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Seasonal temperature variability and economic cycles

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ABSTRACT

This study examines the role of temperature as a driver of seasonal economic cycles. The study first presents a novel dataset of seasonal temperature and seasonal GDP. Stylised facts show that seasonal economic cycles are much more diverse than previous research suggested. The study then attributes seasonal economic cycles to temperature variability. For causal identification, the study proposes a novel econometric approach that accounts for expectations. The results suggest that seasonal temperature has a statistically significantly positive and economically large effect on seasonal GDP. Overall, a substantial share of seasonality in GDP timeseries appears to be due to weather. For a subsample of European countries, the effect of temperature can be attributed to sectors that are relatively more exposed to ambient environmental conditions. Projections of climate change suggest that seasonal economic cycles might substantially change in the future, with larger cycles expected for about half of the countries in the sample.

1. Introduction

Seasonality is an important feature of the time-series of many macroeconomic variables (Hylleberg et al., 1993) and understanding its causes has been an active area of research. While it has long been conjectured that seasonality may be attributable to changes in weather, previous research has come to the conclusion that observed quarterly fluctuations of Gross Domestic Product (GDP) can mostly be explained by recurring shifts in preferences and technologies. These shifts have been attributed primarily to high marginal utility from consumption around Christmas and to absences due to 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 synchronous economic cycles in countries in different hemispheres experiencing opposite annual temperature cycles (Beaulieu et al., 1992). However, the role of temperature was only addressed in passing, data was available only for small samples of mostly OECD countries, and little attention was paid to causal identification of the effect of climate. Given that anthropogenic climate change is projected to change seasonal cycles of temperature (Dwyer et al., 2012), the question about the role of temperature for fluctuations of GDP appears to be very relevant.

In this study, we empirically examine the influence of temperature on seasonal economic cycles. As compared to the earlier literature, our study benefits from new theories and methods to identify the effects of climate on the economy and from much better data availability. To leverage the latter benefit, we first construct a new dataset covering the period 1980–2019 using a global dataset of quarterly GDP for 80 countries, a dataset on quarterly Gross Value Added (GVA) at the industry level for 34 European economies, and climate reanalysis. For this global sample of countries we then define two seasons, summer and winter, in a consistent way for both hemispheres. For causal identification, we propose and apply a novel estimation strategy that is based on

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variation across countries in the differences in temperature and GDP between summer and winter. We introduce this econometric approach in the standard theoretical framework of "climate econometrics" and explain how it allows us to identify the full effect of climate, accounting for expectations, rather than only the partial effect of weather. We also discuss the underlying assumptions and corroborate our main results with a large number of robustness tests.

We first use our novel dataset to identify stylised facts. Earlier studies examined data for fewer countries, mostly in the Northern hemisphere. Those previous studies reported relatively similar quarterly economic cycles across countries with the 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 around the world. Economic cycles also seem to systematically differ between countries in the Northern and in the Southern hemisphere. To make seasons comparable across countries, 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 on average. When doing so, we find that production is larger in summer in 44 countries and larger in winter in 36 countries.

We next quantify the contribution of temperature to seasonal economic cycles. We find that seasonal differences in temperature between summer and winter have a statistically significant, positive association with seasonal differences in GDP. This positive effect of seasonal temperature on seasonal GDP is remarkably similar in countries in both hemispheres that experience summer and winter at different times of the year, suggesting that it cannot be explained by calendar effects. The effect of seasonal temperature also appears large, with a difference in temperature between summer and winter of 10 degrees Celsius corresponding to a difference in GDP between the two seasons of about 4 percent.

In robustness tests, we find that the estimated effect of seasonal temperature on seasonal GDP is robust to the inclusion of several climatic and geographical controls. The estimated coefficient is also robust to the choice between nominal and real GDP and to changes in the time period. Furthermore, we find a similar effect if we consider the warmest and the coldest quarter as summer and winter, respectively, instead of averaging over six-months period. The effect can also be identified if seasonal differences are combined with long-differences, further corroborating the robustness of our result to possibly omitted variables. Consistent with our robustness checks, a statistical test indicates that the risk of omitted variable bias is below typically applied thresholds.

We distinguish several mechanisms through which temperature can affect economic activity. In additional analysis, we do not find evidence that our results can be explained with seasonal cycles in agriculture. We also do not find evidence that seasonal temperature cycles are associated with larger import or export shares or with larger tourism expenses or receipts. Furthermore, we find that seasonal temperature has no significant effect on seasonal employment. However, we find evidence that countries with larger touristic sectors exhibit a stronger response of seasonal GDP to seasonal temperature. Furthermore, we find weak evidence that countries with higher GDP per capita might have smaller responses of seasonal GDP to seasonal temperature, and that countries with more stringent labour market regulations might have larger responses.

For a subset of European countries we are able to examine more explicitly the role of different sectors by using quarterly data on GVA for different industry groups. Overall, we find a statistically significant effect of seasonal temperature on GVA 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. These results are generally consistent with an effect of temperature on the supply side of the economy.

In the last part, we examine possible consequences of climate change. To do so, we 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. In about half of all countries, seasonal economic cycles are projected to increase, whereas in the other half of the sample they are projected to decrease.

Our work 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 for economic cycles, but supports the possibility that temperature is one fundamental driver of those shifts. We believe that 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., 2015a; Pretis et al., 2018; Kalkuhl and Wenz, 2020; Acevedo et al., 2020). Furthermore, previous research has reported negative effects of temperature variability on economic production (Kotz et al., 2022; Linsenmeier, 2023). 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. Given these important differences, our study reveals a new pathway through which climate change will affect 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 present our main results on the influence of seasonal temperature obtained from our econometric estimation and discuss their robustness, before examining possible mechanisms. Furthermore, we combine our empirical estimates with results from climate models to illuminate possible future changes to seasonal economic cycles. Conclusions are drawn in Section 4.

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. Conceptually, seasonal cycles of temperature can be considered as a characteristic of the climate of a location, rather than its weather (Hsiang, 2016). 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, whereas weather $\mathbf{c}$ refers to the (empirical) frequency distribution of their actual realisation. 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 installation of irrigation or indoor climatisation.

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, typically hours or days. In the context of this paper, it is important to note that the climate of a location can also be defined for a subset of the year. For example, the climate of the months January, February, and March in London over the period 1981–2010. Here, we use the term *seasonal climate* to refer to the climate of specific months that correspond to the four quarters of the year.

Given Eq. (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 Eq. (2)) and belief effects (the second term of Eq. (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 Eq. (2) will be captured to a greater or lesser extent by empirical estimates. Generally, variation of economic production 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 climate and economic production 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 runs as a thread through the climate econometrics literature (Hsiang, 2016).

Here we propose a new empirical strategy for navigating this trade-off. The strategy relies on average differences between two seasons. Specifically, identification is based on the variation of average differences between two seasons across units of observations.

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 countries are indexed i and with two seasons indexed by τ_1 and τ_2. The two seasons can be considered as summer and winter, averaged over several years (Section 2.4). In our main specification, $Y_{i\tau}$ is log GDP of country i in season τ averaged over 1990–2019. The use of averages over several years is motivated by the assumption that economic agents consider these averages of weather as information about climate when they form their beliefs about future weather realisations. Eq. (3) also includes a vector of time-varying controls $\mathbf{x}_{i\tau}$ and a vector of season-invariant controls $\tilde{\mathbf{x}}_i$ (Section 2.3).

Eq. (3) can be estimated with OLS. For our main results we estimate heteroskedasticity-robust White standard errors. However, to account for the possible spatial autocorrelation of errors we also estimate models in which we cluster errors by continent. Given the small number of continents/clusters and to account for a more continuous spatial autocorrelation of errors, we additionally estimate models with Conley standard errors with cut-off values of 1000 km, 5000 km, and 10,000 km.

Identification of a causal effect of seasonal climate using Eq. (3) relies on a special form of the *unit homogeneity assumption*:

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

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

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

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.

The seasonal differences approach can be considered a hybrid approach, exploiting variation both across time and across units of observations for identification. In this respect, it resembles the long differences approach of panel data analysis which also aims to identify the total effects of climate including belief effects (Hsiang, 2016). However, the time scale of variation that is used for identification differ. The two approaches are thus not exclusive and can be combined. In the last part of the paper we combine seasonal differences with long-differences. In mathematical terms, we estimate an Equation:

$$\begin{aligned}(Y_{i\tau_1^B} - Y_{i\tau_2^B}) - (Y_{i\tau_1^A} - Y_{i\tau_2^A}) = \alpha_{\mathrm{LD}} &+ \left((\mathbf{c}_{i\tau_1^B} - \mathbf{c}_{i\tau_2^B}) - (\mathbf{c}_{i\tau_1^A} - \mathbf{c}_{i\tau_2^A})\right)\beta_{\mathrm{LD}} \\ &+ \left((\mathbf{x}_{i\tau_1^B} - \mathbf{x}_{i\tau_2^B}) - (\mathbf{x}_{i\tau_1^A} - \mathbf{x}_{i\tau_2^A})\right)\gamma_{\mathrm{LD}} \\ &+ \left((\tilde{\mathbf{x}}_{i,B} - \tilde{\mathbf{x}}_{i,A})\right)\delta_{\mathrm{LD}} + \epsilon_i\end{aligned} \tag{6}$$

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 1980–1999, while $Y_{i\tau_1^B}$ is the same average over the period 2000–2019.

Denoting seasonal differences by Δ and long differences by Δ_{LD} Eq. (6) can be written as:

$$\begin{aligned}\Delta_{LD}\Delta Y_i = \alpha_{\mathrm{LD}} &+ \Delta_{LD}\Delta\mathbf{c}_i\beta_{\mathrm{LD}} \\ &+ \Delta_{LD}\Delta\mathbf{x}_i\gamma_{\mathrm{LD}} \\ &+ \Delta_{LD}\tilde{\mathbf{x}}_i\delta_{\mathrm{LD}} + \epsilon_i\end{aligned} \tag{7}$$

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 than estimates obtained from cross-sectional variation without long differences.

2.3. Mechanisms and biases

The seasonal differences specification (Eq. (3)) addresses some concerns about omitted variable biases relative to a simple regression on cross-sectional variation. Specifically, omitted variables that affect GDP and temperature in both seasons in the same way do not bias the estimate. The combination of seasonal differences with long differences (Eq. (7)) then further reduces the risk of omitted variable biases. However, biases can still arise from omitted variables for which the unit homogeneity assumption (Eq. (5)) is not satisfied. In Eq. (3) this includes country characteristics x that affect both seasonal differences in temperature and seasonal differences in GDP. For the specification in Eq. (7), this concern is much reduced because of the differencing. In that specification, any omitted time-constant country characteristic cannot confound the estimated relationship.

To address the remaining concerns about omitted variable biases, we include four controls in our estimation of Eq. (3) (“controls” in Fig. 1). These are two geographic control variables, latitude of the country’s centroid and land area of the country. Furthermore, because of physical laws that relate different meteorological variables to each other, such as temperature and precipitation, different descriptors of the climate of a location tend to be correlated (Auffhammer et al., 2013). This correlation can result in omitted variable biases if other climatic variables affect economic production. To address this concern, we include two additional climatic controls: annual mean temperature and annual mean precipitation. We also include the seasonality of precipitation in all estimations, which is not our main variable of interest, but for which we report the estimates as secondary result of our study.

Prior research suggests that consumption around Christmas and vacations in summer are important drivers of seasonal economic cycles (Beaulieu and Miron, 1992). These earlier results speak to the broader possible concern that religious holidays and other calendar effects are correlated with the seasonality of temperature and that they might confound the estimated relationship. To address his concern, we use the share of Christians and the share of Muslims of countries as additional controls. Furthermore, the climate of Earth provides the ideal experiment to address possible calendar effects, as summer and winter coincide with different quarters of the year in the two hemispheres. We examine this explicitly at the beginning of Section 3.2.

We consider these four main variables and the two additional variables that describe the religious composition of a country as plausibly exogeneous to seasonal differences in temperature, which is why we refer to them as “controls”. Other variables that we consider as potentially endogeneous are examined in a separate analysis. We refer to those variables as “mediators”, as illustrated in Fig. 1. They are treated in a similar way as the control variables, but we additionally examine them as possible outcomes of seasonal temperature variability.

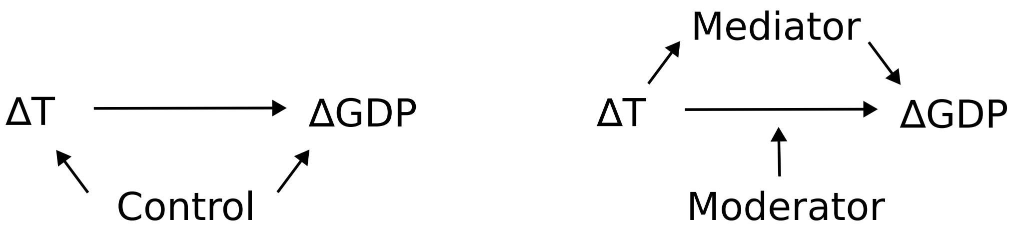

Fig. 1. Causal diagrams.

These mediators relate to four mechanisms — agriculture, tourism, international trade, and productivity. Agricultural production exhibits inherent seasonal cycles due to the influence of weather on plants. Tourism is also influenced by weather and in many countries highly seasonal. International trade allows countries to mitigate negative effects and leverage positive effects of the seasonality of weather on domestic and foreign supply and demand. Given that adjustments to changes of weather between the seasons are costly, larger seasonality might also affect aggregate productivity and economic development in the long run. In addition, we consider seasonal employment as a possible channel through which weather can affect GDP.

For every mediator, we estimate one model in which we include the mediator as an additional explanatory variable, and one model with the mediator as the dependent variable. In the first estimation, the mediator can be considered a "bad control" that potentially absorbs some of the effect of the seasonality of temperature on the seasonality of GDP (Angrist and Pischke, 2008). This is intentional and motivated as follows: If a variable is an important mediator of the effect of the seasonality of temperature on the seasonality of GDP, we expect to find an attenuated coefficient of the seasonality of temperature in the first estimation and a significant coefficient in the second estimation (Fig. 1). For two mediators for which quarterly data is not available, agriculture and international trade, we use their annual mean values. For the other two mediators, tourism and employment, we use their seasonal differences.

In our main model specification, we assume homogeneity of the effect of seasonality on GDP across countries. In additional analysis, we test whether the effect is moderated by certain variables, which we refer to as moderators (Fig. 1). We expect that the results can give additional hints at mechanisms that are at play. Given that the prior literature suggests non-linearities in the effect of average temperature on GDP (Burke et al., 2015b), we test mean temperature and mean precipitation as possible moderators. In addition, we use other moderators to examine specific mechanisms. Some of the variables are considered as both mediators and moderators, such as the share of tourism receipts of GDP. Other variables are considered only as moderators, such as the stringency of labour market regulation. We consider it plausible that in countries with more stringent labour markets seasonal temperature cycles might result in more pronounced seasonal cycles of GDP, but much less plausible that the stringency of labour market regulations is a major channel through which seasonal temperatures affect GDP. An overview over all variables that are considered as controls, mediators, and moderators can be found in SI Table C1.

For more insights on mechanisms, we also use an additional dataset on GVA by industry for a subset of European countries. For this analysis, we estimate our main model with seasonal differences of total GVA and with seasonal differences of GVA for each of the 11 industry groups. Given that quarterly GVA data by industry is only available for this subset of countries, we consider the results of this analysis complementary to the analysis of mediators and moderators described above.

2.4. Data

The main data are timeseries of quarterly Gross Domestic Product (GDP) in USD provided by the International Monetary Fund (IMF). The data are provided in nominal and real terms, with different data availability for different countries and generally less data available in real terms. For this reason, in our main estimation we use the detrended time series in nominal terms. In robustness tests, we find almost identical results when we use data in real terms, suggesting that our main results are primarily driven by an effect of temperature on production volumes, not on prices (SI Figure B1).

We restrict the data to the time period 1990–2019. The first year is set to 1990 to make the dataset more balanced, while the last year is set to 2019 to exclude the COVID-19 pandemic. This length of the time series is also informed by the standard definition of climate as average over a 30 year period. We require at least 10 years of data for every country, which yields 80 countries for our main model specification. In robustness tests, we find that our main results are very similar if we restrict the time period to the years 2010–2019 for all countries (Column 2 in Table 2, SI Figure B1).

We complement the global dataset from the IMF with an additional dataset from EUROSTAT. This dataset covers only 34 countries in Europe, but it has the advantage that it includes data on quarterly Gross Value Added (GVA) for 11 industry groups. The data are reported again for different time periods, with all countries reporting for at least 10 years.

We combine these 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.

To isolate seasonal patterns in the time-series, we first detrend the data (Fig. 2). For detrending we use three alternative approaches: a simple moving average with a window size of 9 quarters, a Hodrick–Prescott (HP) filter with $\lambda = 50$, and a HP filter

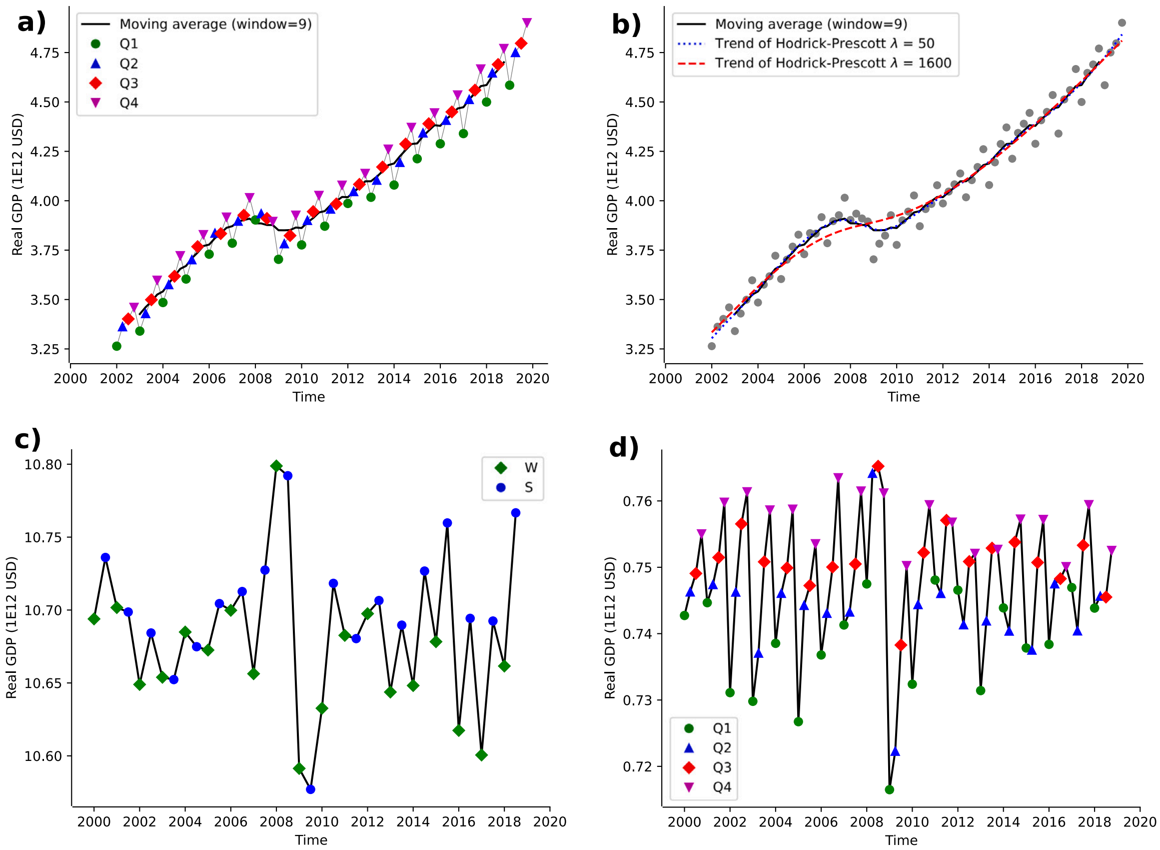

Fig. 2. Time-series of quarterly and seasonal GDP for the USA. Fig. (a) shows the original time-series of real quarterly GDP. Fig. (b) shows three trends estimated for this time series, using a moving average and Hodrick–Prescott filters with two different parameter values. Fig. (c) shows quarterly GDP after subtraction of a moving average. Fig. (d) shows the same data as (c) but with the four quarters aggregated to two seasons: winter (W) and summer (S).

with $\lambda = 1600$. The larger the value of the parameter λ, the smoother the subtracted trend. The HP filter has been criticised (Hamilton, 2018), but these issues are of minor concern here because the filter is only used to subtract a gradual trend and the detrended data are subsequently averaged over time. Nevertheless, we use this criticism as motivation to use the detrending with a moving average for our main specification. In robustness tests, we find that all three approaches yield almost identical estimates (SI Figure B1).

For some countries, detrending does not result in a stationary time series. This is again a minor concern, because the seasonal time series are averaged before being used in our estimation. Reassuringly, we find very similar results if we drop the 11 countries for which an AD Fuller test suggests non-stationarity after detrending with a moving average (Column 2 in SI Table B2).

In the next step, we then aggregate the detrended quarterly timeseries to a seasonal timeseries by summing Q1 + Q4 (Q4 of the preceding year) and Q2 + Q3. Depending on which season is on average warmer, we assign the two seasons the labels “summer” (S) and “winter” (W). For example, for countries in the Northern hemisphere that are not very close to the Equator, this assignment means that summer corresponds to Q2 and Q3. As an alternative approach, we consider the warmest quarter as “summer” and the coldest quarter as “winter”, again separately for every country, and drop the two remaining quarters. In the last step, we average the seasonal timeseries over the different years to one average summer and one average winter for every country. For the long difference specification, we do this separately for an earlier and a later time period (see also Eq. (6) in Section 2.3).

For control variables we use several sources. All datasets are downloaded as time series and averaged over the same years/quarters as the GDP and temperature data. Data on GDP per capita, land area, and the share of agriculture are taken from the World Development Indicator database of the World Bank. For data on trade and tourism we use the TC360 database of the World Bank. Data on seasonal employment and touristic overnight stays is taken from the International Financial Statistics of the IMF. Information on religion is obtained from the Pew Research Center. Data on labour market regulations is from the Economic Freedom of the World reports.

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

Table 1
Descriptive statistics.

Variable	Unit	Mean	Std.	Min.	Max.	No. obs.
Δ log GDP	USD 2010	0.007	0.03	−0.04	0.16	80
Δ T	deg. C	8.862	5.02	−0.00	18.89	80
Δ P	mm day-1	0.020	0.06	−0.11	0.19	80
Δ_{LD} Δ log GDP,2010–2019 minus 2000–2009	USD 2010	0.004	0.02	−0.05	0.07	68
Δ_{LD} Δ T,2010–2019 minus 2000–2009	deg. C	0.143	0.34	−0.44	1.28	70
Mean temperature	deg. C	15.359	6.79	4.21	27.97	80
Mean precipitation	mm day-1	0.090	0.05	0.00	0.26	80
Share of agriculture in GDP	percent	5.983	5.88	0.07	34.36	80
Share of exports of GDP	percent	44.548	32.68	11.07	187.10	80
Share of imports of GDP	percent	46.680	28.99	12.59	165.59	80
Share of tourism receipts of GDP	percent	12.416	12.09	2.22	62.81	80
Share of tourism expenditures of GDP	percent	6.638	3.65	1.37	25.60	80
Share of Christian population	percent	63.606	32.52	0.44	100.00	80
Share of Muslim population	percent	13.285	26.15	0.01	98.05	80
log GDP per capita	USD 2010	9.818	0.83	7.36	11.65	80
Land area	1E6 km2	11.698	2.27	5.77	16.61	80
Latitude	degrees	28.454	27.90	−41.00	65.00	80
Share of employment in agriculture	percent	14.901	15.14	0.15	72.63	80
Δ log Employment	People	−0.010	0.03	−0.10	0.06	54
Δ log Number of touristic overnight stays in hotels	Nights	0.731	0.88	−0.33	4.73	53
Stringency of labour market regulation	Index	6.350	1.21	3.93	9.22	78
Labour productivity	k USD per employee	61.890	39.93	5.53	242.30	80
Change in Δ T for RCP4.5,2041–2070 minus 1990–2014	deg. C	0.064	0.33	−0.98	0.69	80
Change in Δ T for RCP4.5, 2071–2100 minus 1990–2014	deg. C	0.086	0.36	−0.78	0.91	80

Notes: Δ denotes seasonal differences, calculated as summer (S) minus winter (W). Δ_{LD} denotes long differences. Unless otherwise stated, statistics are based on averages over the period 1990–2019 for years in which there is quarterly GDP data for a given country.

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.

Descriptive statistics are shown in Table 1. The magnitude of the seasonal cycle, defined as the average difference between GDP in summer and winter that is divided by the average annual GDP, reveals some geographical heterogeneity (SI Figure A1), which is further examined in the next section.

3. Results

3.1. Stylized facts

We first identify stylised facts about seasonal cycles based on our larger and more representative sample of 80 countries than previous work. Overall, seasonal economic cycles around the world appear quite diverse, with 15 of the 24 possible patterns being exhibited by at least one country (SI Figure A3). This more comprehensive evidence also suggests that some stylised facts identified by previous work are not as widespread as that work might suggest (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).

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 global sample of countries, we find that the peak in the fourth quarter is indeed common, but only exhibited by about 60% of countries. We also find that it is relatively more common in the Northern hemisphere than in the Southern hemisphere (Fig. 3a).

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. In our sample, such a local minimum of production in either the second or the third quarter can however only be found in 42% of countries in the Northern hemisphere and 29% in the Southern hemisphere (Fig. 3b).

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 (82% of countries) more frequently than among countries in the Southern hemisphere (50% of countries) (Fig. 3c).

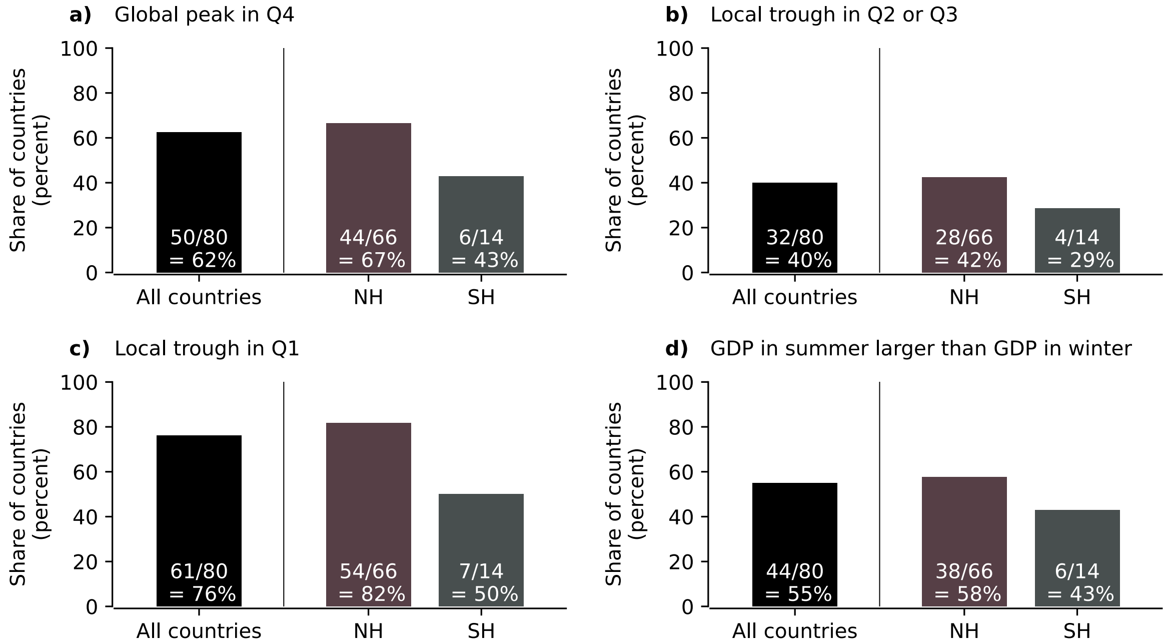

Fig. 3. Stylised facts. Figs. (a)–(c) show the frequency of three stylised facts identified by previous studies in our global sample. Fig. (d) shows how many countries have larger GDP in summer than in winter. Summer and winter are defined by Q1 + Q4 and Q2 + Q3, depending on which of the two six-months periods tends to be warmer. Relative frequencies shown in percentages for different groups of countries.

In sum, the three stylised facts about seasonal economic cycles identified in earlier work seem to be found in only 62%, 40%, and 76% of countries, respectively. Furthermore, they all seem to be more frequently observed in the Northern hemisphere than in the Southern hemisphere. The first of these facts, a peak of economic production in the fourth quarter, has been used to question the influence of temperature on seasonal economic cycles because it was observed in both hemispheres (Beaulieu and Miron, 1992). Our results are different, suggesting systematic differences between the two hemispheres. Regarding the two seasons summer and winter, defined as explained in Section 2.4, we find that 55% percent of countries have higher GDP in summer than in winter. This share of countries is slightly larger in the Northern hemisphere than in the Southern hemisphere (Fig. 3c).

3.2. Main results and robustness

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 2.4). We then take seasonal differences by subtracting GDP and temperature in winter from their values in summer. The results for our sample of 80 countries suggest that countries with larger seasonal differences in temperature also tend to have larger seasonal differences in GDP (Fig. 4a). This positive relationship suggests that higher temperatures in summer tend to increase GDP in summer 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 (Fig. 4b). 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.

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 using Eq. (3). The model includes also seasonal differences in precipitation, as well as our four main control variables (mean temperature, mean precipitation, land area, and latitude; see also SI Table C1). We find a significant positive association between temperature and GDP (Column 1 in Table 2). Furthermore, we find a negative association between precipitation and GDP.

The magnitude of the estimated effect of temperature is large. The sample mean of the seasonal difference in temperatures of about 8.9 degrees Celsius (Table 1) is associated with a seasonal difference in GDP of about 3.4 percent. This effect is larger than the sample mean of the seasonal difference in GDP, which is about 0.7 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 (Fig. 4b). Temperature thus appears to be an important factor contributing to seasonal economic cycles.

We corroborate our main estimates with robustness tests. Our main estimates are obtained from data over the period 1990–2019. Because the availability of data differs across countries, we estimate another model for which we restrict the time period to 2010–2019. The estimates are very similar (Column 2). Furthermore, we find that the results are similar when we use differences between

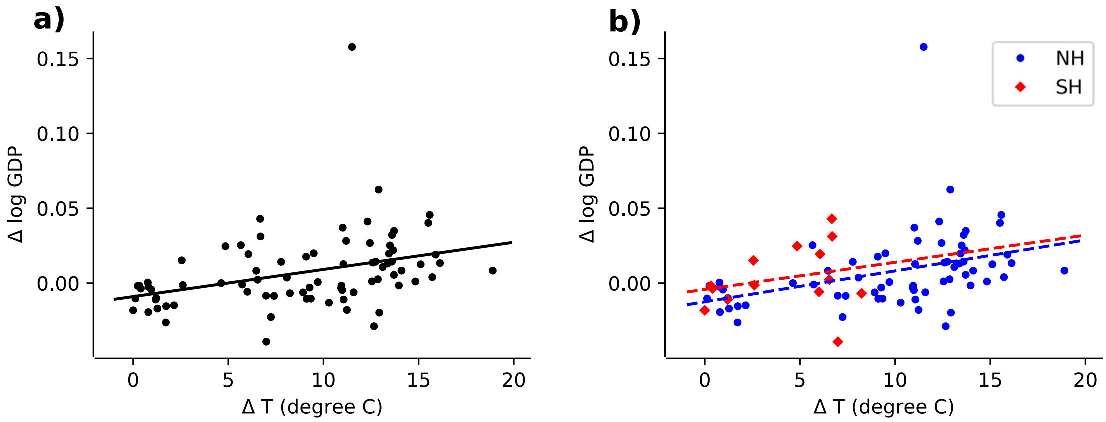

Fig. 4. Statistical association between seasonal differences in temperature and seasonal differences in log GDP. Seasonal differences Δ calculated as summer minus winter. Both figures (a) and (b) show the main treatment variable (horizontal axis) and dependent variable (vertical axis) of the main model as specified in Equation Eq. (3). In Figure (b) the colours and symbols indicate the split of the sample into countries in the Northern hemisphere (NH) and Southern hemisphere (SH).

only the quarters with maximum and minimum temperature instead of differences between averages over six months (Column 3). The effect sizes are slightly larger, possibly because averaging over six-months periods attenuates some of the effect of temperature and precipitation on quarterly GDP.

In additional robustness checks, we estimate the same model with more control variables, with different time periods, with nominal and with real GDP, and with different ways of detrending the GDP timeseries. The additional controls describe the religious composition of the population to proxy for religious holidays. Furthermore, we include latitude interacted with a dummy for the two hemispheres. Overall, we find that the estimated coefficient of temperature is not very sensitive to any of these specification choices (SI Figure B1). We also use the methodology proposed by Oster (2019) to quantify the extent of selection on unobservables, or omitted variable biases, that is needed for the true effect to be zero. With $R_{max} = 1.3\tilde{R}$ this calculation yields $\delta = 1.13$, suggesting that selection on unobservables would need to be stronger than selection on observables. Our reading of this result is that the risk of omitted variable biases cannot be ignored, but a typically applied threshold is satisfied ($\delta > 1$).

In our main specification we use White standard errors to address heteroskedasticity. Another concern is spatial autocorrelation of the errors. To address this concern, we cluster standard errors by continent and we also estimate Conley standard errors. We use alternative specifications for Conley standard errors with cutoffs at 1000 km, 5000 km, and 10,000 km. If we cluster by continent, we find larger standard errors and weaker significance ($p < 0.1$). Given the very small number of clusters, these standard errors are likely strongly biased. When we use Conley standard errors, we find the largest standard errors for a cutoff at 5000 km, for which the standard errors are about 40 percent larger than the White standard errors. With these more conservative standard errors, our main estimate remains significant ($p < 0.05$) (SI Table B1).

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 2000–2009 and 2010–2019. This reduces the sample to 68 countries for which sufficient GDP data is available. Almost all countries experienced warming between these two time periods. In indeed all countries, summers were on average warmer in the later time period than in the earlier time period. In all but five countries, also winters were warmer in the later time period. The long differences specification uses variation in the change in average seasonal temperatures of summer relative to winter for identification. Descriptive statistics show that in about half of all countries, temperatures in summer increased more strongly than in winter, and in the remaining countries winters warmed more strongly than summers (SI Figure A2).

The results with long differences are qualitatively similar to the results obtained from cross-sectional variation in seasonal differences (Column 4 in Table 2). Specifically, we find that seasonal temperature has a positive effect on seasonal GDP. The magnitude of the effect is larger than for the cross-sectional estimation. This difference can partly be explained with the subset of countries in the sample (SI Table B2). We conjecture that the remaining difference may hint at slow adaptation that might have mitigated some of the historical effect of seasonal temperature on seasonal GDP. Furthermore, as for the cross-sectional estimates, we find that seasonal rainfall has a negative effect on seasonal GDP.

Table 2
Results of regressions using a global sample of GDP of 80 countries based on seasonal differences.

	Time period		Quarters	Long diff.
	1990–2019	2010–2019		
	1	2	3	4
ΔT	0.0038***	0.0042***	0.0070***	0.0177*
	(0.0012)	(0.0012)	(0.0019)	(0.0091)
Δ Precipitation	−0.1996**	−0.2297**	−0.3158**	−0.1002***
	(0.0956)	(0.0988)	(0.1527)	(0.0260)
Mean temperature	−0.0001	−0.0005	−0.0000	
	(0.0005)	(0.0005)	(0.0007)	
Mean precipitation	0.1499	0.1494	0.3600*	
	(0.1139)	(0.1128)	(0.2048)	
log Landarea	−0.0031***	−0.0036***	−0.0055**	
	(0.0009)	(0.0012)	(0.0021)	
Latitude	−0.0004***	−0.0005***	−0.0005**	
	(0.0001)	(0.0001)	(0.0002)	
R2	0.41	0.42	0.45	0.19
R2 adj.	0.36	0.38	0.40	0.17
N	80	80	80	68

Notes: Main model specification as in Eq. (3). Main sample period is 1990–2019 (Columns 1 and 3). Results in Column 3 are obtained by considering quarter with maximum and minimum average temperature as summer and winter, respectively. Results in Column 4 are obtained from a model that combines long differences with seasonal differences (Eq. (6)) based on difference 2010–2019 minus 2000–2009. Seasonal differences Δ calculated as summer minus winter. Standard errors in parentheses. Significance:
* $p < 0.1$,
** $p < 0.05$,
*** $p < 0.01$.

3.3. Mechanisms

The results in the previous section suggest that seasonal temperature cycles are statistically associated with seasonal economic cycles across countries. Specifically, we find that higher temperatures in summer than in winter tend to increase GDP in summer relative to winter. In this section, we explore possible mechanisms that can explain this effect.

We first examine whether the effect of seasonal temperature on seasonal GDP is mediated by any one of several explanatory variables. The possible mediators relate to four distinct mechanisms: agriculture, tourism, international trade, and aggregate productivity. Overall, we do not find evidence that any of the variables we consider is an important mediator (SI Figure C1). Our main estimate is mostly unaffected by adding mediators as additional explanatory variables, and seasonal temperature is not statistically significantly associated with any of the mediators.

Specifically, we do not find evidence that countries with larger seasonal temperature cycles have neither a larger share of agricultural GDP nor a larger share of tourism receipts or expenses. Controlling for these variables also does not affect our main estimate. Consistent with the latter result, we do not find that countries with larger seasonality of temperature have a larger seasonality in touristic overnight stays. Furthermore, we do not find that countries exposed to larger seasonal temperature variability have systematically larger or smaller import or export shares of GDP. Also GDP per capita and aggregate labour productivity seem unaffected by the seasonality of temperature. Finally, we do not find evidence that countries with larger seasonality of temperature have larger seasonality of aggregate employment.

We next study heterogeneity in the effect of seasonal temperature. To do so, we include interaction terms with several possible moderator variables in our model (SI Table C1). We first include each moderator individually and then all moderators simultaneously. The results suggest that in countries that attract many international tourists relative to the size of their economy, seasonality of temperature results in larger seasonal economic cycles. All other moderators are insignificant, at least when they are considered simultaneously (SI Figure C2). There is weak evidence that countries with higher GDP per capita might have smaller responses of seasonal GDP to seasonal temperature, and that countries with more stringent labour market regulations might feature larger responses. However, the estimates are only weakly or indeed not significant if the hypotheses are tested simultaneously.

We next examine the role of different sectors for a subsample of countries. To do so, we use data on gross value added (GVA) by industry group for 34 countries in Europe. Focusing on Europe has the advantage that reporting quality is more homogeneous across countries than for the global sample and that also the climate and seasonal temperature cycles are more similar. Furthermore, EUROSTAT provides to our knowledge the most comprehensive homogeneous database of quarterly production by industry group.

We find a similar significantly positive effect of seasonal temperature on seasonal GDP as for the global sample, with a slightly larger magnitude (Column 1 in Table 3). Most of this difference in effect size can be attributed to the different samples (SI Table B2). 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.

Table 3
Results of regressions using a sample of GDP of 34 countries in Europe based on seasonal differences.

	Estimates by industry group		
	All industries	Exposed	Non-Exposed
	1	2	3
ΔT	0.0057***	0.0083**	0.0035
	(0.0021)	(0.0031)	(0.0022)
Δ Precipitation	−0.1744	−0.6895**	0.1342
	(0.1733)	(0.3223)	(0.1798)
Mean temperature	0.0015	−0.0102	0.0064
	(0.0050)	(0.0085)	(0.0049)
Mean precipitation	0.0874	−0.2353	0.2265
	(0.2391)	(0.4234)	(0.2594)
log Landarea	−0.0049**	−0.0066*	−0.0041***
	(0.0019)	(0.0033)	(0.0015)
Latitude	−0.0005	−0.0048	0.0014
	(0.0017)	(0.0033)	(0.0016)
R2	0.48	0.48	0.32
R2 adj.	0.37	0.36	0.17
N	34	34	34

Notes: Sample period is 1990–2019. Exposed industries: Agriculture, Construction, Manufacturing, other Industry. Seasonal differences Δ calculated as summer minus winter. Standard errors in parentheses. Significance:
* $p < 0.1$,
** $p < 0.05$,
*** $p < 0.01$.

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 a smaller and insignificantly positive effect (Table 3 Columns 2 and 3). 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. For Agriculture, the effect is also positive and relatively large but insignificant (SI Table C2). In sum, these results at the industry level for Europe suggest that exposure to ambient temperature in economic production is an important determinant of seasonal economic cycles at the sectoral level, consistent with an effect of temperature on the supply side of economies.

3.4. 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 process climate model projections in a way that makes them compatible with our empirical estimates. We focus on the "middle of the road" RCP4.5 scenario and the two time periods 2041–2070 and 2071–2100. As explained in Section 2.4, the following analysis is based on only one climate model and should therefore be interpreted as an illustration of one possible but by no means the only possible scenario of future climate change. In this scenario, in all but one countries, both summers and winters will warm by more than 1 degree Celsius by the end of the century. In about half of all countries, winters will warm faster than summers. The opposite pattern, faster warming in summers than in winters, is primarily observed in clusters of countries in the Mediterranean region, Africa, the Middle East, and Oceania (SI Figure D1).

Given this unequal warming between the seasons in many countries, our empirical estimates suggest that economic production will on average shift towards the season that warms faster. This will result in an increase in the seasonal economic cycle in countries where economic production is already larger in that season and in a decrease of those cycles in all other countries. For the given climate scenario, seasonal economic cycles are projected to increase in 42 countries and decrease in 38 countries by the end of the century (41 and 39 by mid-century, respectively) (SI Figure D2).

4. Conclusion

We study the effect of seasonal temperature on seasonal economic production. We first describe seasonal economic cycles for a global sample of 80 countries, revealing a large diversity of these cycles and systematic differences between countries in the Northern and in the Southern hemisphere. For causal identification of the effect of temperature, we propose a novel econometric approach that uses variation of differences between seasons across countries. We then apply this seasonal differences estimator to our sample of countries. 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 more limited data 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 effect of seasonal temperature on seasonal GDP is positive and both statistically significant and economically large. On average the effect size is of a similar 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, annual mean precipitation, geographic controls, and religious composition. The results are also robust to considering the quarter with maximum and minimum temperature as summer and winter respectively, focusing only on the most recent time period, using nominal or real quarterly GDP, and detrending the data in different ways. Reassuringly, we also find very similar results when we combine our seasonal differences with long differences. Combining our estimates with a RCP4.5 scenario of future climate change suggests that in about half of the countries in our sample differential warming between summer and winter will work towards an increase in seasonal economic cycles during the 21st century.

We explore possible mechanisms related to agriculture, tourism, international trade, and aggregate productivity. We do not find strong evidence for any of these mechanism, with some weak evidence that countries with larger touristic sectors, with stronger labour market regulations, and with lower GDP per capita levels respond more strongly to seasonal temperature variability. Furthermore, for a subset of European countries we can attribute the effect of seasonal temperature on seasonal GDP to industries that are relatively exposed to ambient temperature, including Construction, Industry, and Manufacturing.

Our analysis is limited in certain ways. The quarterly GDP data used in this paper cover 80 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 omission of some of the warmest countries in the world might also explain why we do not find any evidence that the effect of seasonal temperature on seasonal GDP is negative at higher average temperatures.

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).

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, 2023). 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.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jmacro.2023.103568.

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