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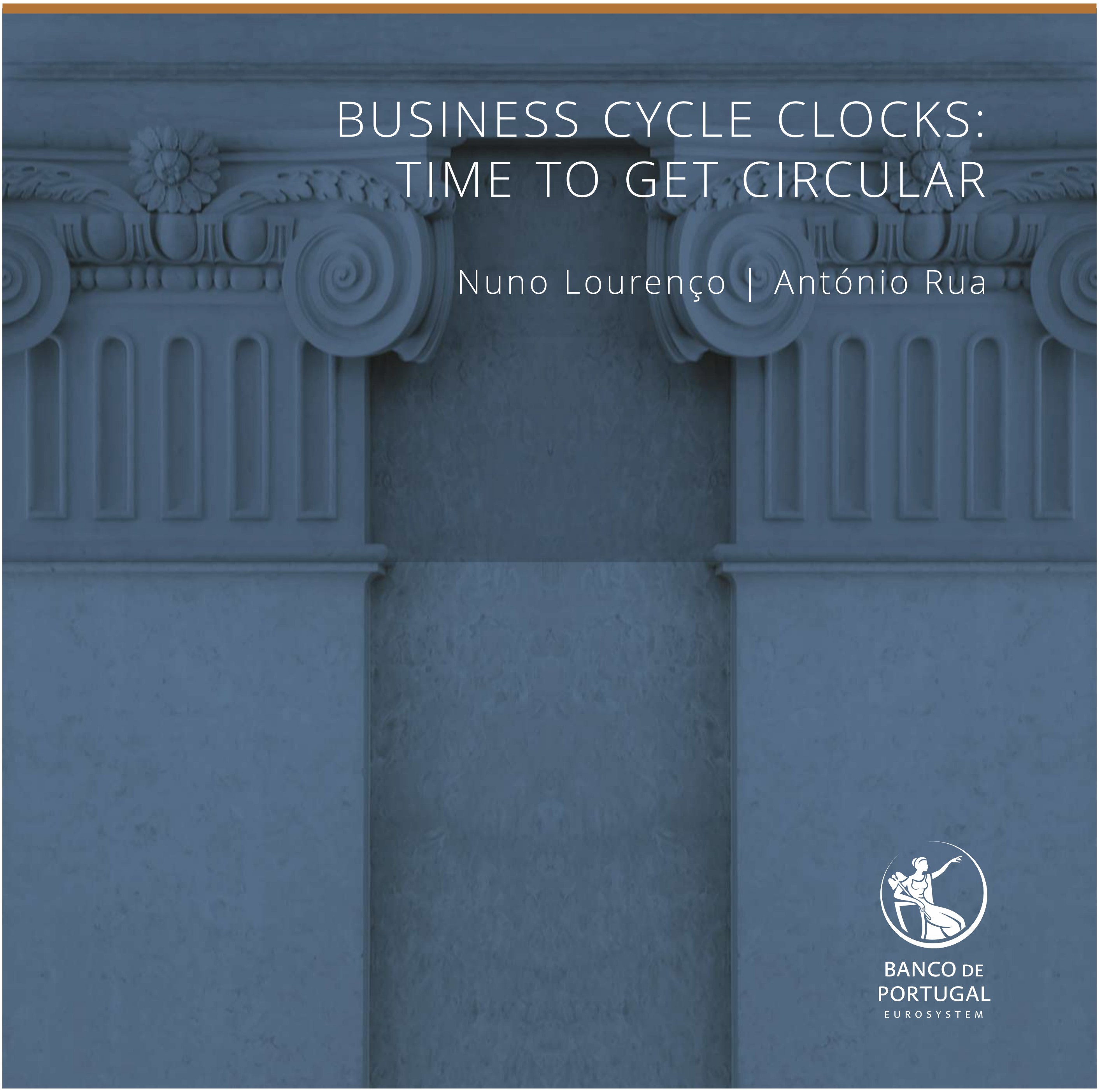

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The analyses, opinions and findings of these papers represent the views of the authors, they are not necessarily those of the Banco de Portugal or the Eurosystem.

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Business cycle clocks: Time to get circular

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Abstract
Assessing the momentum of the business cycle is of utmost importance for policymakers and private agents. In this respect, the use of business cycle clocks has gained prominence among national and international institutions to depict the current stage of the business cycle. Drawing on circular statistics, we propose a novel approach to business cycle clocks in a data-rich environment. The method is applied to the main euro area countries resorting to a large dataset covering the last three decades. We document the usefulness of the circular business cycle clock to capture the business cycle stage, including peaks and troughs, with the findings being supported by the cross-country evidence.

JEL: C30, C55, E32.

Keywords: Business Cycle Clock; Circular Statistics; Peaks; Troughs.

Disclaimer: The opinions expressed in this article are those of the authors and do not necessarily coincide with those of the Banco de Portugal or the Eurosystem. Any errors and omissions are the sole responsibility of the authors.

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1. Introduction

Tracking the business cycle is crucial to understand how an economy evolves over time and inform economic policy responses to dampen cyclical fluctuations. Naturally, there is a considerable interest in devising macroeconomic policies to influence prospects for economic growth and mitigate the distress associated with economic downturns.

Over the last decades, a body of literature has emerged focusing on the development of tools to depict the cyclical pattern of sectoral or economy-wide indicators. One of the tools that has attracted the interest of several institutions that monitor economic conditions regularly is the so-called business cycle clock (henceforth BCC). In fact, several national and international organisations incorporate updates of BCCs on their economic analysis publications. The ultimate goal of a BCC is to provide a dynamic reading of the cyclical evolution of economies through a four-quadrant visualisation, based on the representation of the cyclical component of selected series. Such representation typically resorts to a limited number of indicators, ranging from individual series to a small amount of variables.

However, it has long been acknowledged that the widespread nature of macroeconomic fluctuations is at the heart of the empirical business cycle analysis (see the seminal work for the United States by Mitchell (1927), Mitchell and Burns (1938) and Burns and Mitchell (1946)). In fact, a key notion of the business cycle concerns pervasiveness, i.e. fluctuations must be common across sectors and economic indicators, hence the need to examine a wide range of disaggregated data. On top of that, enhanced data dissemination and increasingly data availability have been key features of advanced economies, giving rise to the so-called data-rich environments (see, for example, Bernanke and Boivin (2003)). This resulted in a fast growing interest on methods capable of bringing together a large number of series. Needless to say, such data-rich environments led to new econometric and statistical challenges.

Departing from previous literature on BCCs, we propose the representation of the business cycle momentum through a clock resorting to circular statistics. The use of circular statistics in the context of business cycle analysis is natural given its recurrent nature while allowing to take on board large information sets. Although circular statistical analysis is more popular in other scientific disciplines, we show that it can be particularly useful for informing on business cycle developments, including the peaks and troughs.

To illustrate the usefulness of the circular business cycle clock, we consider the four major euro area economies, namely Germany, France, Italy and Spain. In particular, we gather for each country a large dataset, of almost one hundred series, covering industrial production and construction, turnover in industry and retail sales, labour market, international trade, tourism and business and consumer surveys. The behaviour of the circular business cycle clock is evaluated over the last three decades. We find that it tracks the business cycle quite well and delivers reliable signals on both peaks and troughs. Such findings are also supported by the cross-country results which reinforces the usefulness of the suggested approach.

The paper is organised as follows. In section 2, the related literature on business cycle clocks is reviewed. In section 3, the concepts and statistical measures underlying the suggested circular business cycle clock are presented. In section 4, the data is described. In section 5, the empirical application is conducted and the results are discussed. Finally, section 6 concludes.

2. Related literature

As alluded above, assessing the business cycle stance on the basis of BCCs has a long tradition in monitoring economic conditions. The Ifo institute pioneered work along this line, when in the mid-1960s the so-called Ifo business climate index was introduced. Initially developed for the manufacturing sector only, the indicator combined responses through a geometric mean to two surveyed questions, the assessment of the current situation and expectations for the next six months. In the years that followed, firms in the construction, retail trade and wholesale trade sectors started to be surveyed and an overall business climate index was computed. To shed light on the business cycle course and enhance visual interpretation of the dynamics underlying the Ifo business climate index, the German institute developed in 1993 a BCC, a tool with a four-quadrant business cycle representation (see e.g. Nerb (2004) and Abberger (2006) for a critical review). The balances of the current business situation were plotted in the x-axis against the balances on the expectations for the next six months in the y-axis, resulting in a clockwise rotation in circular form as expectations typically lead the assessment of the current situation (see Abberger and Nierhaus (2008)).[1] Ideally, the four-quadrant scheme should allude to the four phases of the business cycle. A "boom" ("recession") might be reached when both the current business situation and expectations are positive (negative); an "upswing" ("downswing") might be indicated when the current business situation is assessed negative (positive) but expectations are positive (negative).

With the increase in data availability, the development of new tools to visualise large amounts of statistical information in a comprehensive manner has gained momentum. In this vein, the Statistics Netherlands launched in 2005 a tool named as business cycle tracer (see Ruth *et al.* (2005) for details). By providing a graphical display of a set of selected lagging, coincident and leading indicators, the business cycle tracer intends to map real-time business cycle developments. Currently, thirteen indicators (both quantitative and qualitative) are included: GDP, consumer confidence, exports of goods, hours worked, manufacturing output, house prices,

[1] Initially, the variables in the climate indicator moved counterclockwise due to the arrangement of the axes (Leibfritz and Nierhaus (1993)).

unemployment, investment, consumption of households, bankruptcies of companies and institutions, producers confidence, turnover temporary employment agencies and vacancies in private enterprises. Due to the inherent volatility of these short-term statistics, the business cycle tracer focuses on the cycle of each indicator, filtering out the short-term and erratic movements. The cyclical component of a given indicator is obtained as the deviation from its long-term trend. The comprehensive representation of the set of multiple indicators in a diagram allows for the study of individual series while trying to provide an overview of the current state of the economy. These are displayed according to the coordinates resulting from their cyclical position, leading to a counterclockwise rotation through the diagram as indicators move along the typical business cycle phases.

Similar to the Ifo business climate representation, the European Commission has for several years used a visualisation tool for business cycle analysis called the survey watch. The graph plotted manufacturers' current business perceptions against their production expectations over the next three months. Current business perceptions are estimated through principal component analysis based on four series (production trends, order books, export order books and stocks). As in the Ifo BCC, one should expect circular movements over time through the four quadrants. However, that is not the case. First, the short-term volatility of monthly statistics leads to erratic movements from month to month. Second, the clockwise rotation through the quadrants is critically influenced by the stability and length of the lead of the expectations component over the current assessments component and can still be undermined even after filtering out the input data.[2] Concretely, elliptical movements along the main diagonal arise even after smoothing the data, yielding a concentration of data points in the upper-right ("boom") or lower-left ("recession") part of the diagram.

Against these drawbacks, the European Commission developed in 2010 the so-called economic climate tracer to gauge on the state of the European Union member states (Gayer (2008)). Drawing on the information underlying the climate indicators, it allows for both sectoral and cross-country comparisons. The climate indicators are based on principal component analyses of seasonally adjusted balance series stemming from the business and consumer surveys. Every month, qualitative surveys in the sectors of industry, services, building, retail trade and among consumers are conducted. For the industry sector, five of the surveyed questions are used as input series (employment and price expectations are excluded); for the services and retail sectors all five questions are included; for construction all four questions are considered while for consumers nine questions are included (questions on price trends and on the assessment of the current financial situation are excluded). The economic climate indicator is computed as a weighted average of the five sectoral principal components, using the same weights as in the compilation

[2]Smoothing is performed using a Hodrick-Prescott (HP) filter with lambda equal to 69, which corresponds to eliminate short-term movements of a duration less than 18 months.

of the economic sentiment indicator. In order to eliminate short-term variations of a period less than 18 months, smoothing is carried out using the HP filter. The resulting series are then standardised and the level (y-axis) is plotted against the month-on-month change (x-axis), yielding the economic climate tracer.

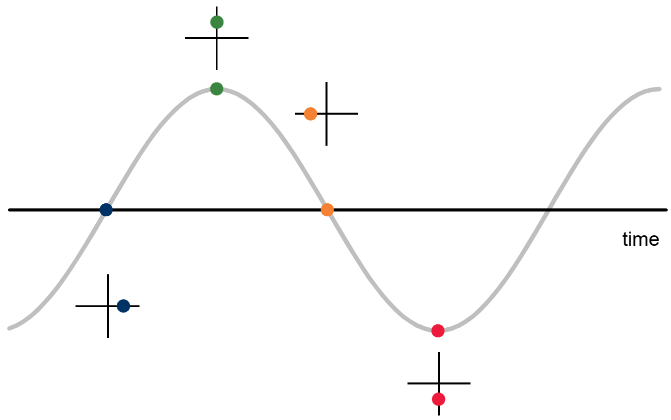


Figure 1: Stylised business cycle and corresponding representation in the economic climate tracer.

Hence, one can assess whether the indicator stands above or below its long-term average and whether the short-term developments are improving or deteriorating. Furthermore, business cycles peaks (troughs) are positioned in the upper- (lower-) centre part of the diagram (see Figure 1 for illustrative purposes).

Given the growing interest and acknowledged usefulness of BCCs, in recent years there has been an increasing number of these tools to ease business cycle readings (see, *inter alia*, OECD (2010), Destatis (2010) or Statistics Denmark (2013)).[3]

3. A primer on circular statistics

Since the business cycle is by definition a recurrent phenomenon it motivates the use of clocks to depict the current stage of the economic cycle. In particular, previous work has drawn on the representation of the business cycle momentum in the Cartesian coordinate plane. However, any point in the plane displayed as (x_i, y_i) according to Cartesian coordinates can also be represented by a distance r_i and an angle θ_i according to polar coordinates.[4] Typically, the angle θ is taken

[3]In a different setting, the Eurostat has also developed a BCC. In its latest version, the clock is based on the probabilistic turning point indicators computed every month by Eurostat as well as on the quarterly historical dating chronologies (see Mazzi (2015) for details).

[4]These conversions are performed using sine and cosine trigonometric functions. In particular, $\cos\theta_i = \frac{x_i}{r_i}$ and $\sin\theta_i = \frac{y_i}{r_i}$.

from the positive x-axis (pointing east) in a counterclockwise rotation (see Figure 2).

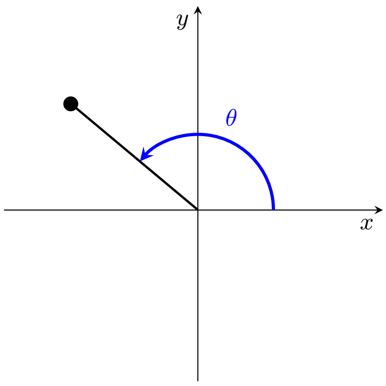


Figure 2: Illustrative angle computation.

Hence, one can assess business cycle conditions in the form of directions. The natural support for such directions is the circumference of the unit circle with the data on it being referred to as circular. Circular data arises in a large variety of research fields such as meteorology, biology, physics, psychology, medicine, political science, among many others.[5]

Suppose we have N directional observations, θ_i with $i = 1, ..., N$. In the context of business cycle analysis with multivariate data, this corresponds to having at each point in time, a direction for each variable. This means that one ends up with multiple directions about the current position of the economic cycle. Hence, with large amounts of data, it is useful to display such directions in the form of histograms and to compute, for example, measures of central tendency and dispersion. However, circular data cannot be treated as linear data. While linear data can be represented on a straight line, circular data is represented on the circumference of a unit circle.[6] The standard statistics that are applied to linear data cannot be used for circular data because of the geometrical properties of circular data. In fact, values of $0°$ and $360°$ represent the same direction whereas in a linear scale they correspond to opposite ends of a scale. If we compute the mean of $0°$ and $360°$ according to the linear measure we would obtain $180°$, which is the opposite to the actual mean direction of the data. Therefore, circular data require specific analysis methods.

[5] The first comprehensive treatment of circular data was published by Mardia (1972), followed by Batschelet (1981), Fisher (1993), Mardia and Jupp (2000) and Jammalamadaka and SenGupta (2001).

[6] Circular data can be measured either in degrees, when distributed in the interval between $0°$ and $360°$, or in radians in the interval between 0 and 2π. The relationship between angles in degrees and radians is given by $\frac{\theta_{degrees}}{360°} = \frac{\theta_{radians}}{2\pi}$.

Let θ be a random angle and consider a sample of N angles, $\theta_1, \theta_2, ..., \theta_N$. The sample uncentred p^{th} trigonometric moment is given by

$$t_{p,0} = \frac{1}{N}\sum_{i=1}^{N}\left(\cos p\theta_i + i\sin p\theta_i\right) = a_p + ib_p \tag{1}$$

where

$$a_p = \frac{1}{N}\sum_{i=1}^{N}\cos p\theta_i \tag{2}$$

and

$$b_p = \frac{1}{N}\sum_{i=1}^{N}\sin p\theta_i. \tag{3}$$

The sample centred p^{th} trigonometric moment is given by

$$t_{p,\overline{\theta}} = \frac{1}{N}\sum_{i=1}^{N}\left[\cos p\left(\theta_i - \overline{\theta}\right) + i\sin p\left(\theta_i - \overline{\theta}\right)\right] = \overline{a}_p + i\overline{b}_p \tag{4}$$

where

$$\overline{a}_p = \frac{1}{N}\sum_{i=1}^{N}\cos p\left(\theta_i - \overline{\theta}\right) \tag{5}$$

and

$$\overline{b}_p = \frac{1}{N}\sum_{i=1}^{N}\sin p\left(\theta_i - \overline{\theta}\right) \tag{6}$$

and $\overline{\theta}$ denotes the mean direction.
The mean direction, $\overline{\theta}$, can be obtained from the inverse tangent function as

$$\overline{\theta} = \begin{cases} \arctan\left(\frac{b_1}{a_1}\right) & \text{if } a_1 > 0,\ b_1 > 0 \\ \arctan\left(\frac{b_1}{a_1}\right) + \pi & \text{if } a_1 < 0 \\ \arctan\left(\frac{b_1}{a_1}\right) + 2\pi & \text{if } a_1 > 0,\ b_1 < 0 \\ \frac{\pi}{2} & \text{if } a_1 = 0,\ b_1 > 0 \\ \frac{3\pi}{2} & \text{if } a_1 = 0,\ b_1 < 0 \\ \text{undefined} & \text{if } a_1 = 0,\ b_1 = 0 \end{cases} \tag{7}$$

The mean resultant vector length is

$$\overline{R} = \sqrt{a_1^2 + b_1^2}. \tag{8}$$

If $a_1 = 0$ and $b_1 = 0$, then $\overline{R} = 0$. This means that the data is not concentrated in any direction and does not have any mean direction. If fact, the length of the mean vector plays an important role in measuring the dispersion around the mean direction. As the data becomes more dispersed around the unit circle the value of $\overline{R}$ tends to 0. In contrast, if all data falls in the same location in the unit circle, $\overline{R}$ will be 1. That is, as $\overline{R}$ decreases from 1 to 0, the variance in the distribution increases. Thus, circular variance can be defined as

$$V = 1 - \overline{R} \tag{9}$$

which measures the variation in the angles about the mean direction. Hence, likewise in linear data, as the sample variance decreases, the distribution becomes more homogeneous. However, in contrast with the linear case, the circular variance only takes values between 0 and 1.

Other measures to characterise the data distribution such as skewness and kurtosis can also be computed. In particular, following Pewsey (2004), the circular skewness can be defined as

$$\bar{b}_2 = \frac{1}{N} \sum_{i=1}^{N} \sin 2 \left(\theta_i - \overline{\theta} \right) \tag{10}$$

and kurtosis by

$$\bar{a}_2 = \frac{1}{N} \sum_{i=1}^{N} \cos 2 \left(\theta_i - \overline{\theta} \right). \tag{11}$$

The most commonly used distribution for circular data is the von Mises distribution. If the circular random variable θ has a normal distribution, the distribution is expressed as the von Mises distribution. The probability density function of the von Mises distribution is

$$f(\theta; \mu, \kappa) = \frac{1}{2\pi I_0(\kappa)} e^{\kappa \cos(\theta - \mu)} \tag{12}$$

where I_0 is a Bessel function of the first kind and order zero

$$I_0(\kappa) = \frac{1}{2\pi} \int_0^{2\pi} e^{\kappa \cos(\theta - \mu)} d\theta. \tag{13}$$

The von Mises distribution is a two-parameter density function where the parameter μ is the mean direction of the population and the parameter κ measures the concentration around the mean direction. The distribution is unimodal and symmetric and plays the same role in circular statistics as the normal distribution in standard linear statistics. In fact, it is shaped like the normal distribution, except that its tails are truncated. When $\kappa = 0$, this distribution is equivalent to the uniform distribution.

As we are interested in using the mean direction as a measure of the business cycle momentum, it is also of interest to place a confidence interval on the mean direction. Under the assumption of a von Mises distribution, Upton (1986) proposed approximate confidence intervals for the mean direction given by

$$\overline{\theta} \pm \arccos \left[\frac{\sqrt{\frac{2N\left(2R^2 - N\chi^2_{\alpha,1}\right)}{4N - \chi^2_{\alpha,1}}}}{R} \right] \tag{14}$$

for $\overline{R} \leq 0.9$, where $R = N\overline{R}$ and $\chi^2_{\alpha,1}$ denotes the upper α point of a χ^2_1 distribution. For $\overline{R} > 0.9$, the confidence interval is defined as

$$\overline{\theta} \pm \arccos \left[\frac{\sqrt{N^2 - (N^2 - R^2)\, e^{\frac{\chi^2_{\alpha,1}}{N}}}}{R} \right]. \tag{15}$$

As the above expressions draw on the von Mises distribution, one should also assess the validity of such assumption. To assess whether the von Mises distribution is appropriate for a given sample of data, Lockhart and Stephens (1985) proposed the following test for samples of size $N \geq 20$. The test statistic is

$$U^2 = \sum_{i=1}^{N} \left(p_{(i)} - \frac{2i-1}{2N} \right)^2 - N \left(\overline{p} - \frac{1}{2} \right)^2 + \frac{1}{12N} \tag{16}$$

with $p_{(1)} \leq p_{(2)} \leq \ldots \leq p_{(N)}$ and $\overline{p} = \frac{\sum_{i=1}^{N} p_{(i)}}{N}$ where $p_{(i)}$ is the value of the cumulative distribution function of the von Mises distribution evaluated at θ_i. The hypothesis that the sample has been drawn from a von Mises distribution is rejected if U^2 is too large. The critical values can be found in Lockhart and Stephens (1985).

In the case of departure from the von Mises distribution, an alternative to the above expressions for the confidence interval on the mean direction should be considered. Fisher and Lewis (1983) relax the assumption of the von Mises distribution and propose the approximate confidence interval

$$\overline{\theta} \pm \arcsin \left(z_{\frac{\alpha}{2}} \sqrt{\frac{1 - \overline{a}_2}{2N\overline{R}^2}} \right) \tag{17}$$

where $z_{\frac{\alpha}{2}}$ denotes the upper quantile $\frac{\alpha}{2}$ of the $N\,(0, 1)$ distribution. One should note that the length of the above confidence interval is at most π. Naturally, for sufficiently large sample sizes, and asymptotically, this restriction does not matter. One should also mention that, in particular for very small sample sizes, the argument of the arcsine function could be outside the interval $[-1, 1]$ and the above asymptotic formula is not applicable.

Although no distributional assumption is made, the above expression assumes that the distribution of θ is symmetric. However, in general, one cannot discard the possibility of skewed distributed circular data. In this respect, Pewsey (2002) proposes an asymptotically distribution-free test for symmetry. The test statistic is given by

$$\frac{\overline{b}_2}{\sqrt{\frac{1}{N}\left[\frac{1-\overline{a}_4}{2}-2\overline{a}_2-\overline{b}_2^2+\frac{2\overline{a}_2}{\overline{R}}\left(\overline{a}_3+\frac{\overline{a}_2(1-\overline{a}_2)}{\overline{R}}\right)\right]}}. \tag{18}$$

Large absolute values of the above statistic compared with the quantiles of the standard normal distribution lead to the rejection of symmetry. In the presence of skewness, Pewsey (2004) derives the following bias-corrected confidence interval for the mean direction of the population

$$\overline{\theta}+\frac{\overline{b}_2}{2N\overline{R}^2}\pm z_{\frac{\alpha}{2}}\sqrt{\frac{1-\overline{a}_2}{2N\overline{R}^2}}. \tag{19}$$

Note that if the underlying distribution is assumed to be symmetric one can drop the bias term, $\frac{\overline{b}_2}{2N\overline{R}^2}$, and the interval becomes $\overline{\theta}\pm z_{\frac{\alpha}{2}}\sqrt{\frac{1-\overline{a}_2}{2N\overline{R}^2}}$. Since $\arcsin(x)\approx x$ for small x, this means that for relatively large samples from less dispersed populations, the results will be close to those given by the interval in (17). However, for skewed and dispersed samples of relatively small size, the differences can be noteworthy.

4. Data

To illustrate empirically the methodology described in the previous section, a comprehensive monthly dataset spanning the last three decades for the largest euro area economies, namely Germany (DE), France (FR), Italy (IT) and Spain (ES) has been collected. The sample period considered runs from January 1990 up to June 2021 for all countries but Germany. For Germany, the period after reunification is considered, i.e. January 1991 onwards.[7] On average, almost one hundred indicators per country have been gathered.[8]

The series comprise the following broad categories: production in industry, turnover in industry (disaggregated between domestic and non-domestic markets), turnover and volume of sales in wholesale and retail trade, labour market outcomes, production in construction, international trade of goods by product group, overnight stays in tourist accommodation establishments, passenger car registrations figures and business and consumer surveys. The panel of variables underlying the latter covers different sectors. Firms in the industry (manufacturing), services, retail trade and construction sectors, as well as consumers are asked on several domains (e.g. assessment of recent and future trends in production,

[7] One should note that the above computations can be performed with an unbalanced dataset. For the time span considered, we end up with around half of the series available at the beginning of the sample period for each country which already ensures a relatively large N.

[8] All series, starting dates and sources are detailed in the Appendix.

current levels of order books and stocks, selling price expectations and employment, assessment on the business situation, of the past and future changes in their company's turnover). The survey on consumers collects information on households' spending and savings intentions and measures their understanding of the factors affecting those decisions. All series have been seasonally and/or calendar adjusted and transformed before further analysis, including sign adjustments.[9] With the exception of survey data and the unemployment rate, all series are log-transformed.

5. Empirical results

5.1. The circular business cycle clock

As discussed earlier, business cycle clocks focus on growth cycles, that is, deviations of economic activity from its long-term trend. In the above mentioned literature, the underlying cyclical pattern of the indicators is typically identified resorting to the well-known HP filter (see Hodrick and Prescott (1997)). The HP filter, which is one the most widely used detrending methods, acts as high-pass filter with the shape of the frequency response function and the cut-off frequency governed by the parameter λ. The features of the HP filter have been intensively studied in the literature (see, among many others, King and Rebelo (1993), Harvey and Jaeger (1993), Cogley and Nason (1995), Kaiser and Maravall (2001)). One should note that the methodology proposed herein can be applied with any filtering procedure and any set of parameters. Hence, the suggested method should be read beyond the pros and cons of the HP filter.

Since we intend to compare the resulting business cycle clocks with the turning points monthly chronology released by the OECD,[10] we follow the OECD approach to extract the cyclical component and run the HP filter as a band-pass filter. In particular, a double HP filter is applied, i.e. the filter is applied twice to obtain a smoothed detrended cycle. Initially, the trend is removed by setting λ to a high value and retain business cycle and high frequencies. Afterwards, the HP filter with a small λ is applied so that the high frequencies are removed. So, the first step detrends while the second one smoothes.[11]

[9]Following the European Commission in the business and consumer surveys compilation, the series on unemployment over the next 12 months (consumers survey) and on assessment of stocks of finished products (manufacturing and retail trade surveys) are sign-adjusted. The unemployment and unemployment rate series have also been sign-inverted.

[10]The reference monthly business cycle chronology can be found in the OECD site at `https://www.oecd.org/sdd/leading-indicators/CLI-components-and-turning-points.csv`.

[11]Alternatively, the removal of the long-term trend and high frequency noise can be performed in a single step resorting to a band-pass filter such as the one proposed by Christiano and Fitzgerald (2003). We find that the main results are qualitatively similar. To save space the results are not reported here but are available from the authors upon request.

In particular, the parameters are set such that the frequency cut-off occurs at frequencies higher than 12 months and lower than 120 months. This corresponds setting $\lambda = 133107.94$ and $\lambda = 13.93$ respectively. The value for λ is obtained via the formula $\lambda = [4(1 - \cos(\omega_0))^2]^{-1}$ where ω_0 is the frequency expressed in radians such that $\omega_0 = 2\pi/\tau$ with τ denoting the number of periods it takes to complete a full cycle (see, for example, Maravall and del Rio (2001)). Hence, in a preliminary stage, the filtering procedure involves the removal of the components that have a cycle length longer than 120 months and those that have a cycle length shorter than 12 months.[12]

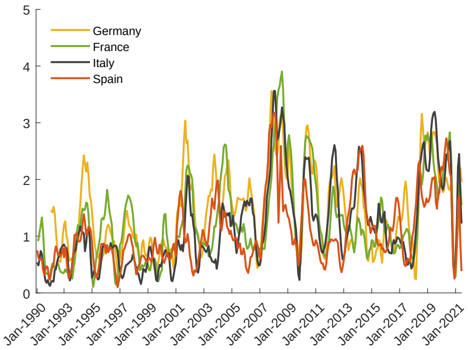


Figure 3: von Mises distribution test statistic.

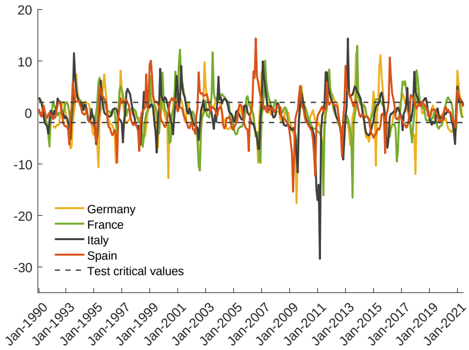


Figure 4: Symmetry test.

At each point in time (in our case, every month), the angle for each variable corresponding to the Cartesian coordinates given by the level and its first difference is computed. The mean direction can be obtained as described earlier for each point in time using the available series for each country. As discussed earlier, it is important to assess whether the sample distribution departs from the von Mises distribution. In Figure 3, we present the results for the test statistic given by (16) for each country and for every month and conclude that the null hypothesis of a von Mises distribution is always rejected at the usual 5 per cent significance level. We also test the validity of the symmetry assumption using the test statistic in (18) with the results displayed in Figure 4. We find that in around half of the time periods there is statistical evidence to reject the null hypothesis of symmetry. Therefore, we compute the confidence interval for the mean direction resorting to (19).

[12] As argued by the OECD, although early papers in business cycle analysis focused on cycles between 1.5 and 8 years, more recent work tend to suggest that economic cycles may last longer, and cyclical fluctuations can be smaller (see, for example, Agresti and Mojon (2001) who consider 10 years as the upper bound for the business cycles in Europe). Nevertheless, as a robustness analysis, we have also considered the case where the business cycles duration ranges from 18 to 96 months and we find that the main findings hold.

In Figures 5-7, we present the resulting business cycle clocks for each of the countries for a few selected turning points according to the OECD business cycle reference chronology.[13] In particular, we display the results for the trough in 2009 following the Great Recession, the peak in 2011 during the deepening of the European sovereign debt crisis and the most recent trough in 2020 in the context of the COVID-19 pandemics. In each business cycle clock, we present the circular histogram for the sample angle data, where the histogram bins are plotted as blue straight bars with a width of ten degrees. The red arrow denotes the mean direction and the corresponding confidence interval is displayed on the outside edge of the circle (with the gray and black lines denoting the 95 and 99 per cent confidence intervals, respectively). On the circle, 0 degrees is on the right (east), 90 degrees is at the top (north), 180 degrees is on the left (west), and 270 degrees is at the bottom (south).

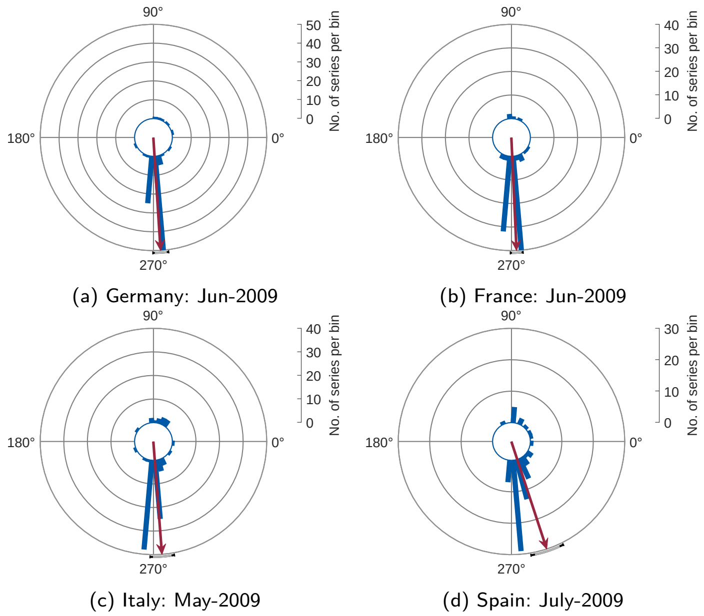
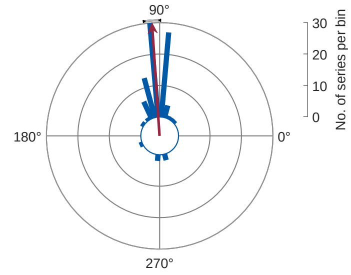
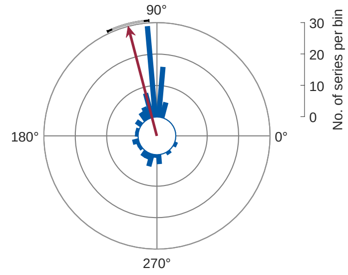


Figure 5: Trough following the Great Recession.

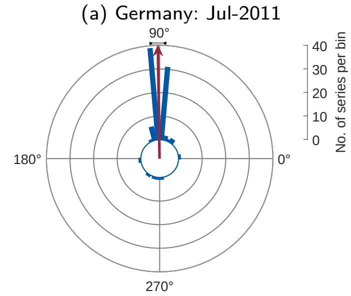
[13] To save space, we do not report the business cycle clock for all turning points for all countries but all results are available from the authors upon request.



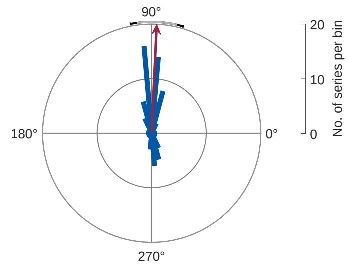
(a) Germany: Jul-2011



(b) France: Sep-2011

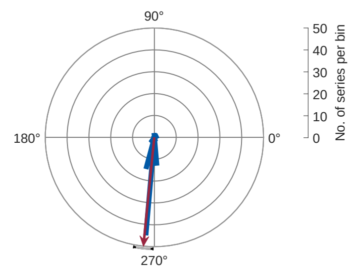


(c) Italy: May-2011

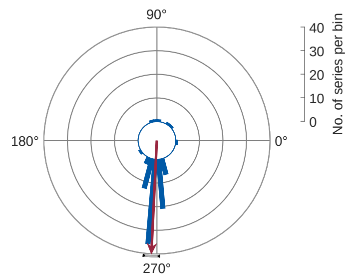


(d) Spain: Mar-2011

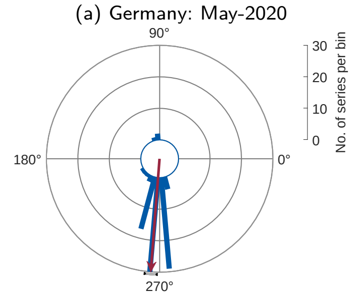
Figure 6: Peak before the sovereign debt crisis.



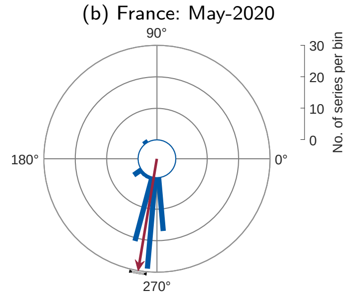
(a) Germany: May-2020



(b) France: May-2020



(c) Italy: May-2020



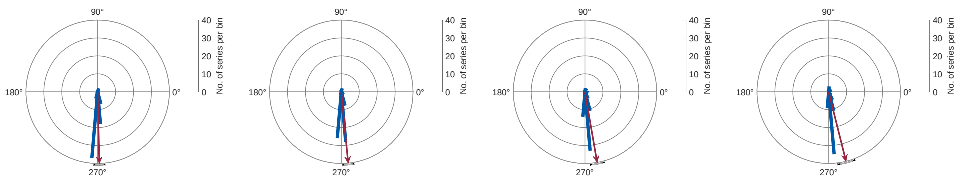
(d) Spain: May-2020

Figure 7: Trough during the COVID-19 pandemics.

In Figure 5, we present the business cycle clock for the month in 2009 identified by the OECD as the trough for each country. One can see that for all countries but Spain, the mean direction is close to, and not statistically different from, 270 degrees, thus signalling the occurrence of a trough in that month. In the case of Spain, where the trough defined by the OECD is July (in contrast with May for Italy and June for Germany and France), the corresponding business cycle clock seems to suggest that the trough has already occurred.

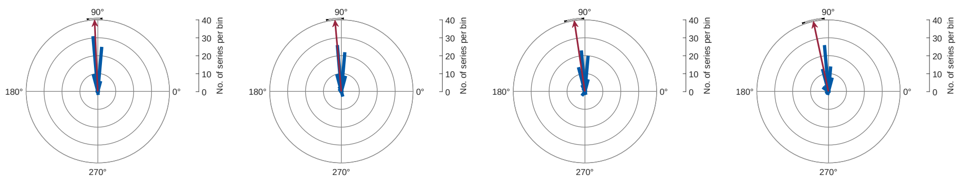
In fact, the computation of the business cycle clock over the previous months (see Figure 8) suggests that the trough may have taken place in the preceding months to July, most notably in March. Naturally, determining peaks and troughs in economic activity is not problem-free and there is always uncertainty surrounding any reference business cycle chronology. In this respect, the ability to provide a confidence interval around the mean direction is of noteworthy interest which along the possibility of assessing its evolution over time reinforces the usefulness of the suggested business cycle clock.

In Figure 6 we report the results for the month identified by the OECD as the peak in 2011 during the European sovereign debt crisis. For all countries but France, one cannot reject that the business cycle has reached a peak in that month. Only in the case of France the confidence interval does not include the 90 degrees direction. Note that the month identified by the OECD as the peak is March for Spain, May for Italy and July for Germany whereas it is September for France. Interestingly, when one computes the business cycle clock for France in the preceding months (see Figure 9), it seems to suggest that the peak may have occurred a few months earlier.



(a) Mar-2009 (b) Apr-2009 (c) May-2009 (d) Jun-2009

Figure 8: Trough in Spain in 2009.



(a) May-2011 (b) Jun-2011 (c) Jul-2011 (d) Aug-2011

Figure 9: Peak in France in 2011.

Finally, regarding the trough in 2020 following the COVID-19 shock, the corresponding business clocks are displayed in Figure 7. The results suggest a strong synchronisation with all countries presenting a mean direction close to the 270 degrees direction in May-2020.

5.2. A circular correlation analysis

To measure the information content of the mean direction regarding the business cycle throughout all points in time we proceed as follows. Firstly, we obtain a monthly reference measure of aggregate economic activity. In particular, we resort to the well-known Chow-Lin method for temporal disaggregation to obtain a monthly GDP series from the available quarterly GDP series. The corresponding cyclical component is computed as described earlier. To evaluate the correlation between the business cycle clock and the GDP cyclical component, we use the measure developed independently by Mardia (1976) and Johnson and Wehrly (1977).[14]

The measure of dependence between a linear variable z and a circular variable θ is obtained by correlating z with $(\cos\theta, \sin\theta)$. The sample correlation is given by

$$r_{z\theta} = \sqrt{\frac{r_{zc}^2 + r_{zs}^2 - 2r_{zc}r_{zs}r_{cs}}{1 - r_{cs}^2}} \tag{20}$$

where $r_{zc} = corr(z, \cos\theta)$, $r_{zs} = corr(z, \sin\theta)$ and $r_{cs} = corr(\cos\theta, \sin\theta)$ where $corr$ denotes the Pearson correlation coefficient.

In Table 1, the correlation between the mean direction and the monthly business cycle for each country is presented. Besides the contemporaneous correlation, we also present the correlation for leads and lags up to six months. We find that for Germany, France and Italy the highest correlation is the contemporaneous correlation which is supportive of its information content about the current business cycle developments. In the case of Spain, the highest correlation is attained at a lead of one month. All correlations are statistically significant and the countries that present the highest correlations are Germany and Italy.

To reinforce the usefulness of the business cycle clock based on the mean direction we assess two possible alternatives. The first alternative considered is using the median direction instead of the mean. Finding the median direction of circular data is similar to that for linear data. The mean direction of a sample is the direction for which half of the data points fall on either side. In particular, the circular data is divided by a diameter that produces two equal sized groups of data on both sides of the diameter. The median is determined by the endpoint of the diameter closer to the centre of mass of the data. If N is odd, it is the data point such that $(N-1)/2$ of the points lie on one side and the other $(N-1)/2$ on the

[14] Abberger (2006) draws on the same measure to assess the correlation between the Ifo business cycle clock and the cyclical component of production.

	Mean direction				Median direction				Factor			
	DE	FR	IT	ES	DE	FR	IT	ES	DE	FR	IT	ES
Lead(-)/Lag(+)												
-6	0.672	0.502	0.613	0.583	0.624	0.504	0.555	0.572	0.647	0.500	0.594	0.577
-5	0.705	0.549	0.652	0.604	0.662	0.550	0.599	0.594	0.683	0.546	0.639	0.598
-4	0.730	0.587	0.683	0.620	0.691	0.585	0.639	0.609	0.711	0.581	0.673	0.612
-3	0.746	0.614	0.704	0.631	0.710	0.608	0.670	0.616	0.726	0.602	0.693	0.618
-2	0.754	0.630	0.716	0.636	0.719	0.618	0.691	0.615	0.733	0.612	0.702	0.617
-1	0.758	0.637	0.721	0.637	0.720	0.620	0.700	0.608	0.734	0.614	0.702	0.612
0	0.758	0.639	0.723	0.634	0.715	0.618	0.702	0.597	0.732	0.614	0.697	0.606
1	0.756	0.637	0.722	0.633	0.706	0.617	0.699	0.587	0.728	0.614	0.691	0.604
2	0.752	0.634	0.719	0.631	0.693	0.617	0.692	0.575	0.722	0.615	0.683	0.599
3	0.745	0.628	0.715	0.626	0.676	0.617	0.681	0.561	0.713	0.615	0.675	0.592
4	0.733	0.618	0.708	0.618	0.655	0.614	0.666	0.543	0.699	0.611	0.662	0.581
5	0.717	0.603	0.698	0.606	0.629	0.605	0.647	0.524	0.680	0.602	0.644	0.567
6	0.696	0.582	0.682	0.589	0.600	0.589	0.623	0.504	0.656	0.584	0.618	0.551

Table 1. Correlations with the monthly business cycle.

other side. If N is even, it lies half-way between the two closest data points such that $N/2$ fall on one side and the other $N/2$ points fall on the other side.

The second alternative approach draws on a factor model. Such an approach is also pursued in the related literature as discussed earlier. In particular, all the information contained in the original data is summarised in a single variable, the common factor, and then the corresponding direction at each point in time is computed to deliver the business cycle clock.

For the median direction, the highest correlation for Germany and France is attained for a one-month lead, for Italy is contemporaneous whereas for Spain is for a three-month lead. In the case of the factor model, the maximum correlation is recorded for a one month lead for Germany and Italy, a three-month lag for France and a three-month lead for Spain. In terms of the size of the correlations, the factor model seems to deliver better results for Germany and the median direction for France while for Italy and Spain the results are very close between the two alternatives.

However, such results are worse than those delivered by the mean direction, which presents among the three approaches the highest correlations for all countries.

5.3. A quasi-real-time exercise

As mentioned earlier, the empirical application draws on the HP filter in line with previous literature on business cycle clocks. As it is well-known, any filtering procedure entails revisions with the revisions at the end of the sample having more prominence in the analysis due to its potential influence in the assessment of the current economic situation. To assess the revisions in the current setup, we computed the circular business cycle clock recursively. This means that at each time t the data considered runs from the beginning of the sample period up to time t using the latest available data, i.e., the so-called quasi-real-time estimate.[15]

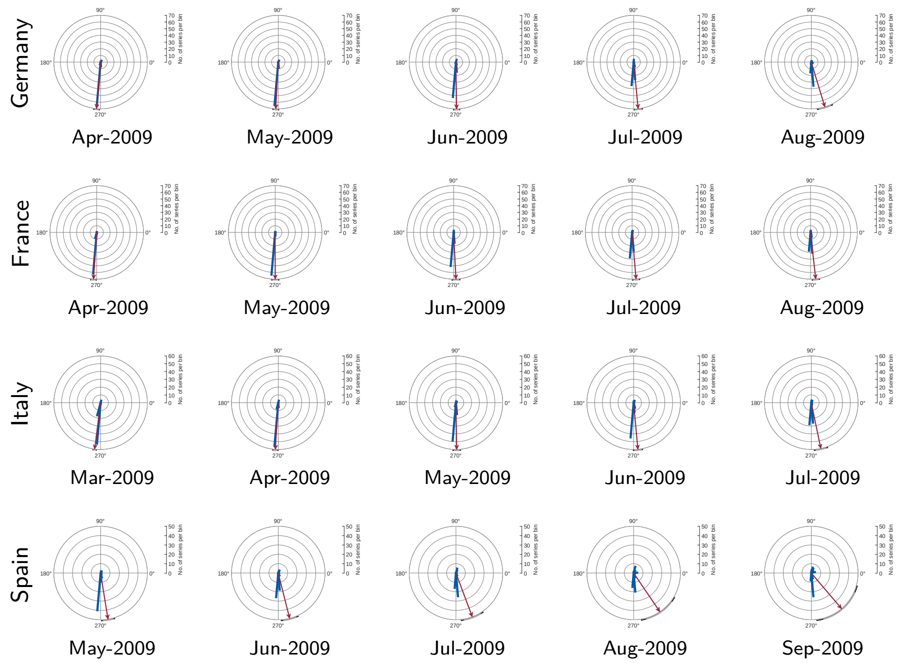


Figure 10: Quasi-real-time clocks during the trough in 2009.

In particular, we display the quasi-real-time business cycle clocks during the above three turning point episodes for all countries (see Figures 10-12). In each figure, we present for each country the business cycle clock for the month determined by the OECD as the turning point as well as for the two previous and the two subsequent months. In the case of the Great Recession, one can see that the quasi-real-time clock was able to capture quite well the corresponding trough in 2009. Only in the case of Spain, it seems to suggest that the trough was earlier which is in accordance with the behaviour of the final estimate discussed above.

[15]What sets apart the quasi-real-time estimate from a real-time one is that the former is computed with the latest vintage of data whereas the latter considers the vintage of data available at time t (see, for example, Orphanides and van Norden (2002)). However, one should note that a large fraction of the series included in the dataset is not subject to revisions such as the business and consumer surveys. Moreover, there is evidence that data revisions are not an important driver of the revisions of business cycle estimates (see, for example, Marcellino and Musso (2011) and Ince and Papell (2013)).

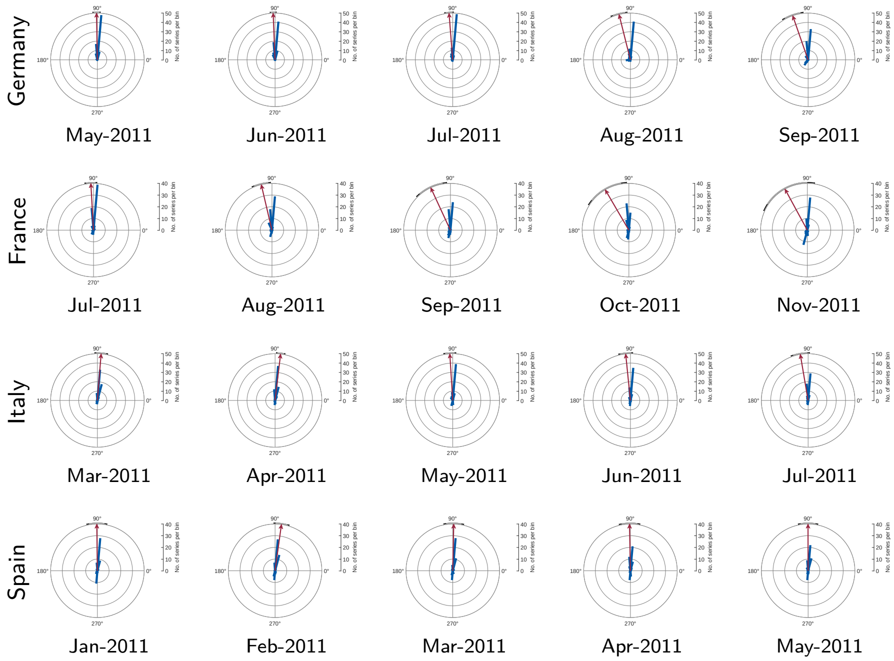


Figure 11: Quasi-real-time clocks during the peak in 2011.

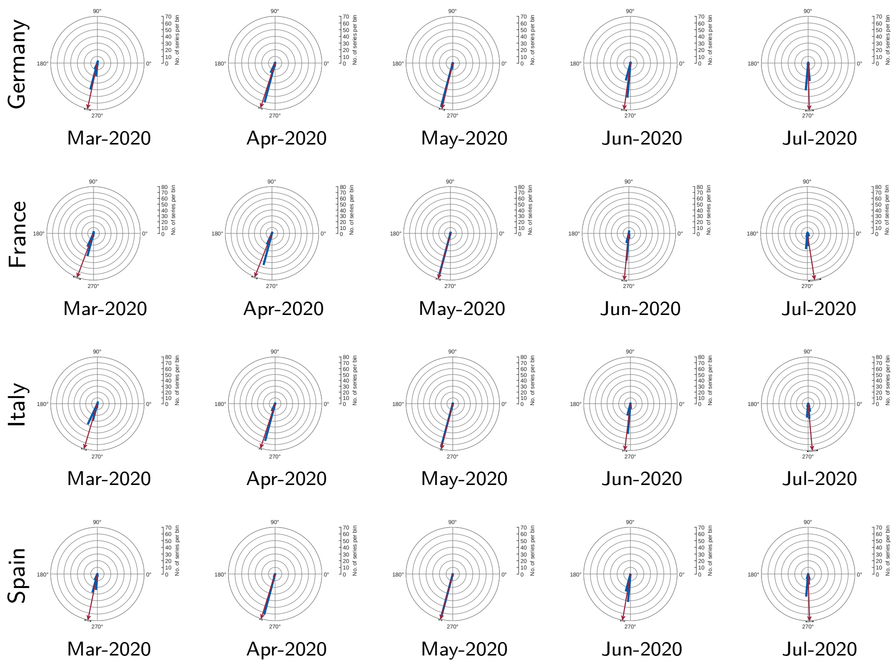


Figure 12: Quasi-real-time clocks during the trough in 2020.

Regarding the peak in 2011, during the European sovereign debt crisis, the quasi-real-time estimates are also quite informative. Again, only in the case of France, likewise in the final estimate, the business cycle clock would have suggested an earlier turning point. Concerning the trough in 2020 with the pandemics, the quasi-real-time clock would have pointed to a trough between June and July.

The results above suggest that the quasi-real-time estimates are quite informative and do not differ substantially from the final estimates. In fact, for the above turning point episodes, the mean absolute revision of the mean direction is around five degrees and in most turning points episodes it is less than ten degrees.

6. Concluding remarks

Monitoring the business cycle momentum is recognised to be of key importance for policymaking and private sector decisions. In this respect, a lot of work has been devoted in national and international institutions on depicting the economic cycle stance through business cycle clocks. Existing business cycle clocks typically have drawn on a limited number of indicators, ranging from single series to a small number of variables.

We depart from the previous literature and propose a novel approach to represent the business cycle momentum resorting to circular statistics. The use of circular statistics in this domain is natural given the recurrent nature of the business cycle. On top of that, it allows to handle large amounts of data. The suggested circular business cycle clock conveys information about the circular histogram, the mean direction and corresponding confidence interval. The latter can be computed in a context where neither the von Mises distribution nor the symmetry assumption hold.

We illustrate the usefulness of the circular business cycle clock by focusing on the largest euro area economies, namely Germany, France, Italy and Spain. For that purpose, we considered a comprehensive monthly dataset of almost one hundred series for each country spanning the last three decades. We find that the proposed circular business cycle clock tracks the business cycle quite well and delivers a reliable signal on the turning points across countries. The behaviour of the mean direction is compared with the median and with the direction based on a factor model and we find that the mean direction outperforms the other alternatives.

A more in depth analysis of the turning points during the Great Recession, sovereign debt crisis and the COVID-19 shock has also been provided through a quasi-real-time exercise. Despite the revisions inherent to the filtering method, we find that the circular business cycle clock is also informative in a quasi-real-time framework. All findings are corroborated by the cross-country results, thus reinforcing the usefulness of the suggested approach.

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Appendix

Table A.1. List of series, starting periods and data sources.

Series	DE	FR	IT	ES	Source
Economic sentiment indicator	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Employment expectations indicator	Feb-01	Jan-91	Apr-96	Jan-91	European Commission
Consumer confidence indicator – Consumers survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Financial situation of households over the last 12 months – Consumers survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Financial situation of households over the next 12 months – Consumers survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
General economic situation over the last 12 months – Consumers survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
General economic situation over the next 12 months – Consumers survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Major purchases at present – Consumers survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Major purchases over the next 12 months – Consumers survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Unemployment over the next 12 months – Consumers survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Savings at present – Consumers survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Savings over the next 12 months – Consumers survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Statement on financial situation of households – Consumers survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Industrial confidence indicator – Manufacturing survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Production trend observed in recent months – Manufacturing survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Production expectations over the next 3 months – Manufacturing survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Assessment of order-book levels – Manufacturing survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Assessment of export order-book levels – Manufacturing survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Assessment of stocks of finished products – Manufacturing survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Employment expectations over the next 3 months – Manufacturing survey	Jul-97	Jan-91	Jan-90	Jan-90	European Commission
Construction confidence indicator – Construction survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Assessment of order-book levels – Construction survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Employment expectations over the next 3 months – Construction survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Trend of activity compared with preceding months – Construction survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Retail trade confidence indicator – Retail trade survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission

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Table A.1 – *Continued from previous page*

Series	DE	FR	IT	ES	Source
Assessment of business situation over the past 3 months – Retail trade survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Volume of stocks – Retail trade survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Expected business situation over the next 3 months – Retail trade survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Intention of placing orders – Retail trade survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Employment expectations over the next 3 months – Retail trade survey	Jan-91	Jan-90	Jan-90	Jan-90	European Commission
Services confidence indicator – Services survey	Apr-95	Jan-90	Jan-98	Oct-96	European Commission
Assessment of business situation over the past 3 months – Services survey	Apr-95	Jan-90	Jan-98	Oct-96	European Commission
Evolution of demand over the past 3 months – Services survey	Apr-95	Jan-90	Apr-96	Oct-96	European Commission
Evolution of demand expected over the next 3 months – Services survey	Apr-95	Jan-90	Apr-96	Oct-96	European Commission
Evolution of employment over the past 3 months – Services survey	Apr-95	Jan-90	Jan-98	Oct-96	European Commission
Evolution of employment expected over the next 3 months – Services survey	Feb-01	Jan-90	Apr-96	Oct-96	European Commission
Total retail trade	Jan-91	Jan-90	Jan-90	Jan-95	OECD
Retail sale of food, beverages and tobacco	Jan-94	Jan-99	Jan-00	Jan-95	Eurostat
Retail sale of non-food products (except fuel)	Jan-94	Jan-99	Jan-00	Jan-95	Eurostat
Retail trade, except of motor vehicles, motorcycles and fuel	Jan-94	Jan-99	Jan-00	Jan-95	Eurostat
Retail sale of automotive fuel in specialised stores	Jan-94	Jan-99	Jan-00	Jan-00	Eurostat
Production of total industry	Jan-91	Jan-90	Jan-90	Jan-90	OECD
Production in total manufacturing	Jan-91	Jan-90	Jan-90	Jan-90	OECD
Production in industry – intermediate goods	Jan-91	Jan-90	Jan-90	Jan-92	Eurostat
Production in industry – energy (except section E)	Jan-91	Jan-90	Jan-90	Jan-92	Eurostat
Production in industry – capital goods	Jan-91	Jan-90	Jan-90	Jan-92	Eurostat
Production in industry – consumer goods	Jan-91	Jan-90	Jan-90	Jan-92	Eurostat
Production in industry – durable consumer goods	Jan-91	Jan-90	Jan-90	Jan-92	Eurostat
Production in industry – non-durable consumer goods	Jan-91	Jan-90	Jan-90	Jan-92	Eurostat
Turnover in industry – intermediate goods	Jan-91	Jan-99	Jan-00	Jan-02	Eurostat
Turnover in industry – energy (except sections D and E)	Jan-91	Jan-99	Jan-00	Jan-02	Eurostat
Turnover in industry – capital goods	Jan-91	Jan-99	Jan-00	Jan-02	Eurostat
Turnover in industry – consumer goods	Jan-91	Jan-99	Jan-00	Jan-02	Eurostat
Turnover in industry – durable consumer goods	Jan-91	Jan-99	Jan-00	Jan-02	Eurostat
Turnover in industry – non-durable consumer goods	Jan-91	Jan-99	Jan-00	Jan-02	Eurostat

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Table A.1 – *Continued from previous page*

Series	**DE**	**FR**	**IT**	**ES**	**Source**
Turnover in industry – mining and quarrying; manufacturing	Jan-91	Jan-99	Jan-00	Jan-02	Eurostat
Turnover in industry – manufacturing	Jan-91	Jan-99	Jan-05	Jan-02	Eurostat
Turnover in industry – intermediate goods, domestic market	Jan-91	Jan-99	Jan-00	-	Eurostat
Turnover in industry – energy (except sections D and E), domestic market	Jan-91	Jan-99	Jan-00	-	Eurostat
Turnover in industry – capital goods, domestic market	Jan-91	Jan-99	Jan-00	-	Eurostat
Turnover in industry – consumer goods, domestic market	Jan-91	Jan-99	Jan-00	-	Eurostat
Turnover in industry – durable consumer goods, domestic market	Jan-91	Jan-99	Jan-00	-	Eurostat
Turnover in industry – non-durable consumer goods, domestic market	Jan-91	Jan-99	Jan-00	-	Eurostat
Turnover in industry – mining and quarrying; manufacturing, domestic market	Jan-91	Jan-99	Jan-00	-	Eurostat
Turnover in industry – manufacturing, domestic market	Jan-91	Jan-99	Jan-05	-	Eurostat
Turnover in industry – intermediate goods, foreign market	Jan-91	Jan-99	Jan-00	-	Eurostat
Turnover in industry – energy (except sections D and E), foreign market	Jan-91	Jan-99	Jan-00	-	Eurostat
Turnover in industry – capital goods, foreign market	Jan-91	Jan-99	Jan-00	-	Eurostat
Turnover in industry – consumer goods, foreign market	Jan-91	Jan-99	Jan-00	-	Eurostat
Turnover in industry – durable consumer goods, foreign market	Jan-91	Jan-99	Jan-00	-	Eurostat
Turnover in industry – non-durable consumer goods, foreign market	Jan-91	Jan-99	Jan-00	-	Eurostat
Turnover in industry – mining and quarrying; manufacturing, foreign market	Jan-91	Jan-99	Jan-00	-	Eurostat
Turnover in industry – manufacturing, foreign market	Jan-91	Jan-99	Jan-05	-	Eurostat
Production of total construction	Jan-91	Jan-90	Jan-95	Jan-90	OECD
Production in construction – buildings	Jan-91	Jan-90	-	Jan-00	Eurostat
Production in construction – civil engineering works	Jan-91	Jan-90	-	Jan-00	Eurostat
Imports	Jan-00	Jan-00	Jan-00	Jan-00	Eurostat
Imports of intermediate goods	Jan-00	Jan-00	Jan-00	Jan-00	Eurostat
Imports of capital goods	Jan-00	Jan-00	Jan-00	Jan-00	Eurostat
Imports of consumption goods	Jan-00	Jan-00	Jan-00	Jan-00	Eurostat
Exports	Jan-00	Jan-00	Jan-00	Jan-00	Eurostat
Exports of intermediate goods	Jan-00	Jan-00	Jan-00	Jan-00	Eurostat
Exports of capital goods	Jan-00	Jan-00	Jan-00	Jan-00	Eurostat
Exports of consumption goods	Jan-00	Jan-00	Jan-00	Jan-00	Eurostat
Nights spent at tourist accommodation establishments, foreign country	Jan-91	-	Jan-90	Jan-90	Eurostat

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Table A.1 – *Continued from previous page*

Series	**DE**	**FR**	**IT**	**ES**	**Source**
Nights spent at tourist accommodation establishments, reporting country	Jan-91	-	Jan-90	Jan-90	Eurostat
Nights spent at tourist accommodation establishments, total	Jan-91	-	Jan-90	Jan-90	Eurostat
Unemployment	Jan-91	Jan-90	Jan-90	Jan-90	Eurostat
Unemployment rate	Jan-91	Jan-90	Jan-90	Jan-90	Eurostat
Passenger car registrations	Jan-91	Jan-90	Jan-90	Jan-90	ACEA

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