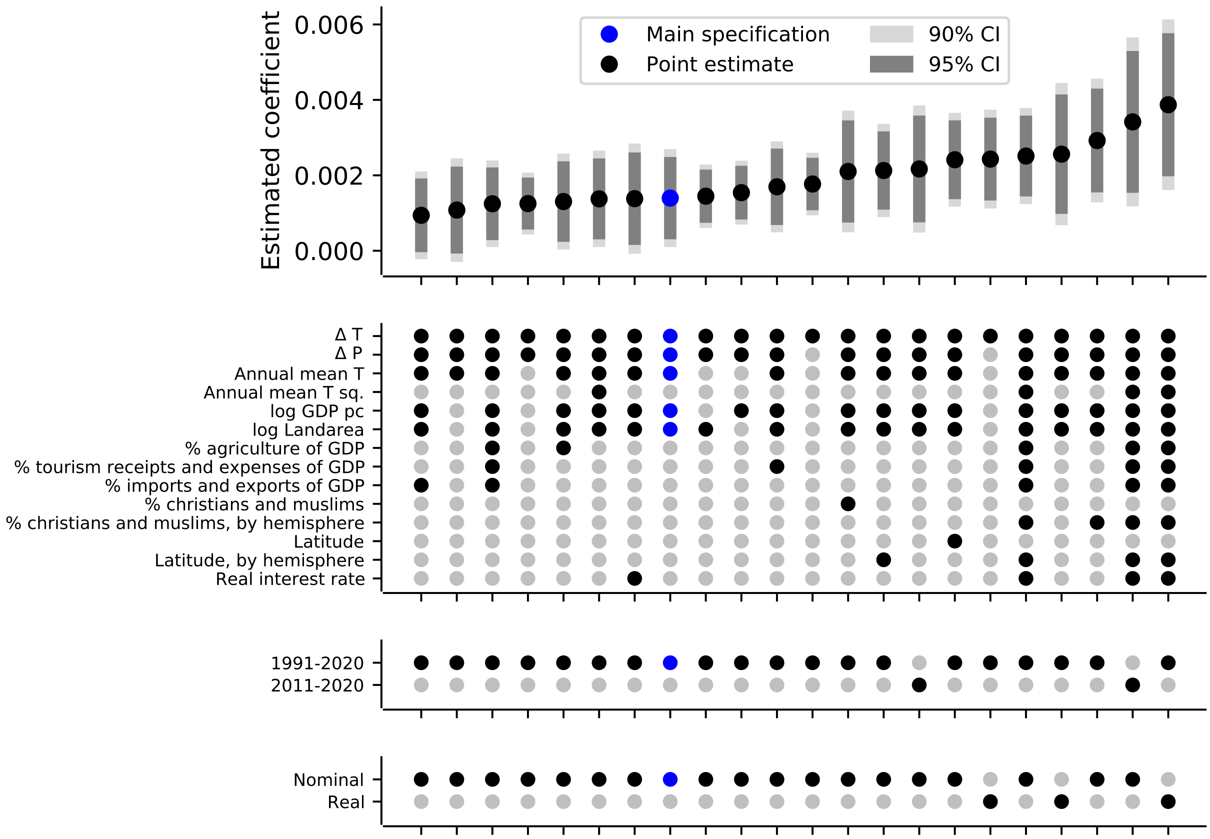
Table B1. Results of regressions to explore possible channels through with temperature variability might affect seasonal economic cycles.

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:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C Specification chart

Figure C1. 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).

D Results by industry group

Table D1. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

E Estimation results for different samples

Table E1. 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 3. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

F Past climate trends and future projections

Figure F1. Change in seasonal temperatures between 1981-2000 and 2001-2020 for winter and summer months.

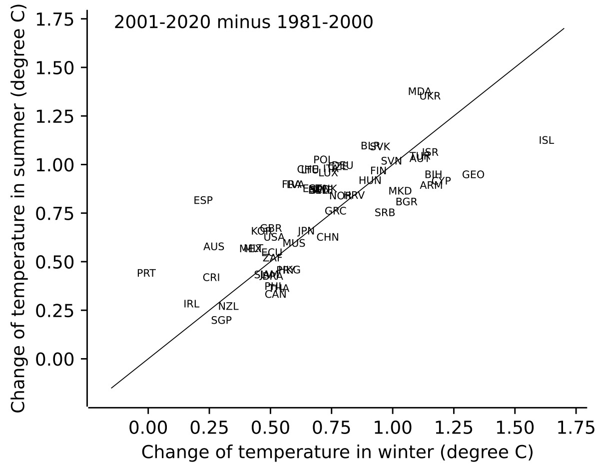
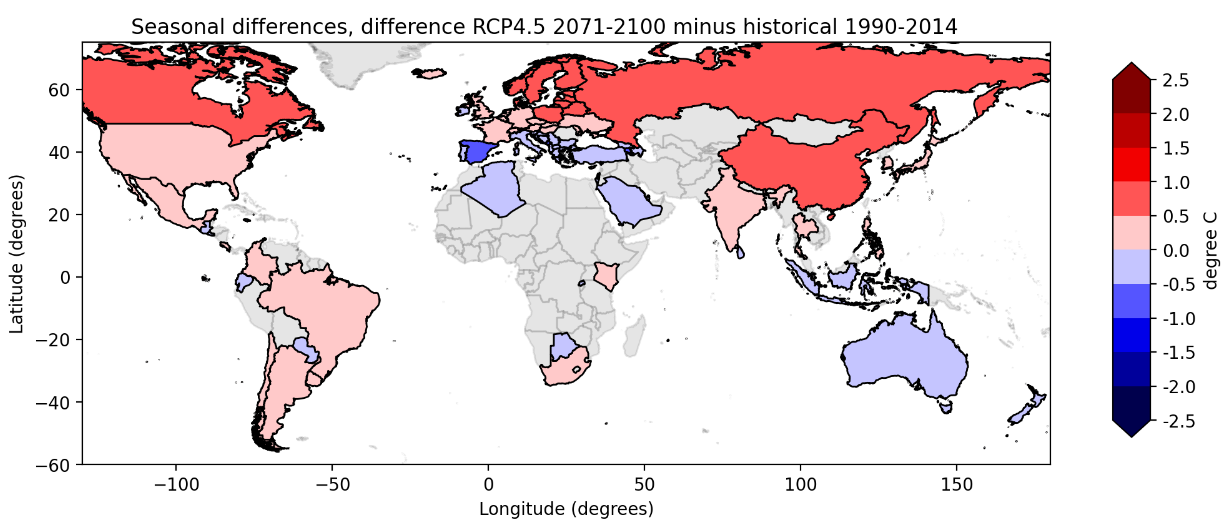


Figure F2. Future projections of ΔT for RCP4.5 for 2071-2100.



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