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The euro area business cycle and its drivers

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Contents

Abstract

The monitoring and analysis of the business cycle is a central element of inputs to monetary policy decision-making. This report contributes to the analysis of business cycles in the euro area in three dimensions. First, in terms of business cycle dating, it proposes automated procedures to characterise the business cycle situation of the euro area and its main components, across countries and sectors. Second, it investigates how business cycle synchronisation has evolved over the last 20 years. Third, it analyses business cycle drivers from several perspectives, including the financial and international dimension, interconnectedness, demand and supply. It also features an early analysis of the economic implications of the COVID-19 pandemic. Rather than reaching strong conclusions on the history of the euro area business cycle, the primary aim of the report is to promote sound methods and approaches that are part of ongoing enhancements of the analytical infrastructure designed to analyse hard-to-ascertain questions on the nature and characteristics of euro area business cycle dynamics.

JEL codes: C10, E32, E37

Keywords: business cycle dating, characteristics, synchronisation, drivers

Executive summary

The monitoring and analysis of the business cycle – fluctuations in aggregate economic activity between alternating expansions and contractions – is a central element in monetary policy analysis. A sound real-time assessment of the business cycle is key in gauging the growth outlook and thus also medium-term price developments. Linking observed economic activity to the business cycle assessment is key to the overall narrative and communication of monetary policy decisions. A central bank therefore needs to use state-of-the-art business cycle dating and analysis methods. This is even more important in a large and complex monetary union, where area-wide developments interact in a complex manner with heterogenous growth dynamics at sub-area level.

This report contributes to the analysis of business cycles in the euro area in three main dimensions. First, in terms of business cycle measurement and dating, it proposes easily replicable state-of the-art procedures to characterise the business cycle situation of the euro area and its main underlying components, across both countries and sectors. Second, it provides a comprehensive analysis of business cycle synchronicity, evaluating its evolution in the euro area both internally (across the euro area countries and sectors) and externally (relative to other advanced economies). A high degree of congruence or similarity of the euro area business cycle with that of its Member States, together with a high degree of synchronisation among the participating countries, makes the single monetary policy more coherent and effective, and enhances the appropriateness of its stance across all Member States. Third, the report explores some causality aspects in terms of the main business cycle drivers in the euro area. This analysis is more conceptual in nature and addresses several research questions, notably the role of financial factors and structural shock transmission within the euro area.

Some caveats should be mentioned. Business cycle drivers are not the only cause of macroeconomic fluctuations. Shocks, policy impacts (such as changes in taxation) and external factors generate macroeconomic volatility: these may interact with, but are not a genuine part of, the business cycle. Similarly, structural changes are an important source of macroeconomic fluctuations that also affect business cycle dynamics. The latter may be associated with persistent factors, often in the field of information-related market imperfections, or the long-term impact of structural shocks, for example to total factor productivity. However, disentangling genuine business cycle signals from short-term volatility or the more permanent impact of structural change is a daunting task. This is even more challenging for the euro area, which has a data history of just 25 years.

Against this background, rather than reaching strong conclusions on the business cycle of the euro area, the aim of the report is to promote sound methods and analytical approaches that are part of ongoing efforts to enhance the analytical infrastructure and improve our understanding of important, but hard-to-ascertain, questions on the nature and characteristics of euro area business cycle dynamics.

1 Business cycle dating

The monitoring and analysis of the business cycle – fluctuations of aggregate economic activity between alternating expansion and contraction periods – is of paramount importance for policy making and the general public. The business cycle is a key concept in the organisation of macroeconomic information, from both a historic and a conjunctural perspective. For a central bank, the understanding (particularly in real time) of the nature of, and factors underlying, ongoing economic growth forms the basis of a sound understanding of price pressures (or lack thereof) and thus of inflation dynamics, and ultimately the appropriate monetary policy stance. A central bank therefore needs to use state-of-the-art business cycle dating and analysis. This is even more important in a large and complex monetary union, where an area-wide business cycle interacts in a complex manner with heterogenous but persistent growth dynamics at sub-area level.

Against this backdrop, establishing a chronology of the business cycle should not be a mechanical endeavour. In practice, it is done by dedicated committees of expert economists. For the euro area, a chronology is provided by the Centre of Economic Policy Research (CEPR) Business Cycle Dating Committee, whereas for the United States, it is the task of the National Bureau of Economic Research (NBER) Business Cycle Dating Committee. For some countries, dating assessments are provided by independent institutions, such as the Economic Cycle Research Institute (ECRI) assessment for the four largest euro area economies. However, there is no chronology, unified and comparable across countries, available for all EU Member States. For a large monetary union, such as the euro area, the absence of a common agreed standard that can be applied in real time to date business cycles is problematic from a policy perspective. It impedes the monitoring of the business cycle situation of the monetary union components (at country, regional and sectoral levels) relative to that of the area as a whole. Without an agreed common standard, therefore, it becomes difficult to assess the synchronicity and coherence of business cycle fluctuations among the countries and sectors that make up the monetary union.

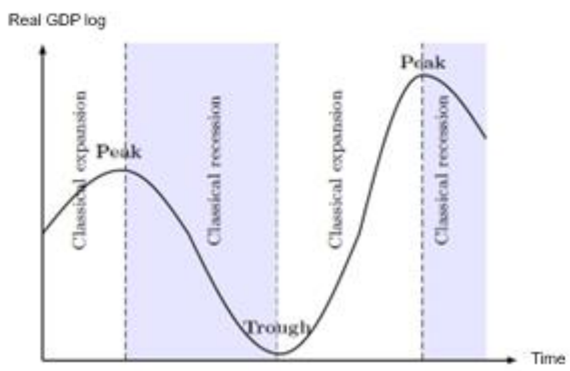
To address these needs, this chapter proposes procedures to date the business cycle fluctuations of any given entity (be it a monetary union as a whole or its constituent components), based on transparent and user-friendly tools aligned with cutting-edge methods in this area. Specifically, this chapter provides highly automated, replicable and updatable tools that deliver methodologically comparable findings across countries. These results complement the chronologies provided by official business cycle dating committees and other institutions, with the advantage of being harmonised across countries, easily updatable and thus readily available. The developed tools provide a business cycle chronology utilising both classical and growth cycle dating approaches for the euro area and its member countries, based on harmonised time series and parameters.

1.1 The classical business cycle

In this section we follow the classical approach to identifying business cycle turning points, as proposed by Burns and Mitchell (1946). This is also the approach usually implemented by the Business Cycle Dating Committees of the NBER and the CEPR when dating peaks and troughs in the United States and the euro area, respectively. In this approach, two phases of the business cycle are identified: i) a recession (or contraction) phase is a period between a peak and a trough, characterised by a decline in economic activity (e.g. real gross domestic product (GDP)), typically for at least two consecutive quarters; and ii) an expansion is the period between a trough and a peak, i.e. the non-recession phase of the economy, which is its normal (prevailing most of the time) state (**Chart 1**).

Chart 1
Classical business cycle phases

(level)



Source: Authors' illustration.

There are several advantages to the classical dating approach. First, the dating results are stable and do not change retrospectively with the accrual of new observations, unless the historical data are revised. Second, classical business cycle dating does not require the initial econometric estimation and extraction of an unobserved component from the time series, which is a requirement for the main alternative, the growth cycle approach. For the latter, the filtering of the underlying long-term trend is usually a challenging exercise, especially with short data samples – such as in the euro area – and it is therefore subject to real-time reliability issues. Third, apart from broadly acceptable assumptions defining the general characteristics of the business cycle (such as the minimum length of a phase or length of a complete cycle), the classical approach is model-independent, hence more transparent and less controversial. Fourth, this approach generates a simple narrative of fluctuations in economic activity, which is generally well understood by business sector observers and the general public. These four reasons are why this is the main approach implemented by the official dating committees.

The term "classical expansion" refers to expansion in classical business cycle dating. This definition differs from the corresponding definition in the growth cycle approach. We use univariate and multivariate Bry-Boschan (BB)[1] algorithms based on quarterly logs of real GDP or its components to determine cyclical peaks and troughs. Following Bry and Boschan (1971) and Harding and Pagan (2002), we also subscribe to their conclusion that turning point determination cannot be regarded as objective, i.e. it cannot be unequivocally agreed upon, but that there should be agreement on the procedures used to establish turning points.

Similar to the CEPR dating committee, the main univariate procedure relies on real quarterly GDP data for the euro area or the individual EU Member States. The quarterly frequency provides a sound balance between the reliability of the economic signals and the timeliness of the information (for monthly dating, see **Box 1**). Real GDP is widely accepted as the main single indicator of macroeconomic activity.

However, as GDP data are often revised after their release – and thus may provide inconclusive signals in real time – the multivariate analysis incorporates additional macroeconomic variables. Some of these are available earlier or more frequently than the GDP data, and many of them show higher cyclicality than GDP, helping to confirm the phase of the cycle.

The classical dating tools presented in this chapter incorporate options for data cleaning and implementing expert judgement. These adjustments are intended to be used in exceptional circumstances and are provided to ensure consistent results, also for episodes for which the algorithm is deemed to have mis-specified the phase. The methods presented here to date classical business cycles make use of raw series that do not require initial de-trending, filtering or smoothing (apart from using seasonally and working day adjusted data). Thus, they provide timely, reliable results, which remain stable in terms of limited ex post re-dating of business cycles, i.e. dated business cycles are not re-assessed or revised as long as data revisions do not take place.

Box 1
Dating the euro area business cycle on a monthly basis

Prepared by Johannes Gareis

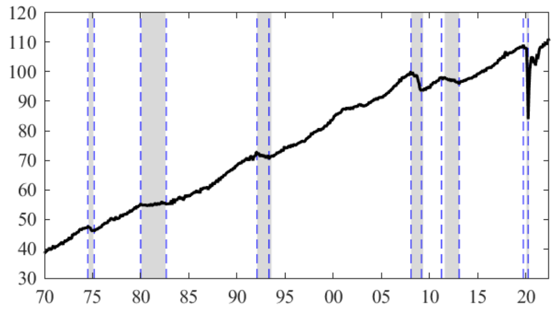
This box presents dating for business cycle turning points in the euro area in terms of months, as an addition to the main approach in this paper, which is quarterly. To this end, a two-step approach is used, as in Mönch and Uhlig (2005). First, a monthly time series for euro area real GDP is estimated, using interpolation techniques that exploit information contained in monthly economic indicators. Second, an updated version of the augmented Bry and Boschan (1971) algorithm proposed by Mönch and Uhlig (2005) is applied. Importantly, this algorithm allows for asymmetries in the business cycle and translates the quarterly sequence of business cycle turning points identified by the CEPR dating committee into a monthly chronology.

[1] We use the Modified Bry-Boschan Quarterly (MBBQ) algorithm, which is the adaption by James Engel for cycle length restrictions based on the quarterly adaption of the original Bry and Boschan algorithm.

Chart A shows the peaks and troughs in the estimated monthly real GDP series obtained by applying the augmented BB algorithm as well as the recessions dated by the CEPR.[2] As the CEPR usually dates business cycle turning points in terms of quarters rather than months, we have assigned the CEPR dates to the middle month of each quarter. The only exception to this is the pre-pandemic business cycle peak, which lags the identified quarterly peak, according to the CEPR. As can be seen, the results of the augmented BB algorithm are very similar to those of the CEPR. In line with the CEPR's chronology, the algorithm identifies six contractions in the post-1970 period: from August 1974 to March 1975, from February 1980 to September 1982, from March 1992 to May 1993, from March 2008 to March 2009, from May 2011 to February 2013 and from November 2019 to April 2020. In most cases, the monthly peaks and troughs fall within the peak or trough quarters dated by the CEPR. For those cases that do not match, the maximum deviation between the turning points determined by the augmented BB algorithm and those identified by the CEPR is four months, with no clear lead-lag pattern.

Chart A

Turning points in euro area monthly real GDP



Source: Eurostat, AWM database, CEPR and own calculations.
Notes: CEPR recessions are indicated by the shaded areas. Since the CEPR usually dates business cycle turning points in terms of quarters rather than months, the CEPR dates are assigned to the middle month of each quarter. The only exception to this is the most recent business cycle peak, which lags the identified quarterly peak.

Regarding the pandemic recession, the algorithm suggests that the euro area reached a business cycle peak in October 2019, while the CEPR determined that the euro area economy reached a peak in February 2020.[3] In fact, euro area quarterly real GDP stagnated in the last quarter of 2019, with industrial production and total exports falling significantly short of their October levels at the end of the year. In the first two months of 2020 (i.e. ahead of the COVID-19 shock), the losses did not seem to have been recovered, according to the monthly GDP estimates. In February 2020 – the month before economic activity started to contract sharply in response to the containment of the spread of the coronavirus in the euro area – only retail sales were at a higher level than in October 2019. According to the estimated monthly real GDP series, economic activity in the euro area again decreased sharply in April 2020, but grew strongly in May and June and increased further in the

[2] Quarterly real GDP is broken down into monthly observations by using a variant of the Chow and Lin (1971) linear regression model. The monthly indicators are industrial production, deflated retail sales and goods exports. The data sample is 1970Q1-2022Q3. The data for quarterly real GDP and the monthly indicators are taken from Eurostat and are backdated with the area-wide model (AWM) and the OECD Main Economic Indicators databases. In the extended Bry-Boschan algorithm, the threshold for the duration of expansions is set at 14 quarters (42 months) and the amplitude threshold is set at 1.7%.

[3] On 29 September 2020, the Business Cycle Dating Committee of the CEPR determined that a peak in quarterly economic activity had occurred in 2019Q4. While the Committee does not provide a monthly dating, it also stressed that the euro area had probably reached a peak in monthly economic activity in February 2020, which lags the quarterly peak. The Committee based this decision on the timing of the pandemic and the sharp decline in industrial production and other indicators in March 2020.

summer months, i.e. a business cycle trough occurred in April 2020. While real GDP in the euro area was significantly affected by the further waves of the pandemic and the associated restrictions in the winter of 2020-21, no further recession occurred, according to the model, which is consistent with the CEPR’s assessment.

1.1.1 Univariate results

1.1.1.1 Business cycle dating of the EU countries

GDP is widely acknowledged to be the single most important indicator of aggregate economic activity. On the basis of the log level of real GDP and by implementing the modified BB approach (see **Box 2**), we establish a business cycle dating chronology for the euro area and EU countries.

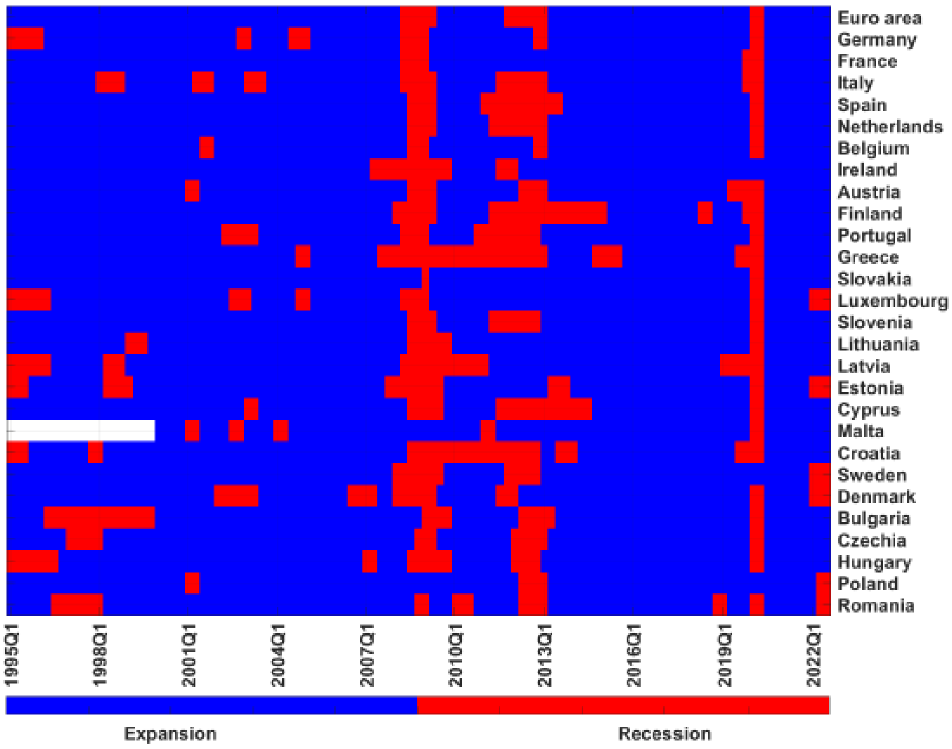
The underlying data for all countries is the European System of Accounts-2010 (ESA-2010) with GDP at constant market prices. The Eurostat national accounts database provides harmonised series for the euro area and the EU Member States since 1995, although for a few countries – Finland, France, Germany and the United Kingdom – the Eurostat data are available for a longer period, whereas for others, notably Malta, the sample is shorter. The advantage of using the real GDP data from Eurostat is that these time series are harmonised across countries, while a disadvantage is the relatively short sample period (1995-2022) for most countries.

The algorithm highlights three major episodes of synchronised recessions being relatively widespread across the EU countries. Chart 2 summarises the chronology after applying the univariate modified BB quarterly (MBBQ) algorithm (see **Box 2**), showing expansions and contractions for the euro area and the EU Member States. The identified synchronised recessions are the Global Financial Crisis (GFC), the sovereign debt crisis and the contraction triggered by the COVID-19 pandemic. For the first two episodes, Croatia and Greece show one long-lasting recessionary period, encompassing both sub-periods.

Looking at the euro area business cycle and its phases since 1995, several turning points are identified (Chart 2). While there was some weakness in 2003, possibly a delayed response to the bursting of the dot-com bubble and the subsequent recession in 2001 in the United States, this did not lead to a GDP contraction for longer than a quarter in the euro area. Similarly, the CEPR identifies the first two quarters of 2003 as a slow growth period. The GFC had a widespread negative effect across the EU countries from the second quarter of 2008 onwards. Between the peak in the first quarter of 2008 and the trough in the second quarter of 2009, the euro area economy shrank by 5.7%. The subsequent recovery was relatively short-lived, lasting for only nine quarters, compared with an average of 29 quarters for all euro area expansions. The euro area recession triggered by the sovereign debt crisis started in the fourth quarter of 2011 and lasted until the first quarter of 2013, entailing a substantial decline in consumption, along with the drop in GDP, reflecting deteriorating confidence and increased uncertainty. The GDP decline was strongest in several southern European countries. During the recovery that followed, growth rates were similar to pre-GFC averages. However, two years of uninterrupted growth could not make up for the accumulated losses caused by the double-dip recession. There was no return to the pre-crisis level of activity until early 2015. During 2019, the euro area business cycle was in a mature phase, with economic activity decelerating in a number of countries. Since the first quarter of 2020, and in particular since March 2020, the COVID-19 pandemic led to policy-induced widespread lockdowns and other containment measures that entailed an unprecedented broad-based fall in economic activity across the euro area. Real GDP declined by 3.7% in the first quarter of 2020 and by a cumulative 15.1% in the first half of 2020.

Chart 2

Business cycle dating based on the univariate MBBQ



Source: Eurostat and authors' calculations.
Note: Contractions/recessions are depicted in red, while expansions are in blue. The dating of Cyprus, Denmark, Finland, Germany, Romania, and Slovakia is subject to expert judgement for specific periods. Latest observation: 2022Q3.

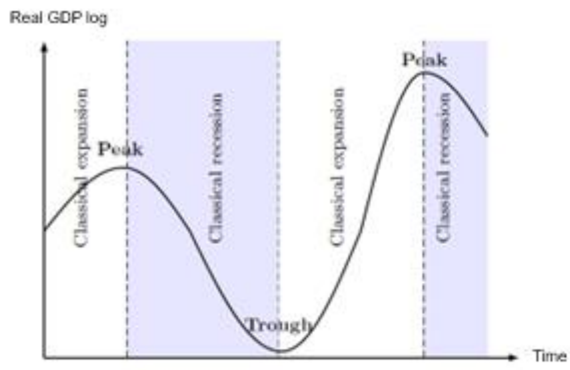
Box 2
Identification of turning points according to the MBBQ algorithm

Prepared by Veaceslav Grigoraș

The MBBQ algorithm is a parametric approach that identifies the local peaks and troughs of the cycle of any given time series, by applying several steps. First, it identifies local maxima and minima as candidates for economic peaks and troughs. Second, it performs checks on the identified local candidates to ensure that the points meet the criteria for turning points of the phases of the economic cycle and drops those that do not meet these criteria. These checks concern the minimum length of the economic phase (L), the minimum length of the business cycle (C) and the proper alternation of peaks and troughs. In addition, a threshold parameter (U) overrides the phase duration criterion if the change in the series is larger than this threshold level. Imposing these criteria ensures that the phases of the business cycle are properly identified.

Chart A

Visualisation of parameters in the MBBQ algorithm



Source: Authors' illustration.

The MBBQ algorithm steps in a nutshell:

I. Identify local maxima and minima as candidates for economic peaks and troughs:
1. Local maximum (P) at date t: if ys<yt for all s with t-K<s<t and t+K>s>t.
2. Local minimum (T) at date t: if ys>yt for all s with t-K<s<t and t+K>s>t.

II. Censor the identified turning points (i.e. keep only those that satisfy certain rules):
1. Window width (K=2): the number of quarters needed to identify a turning point.
2. Minimum duration of a phase (L=2): at least two quarters of a phase.
3. Minimum duration of a complete cycle (C=5): Trough-Peak-Trough or Peak-Trough-Peak.
4. Threshold parameter U=10% for quarterly series, and 25% for monthly series converted to quarterly series, which tend to be more volatile. If quarterly dynamics exceed U in absolute terms, it is assumed that a new phase has started, and the minimum phase length (L) is ignored.

A key advantage of the MBBQ approach is that the business cycle dating is not re-classified retrospectively when a series is extended. However, historical revisions to GDP data create the need for a harmonised and automatic procedure to re-date the series over the whole available sample.[4] While the algorithm performs well with smooth time series, in some cases there are spikes or non-smooth changes, which are not related to the economic cycle, but rather to structural shifts or statistical reclassifications. Furthermore, episodes with growth hovering around zero might result in misclassifications by the automatic algorithm. Along with using parameters that are harmonised across all countries, this underlines the need to introduce expert judgement on the mechanical outcome for some episodes. This is also required in some cases at the beginning or end of the time series, given that the observed cycles are typically truncated in these periods. In the application reported

[4] For example, the MBBQ applied to the 2014 vintage of real GDP matches the contemporaneous dating by the Spanish Economic Association, while the revised 2019 data series would result in an extended recession for the GFC and a shorter one during the sovereign debt crisis.

in this chapter, imposed expert judgement implies a changed classification of the mechanical dating results in order to correct for troughs at the beginning of the sample in Germany (1991Q1-Q3), Cyprus (1995Q1-Q4) and Romania (1995Q1-Q4). In addition, expert judgement has been imposed to account for flat growth episodes, but not widespread recessionary periods, in Denmark (2012Q2-Q4) and Ireland (2009Q4-2013Q1). Similarly, a very short-lived expansion has been eliminated in the case of Finland (2013Q1-Q2). In contrast, to account for an abrupt but short-lived recession, which, given the harmonised parameters, is not captured by the algorithm, judgement has also been introduced for Slovakia (2008Q4-2009Q1).

1.1.1.2 Business cycle dating of the euro area indicators

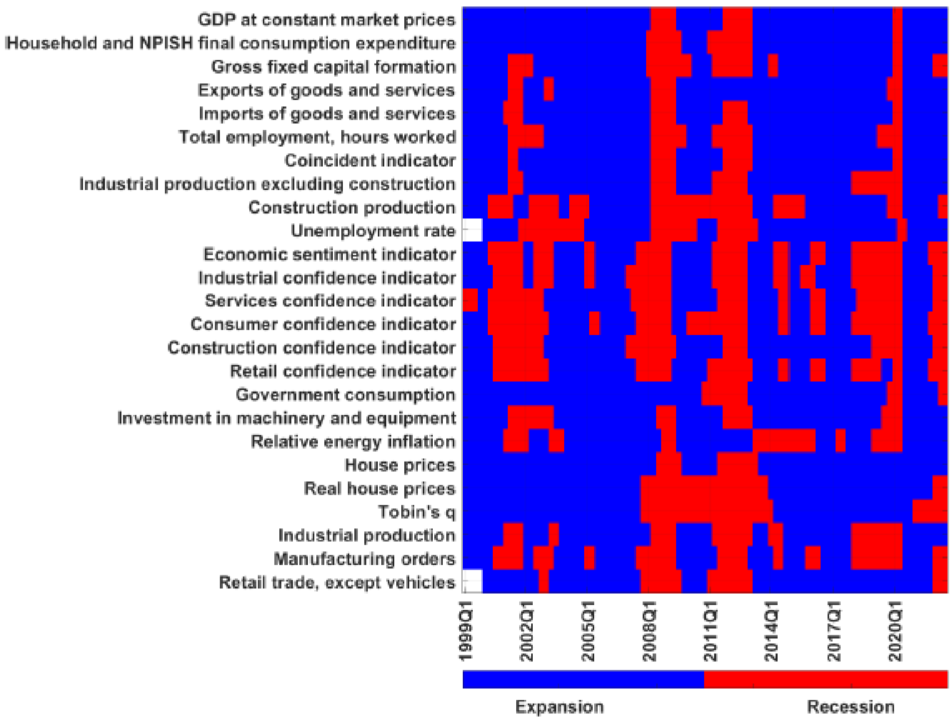
Classical business cycle dating is also applied to a wide range of macroeconomic indicators for the euro area. Incorporating additional macroeconomic variables is useful for several reasons. First, as GDP data are subject to considerable ex post revisions, they are an imperfect indicator of the state of the business cycle in real time. Second, the additional macroeconomic variables provide complementary information about the state of specific aspects of the economy, for example the economic phase of the labour market, or of the manufacturing or services sectors. Third, some of these indicators are more cyclical than GDP, thus possibly strengthening (or weakening) the conclusions reached on a particular cyclical phase based on analysing the GDP series alone. Fourth, given their additional information content, the relevant macroeconomic aggregates could be used in a complementary multivariate analysis, to derive alternative synthetic indicators for aggregate economic activity or to cluster the turning points. Fifth, the additional indicators might have systematic lead/lag properties relative to the cycles in GDP, whereas their own cyclical phases might reveal distinct characteristics for the different recessionary/expansionary episodes of the economy.

In order to achieve a comprehensive and reliable assessment of the cyclical properties of economic activity and to substantiate the economic narrative for the separate phases, the multivariate exercises presented below include a broad set of indicators. As the purpose of the multivariate dating exercises is not to derive a synthetic indicator showing leading properties for GDP, they do not include only macroeconomic aggregates which tend to lead the GDP turning points. In fact, the purpose of the multivariate dating exercises is to provide a complementary assessment on the business cycle phases of the economy, in view of the limitations of the single GDP series (historical revisions) and of the univariate algorithm (e.g. in episodes with flat growth). Hence, they include both leading and lagging indicators, which provide useful complementary information and help to substantiate the economic narrative for each episode. Furthermore, in order to analyse the distinct characteristics of the separate historical recessionary and expansionary phases of the economy, it is useful to also include in the multivariate dating exercise indicators with cyclical properties other than those of the GDP series in terms of higher/lower durations, amplitudes, slopes, etc. (see **Annex 1**).

Looking at the business cycle chronology across indicators, the three major episodes of synchronised recessions across the EU countries identified in Section 1.1.1.1 and the downturn in the early 2000s also appear to be periods of widespread contraction across a range of euro area indicators (Chart 3). It is worth noting that the heatmap based on this univariate analysis suggests a relatively widespread weakness in activity in 2001, a point further highlighted by several multivariate approaches. While some indicators enter contractionary territory only with a lag, others appear to have signalled forthcoming recessions in advance. For example, confidence indicators reached their peaks and turned into contractions ahead of the GFC, the sovereign debt crisis and the COVID-19 recession. However, these indicators have much more volatile cycles than GDP – as exemplified by the lower durations and steeper slopes of their economic phases – and also tend to give many false signals of imminent recessions. Hence, while not reliable as leading indicators without further analysis, they are very useful in analysing the specific features of each business cycle phase (e.g. concluding that a phase is predominantly confidence-driven, manufacturing-driven, etc., or relatively broad-based across sectors and indicators). In addition, one possible way to alleviate the false signal problem would be to introduce a threshold rule (an additional parameter in the algorithm) for the turning points of some indicators, which could reduce their observed high cyclicality.[5]

Chart 3

Macroeconomic aggregate indicators for the euro area



Source: Eurostat and authors' calculations.
Note: The blue colour indicates expansions and red indicates contractions. Tobin's q refers to the ratio of the residential property price index to the housing investment deflator. Latest observation: 2022Q3.

[5] For example, for the economic sentiment indicator, a threshold of 97 could provide a better leading signal.

Measures for the manufacturing sector, such as industrial production, have historically been highly cyclical, with short and steep economic phases. Notably, industrial production excluding construction, while giving some false signals in the more distant past, has more recently led the peaks in the last two recessions, and signalled the end of the sovereign debt crisis with a lead of one quarter.

Turning to key business cycle statistics, one observation is that series pertaining to the labour market are among the least cyclical. The employment and unemployment rate indicators, together with private consumption and retail trade, show relatively long durations with small steepness of the economic phases (**Annex 1, Chart A1.2**).

Looking at the duration of the phases across the macroeconomic indicators, while most have an average contractionary phase duration within one standard deviation of that of GDP, only a few – consumption, retail trade, employment and turnover in services – are within the respective one standard deviation range for expansions. While all indicators have a lower expansionary phase duration than that of GDP, the values for private consumption and retail trade are relatively close to it. In contrast, certain confidence indicators show the lowest expansion duration. Regarding the average slope of the economic phases of the euro area indicators, employment, unemployment and consumption not only have the least steep slope during recessions, but also do not record very steep rises during expansions. The export expectations and new orders, and sentiment and confidence indicators show the steepest average contractions and expansions.

For the amplitude, gain/loss and excess statistics, the picture is relatively heterogeneous across indicators and economic phases. While most indicators, apart from the average gain in expansions, fall within one standard deviation of the GDP business cycle statistics, they still show a relatively wide range of average amplitudes, cumulative gains or losses and excesses (**Annex 1, Chart A1.2**). For the latter, the GDP pattern of a negative excess in recessions (a convex trajectory) is shared by most indicators, including private consumption (but not retail trade or consumer confidence). Similarly, a positive excess in expansions (a concave trajectory), similar to GDP, is shown by most indicators, including exports, retail trade and construction.

Box 3
Global business cycle dating based on the MBBQ algorithm

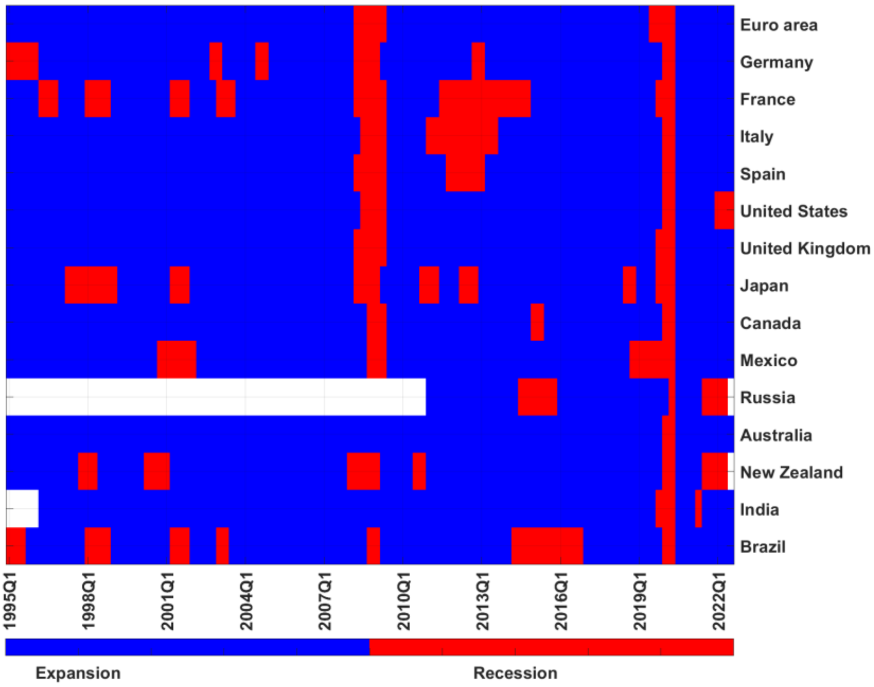
Prepared by Alina Bobasu

A useful exercise is to compare the features of the euro area business cycle with those observed in the other main economies at the global level. To this end, in order to date the global business cycle, we use quarterly national accounts data up to the third quarter of 2022 for a number of economies outside the euro area. Global activity is measured by real quarterly world GDP and its components, as well as global industrial production and sentiment indicators derived from a PPP-weighted aggregation of national GDP data based on national sources. We also distinguish between business cycles for advanced economies and emerging economies.

At the country level, **Chart A** (showing selected advanced and emerging market economies) identifies two episodes of broadly synchronised recessions (the GFC and COVID-19), as well as many cases of heterogenous country developments. At the indicator level (**Annex 1, Chart A1.3**), we identify three major episodes of contractions in GDP and its components, also highlighted by high frequency information (2001Q4, 2008Q4 and 2019Q4). These contractions were broad-based across components and were also indicated by global industrial production and economic sentiment. In contrast, there are contractionary episodes suggested by high frequency indicators, which, however, are not supported by national accounts data.

Chart A

Business cycle dating chronology for global activity



Source: Eurostat and authors' calculations.
Notes: ECB staff calculations. China is not reported as the automatic procedure fails to identify cyclical phases based on its GDP. Latest observation: 2022Q3.

Relevant business cycle indicators, such as the duration of a phase, show that in both expansions and recessions, consumption and gross fixed capital formation show durations comparable to those of global GDP, while imports and exports show lower durations in both phases of the cycle (**Annex 1, Chart A1.4**). These findings, mainly driven by the advanced economies, are broadly comparable to the results for the euro area, in particular as regards private consumption.

1.1.2 Multivariate MBBQ algorithm results

While GDP is the best single indicator to measure economic activity, cross-sectional analysis (over groups of countries or macroeconomic aggregates) provides complementary information and helps to better approximate the state of the economy. There are different ways of incorporating multiple series into a business cycle dating procedure. We discuss two alternative approaches: (i) dating of turning points after aggregating the time series, i.e. average-then-date methods, implemented with an inverse variance weighted coincident index or principal component analysis; and (ii) a method that aggregates already dated turning points, i.e. a date-then-average approach, based on a clustering analysis.

1.1.2.1 Turning points in an aggregate indicator

In this approach, the individual series (macroeconomic aggregates or country GDP data) are aggregated and then dated using the MBBQ algorithm. The aggregation could be based on a synthetic index, e.g. a coincident indicator, or on a principle components analysis.

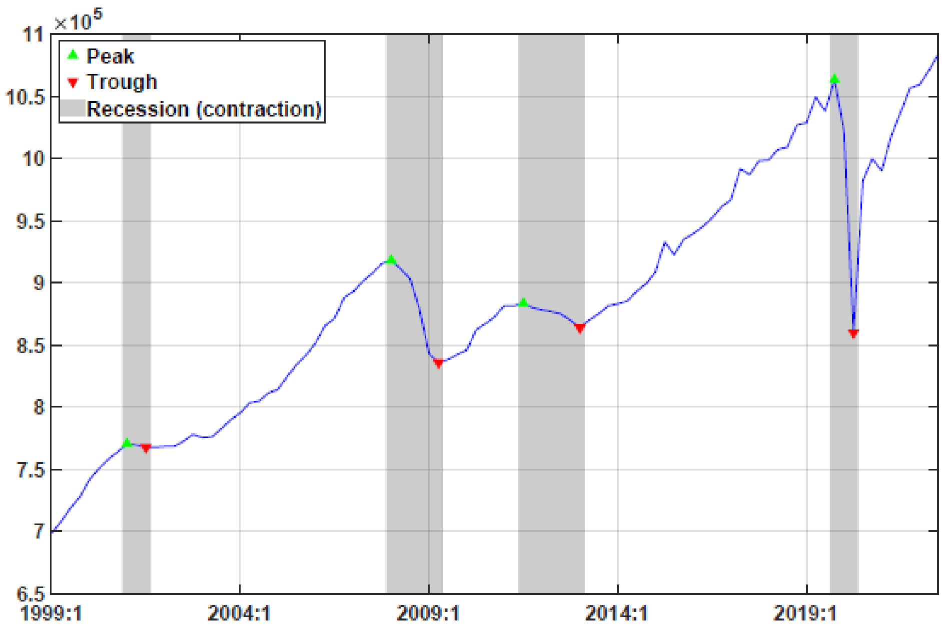
a. Coincident indicator

We follow Stock and Watson (2014) and construct a coincident index based on inverse standard deviation (ISD) weighting. With this method, a coincident series is constructed based on the summation of different series, weighted with their inverse relative variance:

$$C_{it}^{ISD} = exp\left[\sum_{i=1}^{3} \alpha_i \ln(X_{it})\right], where\ \alpha_i = \frac{\frac{1}{s_i}}{\sum_{j=1}^{3} s_j^{-1}}$$

Chart 4

Coincident indicator, based on macroeconomic aggregates for the euro area



Source: Eurostat and authors' calculations.
Notes: Shaded bars show dated recessions. Latest observation: 2022Q3.

The constructed coincident indicator based on euro area consumption, investment and exports is shown in Chart 4. The coincident indicator identifies the financial and sovereign debt crises, based on these macroeconomic aggregates. In addition, the indicator shows a softening in activity in the period 2001Q1-Q3, as well as around 2002Q4 to 2003Q2, which is not identified as a contractionary phase. Lastly, the contraction in 2020Q1-Q2 is also correctly identified by this index.

b. Principal component analysis

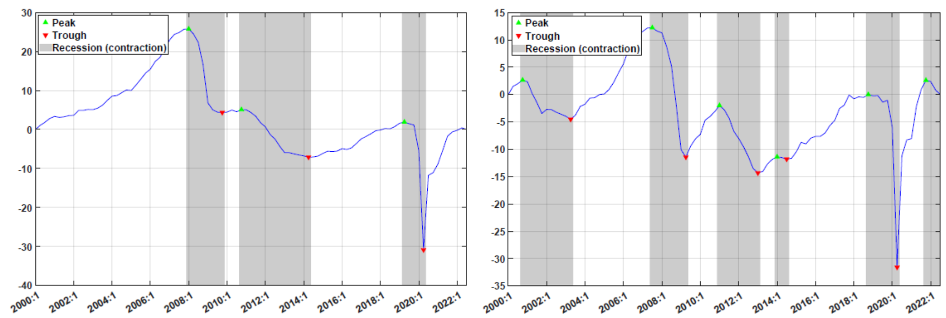
Another commonly used average-then-date procedure, as proposed by Bry and Boschan (1971), is the principal component analysis (PCA), which allows for the extraction of a common cyclical component from numerous series. The procedure converts the original variables into a set of orthogonal, linearly uncorrelated indicators called principal components. The first principal component, which has the greatest variance, is commonly regarded as a proxy for the business cycle.

PCA dating for the euro area (EA) countries, based on the log of their real GDP series, is illustrated in Chart 5, panel a), while panel b) shows the PCA dating of the euro area macroeconomic indicators. The chronology obtained by dating the EA countries' first principal component results in peaks in 2008Q1, 2010Q4 and 2019Q2, while the chronology based on macroeconomic indicators suggests peaks in 2000Q4, 2007Q3, 2011Q1, 2014Q1, 2018Q4 and 2021Q4. For the three synchronised major recessions, both of these indicators suggest earlier peaks than the univariate GDP results. Regarding the dating of troughs, both indicators suggest turning points in the major recessionary episodes that are relatively aligned with those resulting from the univariate GDP dating. It is worth noting that dating the principal component based on the macroeconomic indicators emphasises the economic weakness from 2001 to 2003, as reflected in investment, exports and construction, as well as in many confidence indicators, thus providing highly relevant complementary information to the univariate dating results described in the previous section.

Chart 5

Principal component

a) Based on EA countries' GDP data **b) Based on EA macroeconomic indicators**



Sources: OECD, Eurostat and authors' calculations.
Notes: Shaded bars show dated recessions. Latest observation: 2022Q3.

1.1.2.2 Aggregation of turning points

The second approach implemented in the automatic tool and reported here is to aggregate the already dated turning points within a specific period by choosing a date that is, on average, the closest to the identified turning points, as proposed by Harding and Pagan (2006). The first step in the analysis requires splitting the points into clusters. Since the original paper of Harding and Pagan (2006) does not discuss an automated method that can easily be applied to many series, we had to achieve this by building an agglomerative hierarchical cluster tree and splitting the turning points into clusters, based on distance. The idea is that the points that are closest to each other are part of the same cluster. The next step implies finding, for each cluster, a date that minimises the median distance to all the turning points within that cluster. Since the median value is discrete, it is possible that the algorithm will identify more than one point within the same cluster. In this case an additional step is applied using expert judgement and previously obtained results. Expert judgement might also be necessary to ensure that peaks and troughs alternate. The clustering of turning points is a major part of the work of Burns and Mitchell (1946).

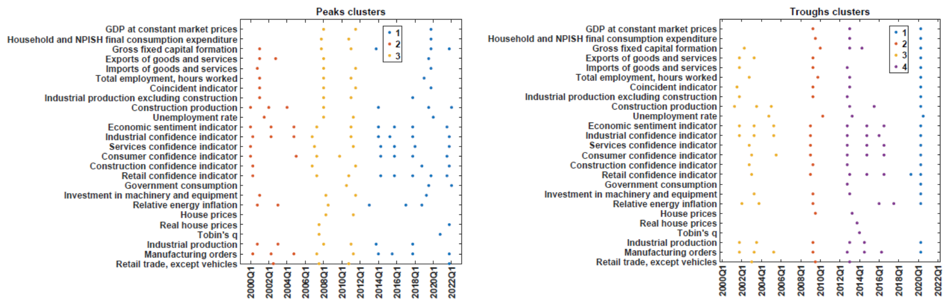
Similar to the results described above (obtained with univariate and multivariate settings), the cluster analysis identifies three major periods of contraction and an additional weak growth period in early 2001. **Chart 6** shows the clusters of turning points for the macroeconomic indicators for the euro area, with panel a) focusing on the peaks and panel b) focusing on the troughs. Each cluster is identified with a unique cluster ID that is presented in the legend. **Chart 7** shows the clustered turning points across the EA countries. Starting chronologically, the first peak identified is around 2001Q1 (with candidate points from 2000Q2 to 2001Q2). The time span of the economic weakness is around two years, with the trough identified in 2003Q1. The next period of economic decline corresponds to the GFC, with the peak in 2008Q1 and the trough in 2009Q2 (and 2009Q1 and Q3 are also candidates). There is also a clustering of turning points around the beginning of the sovereign debt crisis, but since they are very close to those of the GFC, the algorithm considers them as the same cluster, with the trough in 2013Q1. The last peak identified corresponds to 2019Q2 (across indicators) or 2019Q4 (across countries), with economic activity weakening at the end of 2019 and entering a decline at the start of 2020, caused by the COVID-19 pandemic. Both datasets identify a clustered through at 2020Q2.

Chart 6

Clusters based on EA macroeconomic indicators

a) Peaks

b) Troughs



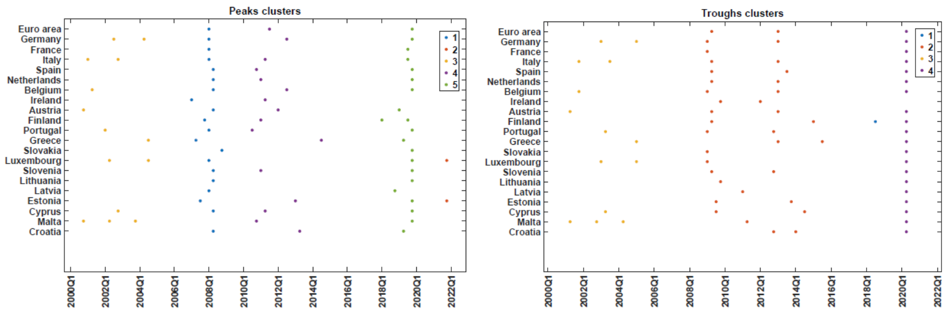
Sources: OECD, Eurostat and authors' calculations.

Chart 7

Clusters based on EA countries

a) Peaks

b) Troughs



Sources: OECD, Eurostat and authors' calculations.

The date-then-average method implemented in this part represents just one of the proposed approaches in the field, chosen for its simplicity and complementarity to the other results. An alternative available method is proposed by Stock and Watson (2010), who compute the reference cycles as the means of individual series of turning points. In addition, Stock and Watson (2014) innovate by considering turning points as population concepts. Both approaches allow inference, unlike the method utilised here, as proposed by Harding and Pagan (2006) or the modified algorithm of Harding and Pagan (2016), but require a given sequence of business cycles. Furthermore, in a recent paper using the date-then-average approach, Camacho et al. (2020) assume that the peaks and troughs result from a model of a mixture of an unspecified number of separate bivariate Gaussian distributions, whose different means are the reference turning points. These dates break the sample into separate reference cycle phases, whose transitions are determined from a Markov chain, restricted as in multiple structural change models.

1.2 The deviation cycle approach

The deviation (or growth) cycle approach is an alternative concept to business cycle chronology, in which economic phases are defined according to deviations of the GDP growth rate from an estimated trend growth rate: see, for example, Artis et al. (2003). This method allows for a more detailed classification of the phases of the business cycle than in the classical approach, with higher relevance from a policy perspective, provided that an estimate of the trend is also available. The main drawback of the approach is its dependence on an unobservable trend GDP measure that can only be estimated using a set of assumptions about the long-run behaviour of the economy and is subject to revisions over time.

The deviation cycle approach differentiates between four phases of the business cycle, providing more information about the state of the economy between peaks and troughs than the classical method. While the binary classification provided by the classical approach (being in recession vs. not being in recession) is easier to communicate to the general public, its usefulness for demand side policies is more limited, as an economy is typically in a non-recessionary phase more than 90% of the time. Furthermore, a non-recessionary state does not indicate whether inflationary pressures are building up or not. Using a deviation cycle approach – and employing OECD terminology, see OECD (2020) – we can distinguish between four phases of the business cycle: *expansion*, when the cycle is positive and increasing (i.e. actual GDP and its growth are above its trend and the trend growth, or the output gap – defined as the log difference between GDP and its estimated trend – is positive and increasing); *downturn*, when the cycle is positive but decreasing; *slowdown*, when the cycle is negative and decreasing; and *recovery*, when the cycle is negative but increasing (**Annex 1, Table A1.1**).

This section employs an unobserved components model to implement the deviation cycle approach, in the same way as Artis et al. (2003). The unobserved components model (UCM) used in this exercise is a state space model built around a Cobb-Douglas production function, as in Tóth (2021)[6]. This modelling approach identifies the long-term trend – and simultaneously an estimate of the business cycle – incorporating more structural relationships than the traditional production function approach, which is typically based on univariate filters. The model is backward-looking and estimated with Bayesian methods, employing the Kalman filter and smoother to jointly decompose six key observable variables (real GDP, unemployment rate, labour force participation rate, hours worked per person, core inflation and wage growth) into trend and cyclical components. It relies on several economic relationships, such as wage and price Phillips curves and an Okun's law type relationship. Two additional variables enter the model as exogenously determined observables, namely capital stock and working age population. The model is estimated for the euro area and its member countries using the same benchmark specification, with the same set of priors on the model parameters. The

[6] The model has been discussed and adopted by the WGF in the context of its Task Force on Potential Output. This section builds on the benchmark specification of the model, which has been estimated on euro area and country-specific data, on a sample from 1995Q1 to 2019Q4.

advantage of applying the same modelling approach to all countries is that the resulting business cycle estimates are fully comparable from a methodological perspective.

The UCM-based deviation cycle approach is applied to the euro area and its 19 Member States up to the end of 2022. Besides providing a range of measures of the business cycle, such as the output gap and its supply side components – i.e. the unemployment gap, the average hours worked gap, the participation gap and the total factor productivity (TFP) gap – the exercise allows for the analysis of cyclical co-movements or synchronisation across EA member countries (see **Chapter 2**) along several dimensions. The classification introduced above can be applied for the purposes of determining business cycle phases by country and by supply components, such as the TFP gap or the unemployment gap (i.e. the same rule is used for all variables, except for the unemployment gap, where the criteria are inverted, as the unemployment rate is assumed to be countercyclical).

The four-phase classification of the state of the business cycle in terms of GDP shows a pattern that is broadly similar across euro area countries, starting from the run-up to the GFC (Chart 8). The financial crisis was preceded by a relatively long period of expansion that started in the mid-2000s, morphing into a downturn and a relatively short slowdown phase. These were followed by a recovery phase – except for Greece and Spain – starting in 2009, which was interrupted by another slowdown due to the sovereign debt crisis. Among the largest five euro area economies, only Germany avoided a slowdown – except in a single quarter – in this period. The sovereign debt crisis was followed by a long recovery in the euro area – with the notable exception of Germany, which alternated between expansionary and downturn phases – that turned into an expansion in 2017. The expansion phase was again followed by a downturn in the euro area and most of its Member States that started in 2019. The extraordinary shock of the pandemic, starting in the first quarter of 2020, was identified as a slowdown phase in most countries, with the second quarter of 2020 accounted for as a slowdown across all countries.

Chart 8

Business cycle phases in the euro area – output gap

(level)

Source: Authors' illustration. Data sample: 2000Q1-2022Q3.

2 Business cycle synchronisation

2.1 Motivation and stylised facts

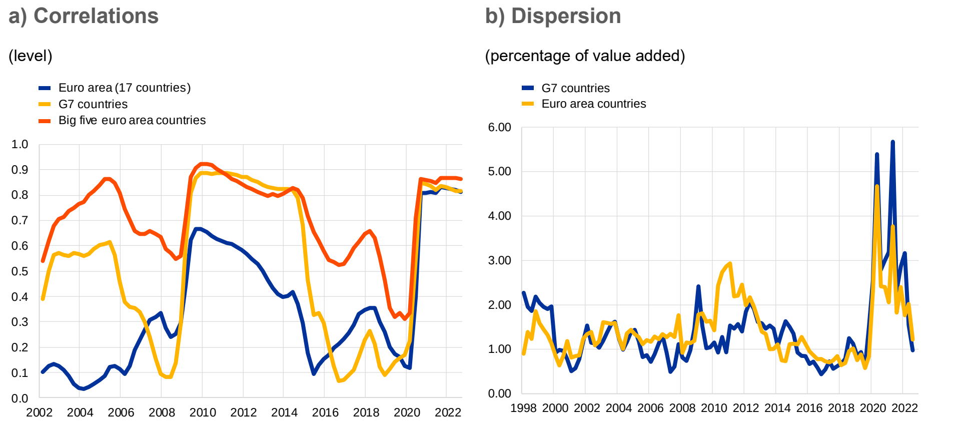
In the context of a well-functioning monetary union, a natural question to explore is whether synchronicity has increased over time. The endogenous optimum currency area (OCA) hypothesis (Frankel and Rose (1998)) promotes the view that the degree of business cycle synchronisation among the participating countries in the currency area should increase over time, particularly in an environment of deepening financial and trade integration in the European Union. As a result, the role of idiosyncratic shocks as drivers of individual countries' economies would be expected to weaken over time, overall facilitating the effectiveness of the single monetary policy. These conclusions, however, hinge on specific assumptions about a sufficient degree of integration in factor markets and real and nominal flexibility in goods and labour markets. In practice, insufficient structural reforms in some countries may tend to block, at least partially, those adjustment mechanisms, particularly if they are market driven. Therefore, the question of whether a monetary union is undergoing a favourable development in its underlying OCA conditions is not warranted, needing to be empirically examined periodically.

The literature that examines business cycle synchronicity among connected regions is extensive, offering rather mixed results, depending on the period, set of countries and measures considered. Miles and Vijverberg (2018) show that the endogeneity of the OCA does not necessarily lead to an increase in business cycle synchronisation. While adopting a common currency may increase synchronisation for countries ready for a common currency (i.e. those that have already achieved sufficient real and nominal convergence), it may also diminish synchronisation for countries that did not show sufficient convergence before monetary unification. Campos et al. (2019) conducted a meta-regression analysis based on almost 3,000 estimates of business synchronisation from 62 studies and concluded that synchronisation across euro area countries increased from about 0.4 before the introduction of the euro in 1999 to 0.6-0.7 afterwards. A comparable trend can be observed in non-euro countries, but to a much lesser extent. The study also concluded that despite the observed increase in synchronisation, there is considerable heterogeneity across countries and regions.

A simple correlation analysis of GDP growth among the euro area countries, a rough measure of synchronicity, suggests prima facie that synchronicity increased gradually in the first years of the Economic and Monetary Union (EMU), and then increased sharply around GFC. While this result should not be surprising, as the GFC was a severe common negative shock, as will be shown later, more sophisticated model-based measures of synchronicity provide a much more nuanced picture. Nevertheless, from the perspective of sheer statistical correlation, among the euro area countries (and also among the group of seven advanced economies (G7), which are interlinked but independent economies), the correlations reached a peak during the financial crisis, before gradually declining over the recovery period, particularly after 2014 (**Chart 9**, panel a). The temporary surge in synchronicity thus measured should therefore not be confused with greater integration driven by currency union dynamics. Indeed, the sudden co-movement of countries when a major common shock occurs (such as the GFC or, more recently, COVID-19) highlights one of the difficulties in interpreting developments in synchronicity measures. Nonetheless, this measure also suggests that later on, in the course of 2017, there was a renewed trend towards synchronisation (of a more genuine kind) across euro area countries. Overall, these considerations illustrate the need to distinguish between "genuine" synchronicity of business cycles within the euro area, supported by OCA-type factors, and episodes of increased correlation, brought about by large and common (and typically external) shocks, which generate positive co-movement in fluctuations but are not evidence of increasing integration or improving OCA conditions.

Chart 9

Business cycle synchronicity in the euro area and G7 countries



Sources: OECD, Eurostat and authors' calculations.
Notes: The measure of business cycle correlation is a weighted average of pairwise cross-country correlations of real GDP growth, as in Stock and Watson (2008). The pairwise correlations have been computed over a five-year rolling window. For the euro area, two different groupings are considered: the "euro area" (all euro area countries, excluding Malta and Ireland, owing to data availability) and the "big five" euro area countries (the five largest euro area economies). The dispersion of growth in the euro area is measured as the weighted standard deviation of year-on-year growth in real GDP in the 19 euro area countries, excluding Ireland to avoid distortions in the analysis caused by the high volatility of Irish GDP. The dispersion of growth in advanced economies, proxied by the G7 group (Canada, France, Germany, Italy, Japan, the United Kingdom and the United States) is the unweighted standard deviation of year-on-year growth in real GDP for those countries. Latest observation: 2022Q3.

Over the last two decades, synchronisation has been higher among the five largest euro area economies relative to a broader group of 17 euro area countries. Recently, and unsurprisingly – as with the GFC – the pandemic crisis led to a marked increase in synchronisation for all groups of countries, given the global nature of this crisis.

The dispersion of quarterly real GDP growth across euro area countries since the inception of the EMU does not differ significantly from that of other advanced economies (**Chart 9**, panel b). The dispersion was very high in the aftermath of the GFC, particularly for the G7 countries. In the case of the euro area, growth dispersion was particularly high during the sovereign debt crisis, implying that the impact of the shocks across countries was very heterogenous. Since then, growth dispersion progressively decreased for both the euro area and the G7 countries, until the outbreak of the COVID-19 crisis. This had a very extensive and uneven effect across countries globally, leading to historically high levels of growth dispersion.

Against this background, this chapter primarily examines the basic synchronicity features of real economic activity in the euro area and its Member States or regions, and investigates whether, and to what extent, dynamics between economic cycles (in particular their degree of synchronicity) have changed. In the next sections, a variety of measures of business cycle synchronisation are proposed, across euro area countries and with respect to the euro area aggregate, based on different approaches. A more granular analysis is then conducted by looking at the role of sectoral and firm-level idiosyncratic shocks in explaining economic fluctuations.

2.2 Synchronisation in the euro area

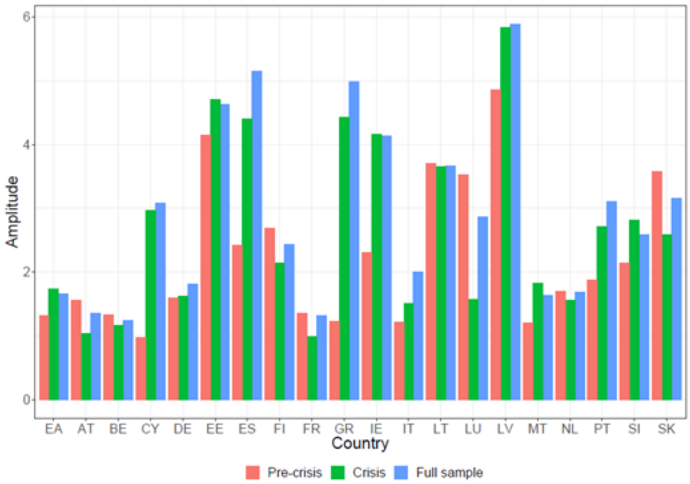
2.2.1 A deviation cycle approach

This section investigates the co-movements between the estimated business cycle for the euro area aggregate and those of the euro area Member States. The business cycle is approximated with the estimated cyclical components in a UCM, and therefore corresponds to the deviation cycle approach. Although this method is based on unobservable variables that are surrounded by estimation uncertainty, the harmonised nature of the procedure ensures that the resulting business cycle measures are comparable from a methodological perspective. In particular, the aggregate and the country level cycles are calculated independently from each other, i.e. the procedure "does not know" that the euro area data are aggregated from the country data.

First, the analysis looks at country-specific business cycle amplitudes in the euro area, proxied by the standard deviation of the estimated cyclical components. The focus is on the pre- and post-GFC sample periods, subsequently also compared with the full sample period. Considerable differences in the amplitudes of business cycles across euro area countries can be observed (**Chart 10**). As might be expected, given the depth of the GFC recession, business cycle amplitudes generally increased after the GFC, albeit to a relatively small extent and with strong cross-country variation overall. For the euro area as a whole, the results also point to a relatively contained increase in its business cycle amplitude between pre-GFC and post-GFC periods.

Chart 10
Amplitude of business cycles

(percentages)



Source: Authors' calculations.
Note: The amplitude is the standard deviation of the cyclical component or output gap.

The beta coefficient of simple regression analysis between each country business cycle and the euro area cycle indicates a positive contemporaneous co-movement (**Chart 11**, panel a). The beta coefficient for Germany (0.5, which is one of the smallest found across countries) is roughly only one-fifth of the corresponding beta for Spain (which is the largest coefficient, at around 2.5). The smaller economies, including Greece and Ireland, also show relatively large betas, with point estimates above 1.5, while other large euro area economies, such as France, the Netherlands and Italy, show less sensitivity to the euro area cycle. Divergences across country cyclical positions would therefore be amplified in response to aggregate fluctuations.

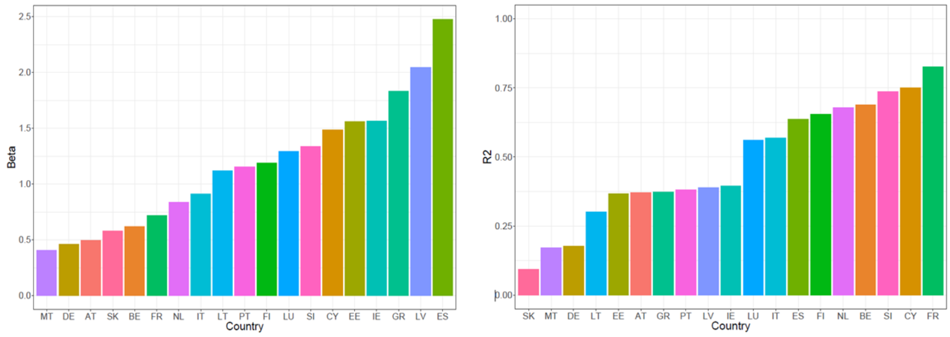
The euro area cycle is also an important factor in explaining the proportion of the variability of domestic business cycles, as proxied by R-squared statistics from the regression analysis (**Chart 11**, panel b). Despite a large degree of heterogeneity, the variation in most country-level cycles is indeed tightly linked to the euro area cycle. With the exception of Germany, the largest euro area countries show a tight correlation to the euro area business cycle, with R-squared statistics ranging from above 50% for Italy to around 80% for France, while lower values are generally observed among the smaller economies, including Greece, Portugal and Ireland. While Germany is the largest euro area Member State, its economy is more industry- and export-oriented than the other large euro area countries, and thus more connected to global factors, which probably accounts for this result.

Chart 11

Relevance of the euro area cycle for domestic cycles

a) Contemporaneous effect (regression coefficients)

b) Percentage of variance explained (R-squared)



Source: Authors' calculations.

Finally, looking at estimated contemporaneous beta coefficients and business cycle amplitudes together, there is a strong positive correlation between the elasticity of domestic cycles to the euro area cycle and country-level business cycle volatility. This close correlation may indicate that the much greater variability observed in some euro area countries could be due to certain economic structures being more reactive to the euro area cycle than others, such as dependence on tourism and trade links concentrated in the rest of the euro area.

Next, two measures of business cycle concordance based on Mink, Jacobs and De Haan (2012) are presented for a group of 18 euro area Member States. These are: *synchronicity*, measuring the phase concordance of each cycle and the reference cycle, and *similarity*, looking at the absolute difference between their amplitudes.[7] The average (cross-country) synchronicity and similarity are a measure of total business cycle co-movements at euro area level. The reference cycle used is the median output gap, calculated across all the countries under analysis.[8] Aggregate measures of synchronicity and similarity are normalised to lie between zero (minimal cycle coherence with euro area level) and unity (maximal cycle coherence with euro area level). In addition to its good statistical properties, the median reference cycle is also almost identical to the euro area output gap, and therefore relatively straightforward to interpret. The analysis focuses on three groups of countries: i) a group of euro area countries more acutely stressed during the sovereign debt crisis (Greece, Ireland, Italy, Portugal and Spain); ii) a group of old Member States (Austria, Belgium, Germany, France, Netherlands, Finland and Luxemburg); and iii) a group of new Member States (Cyprus, Estonia, Latvia, Lithuania, Slovenia and Slovakia).

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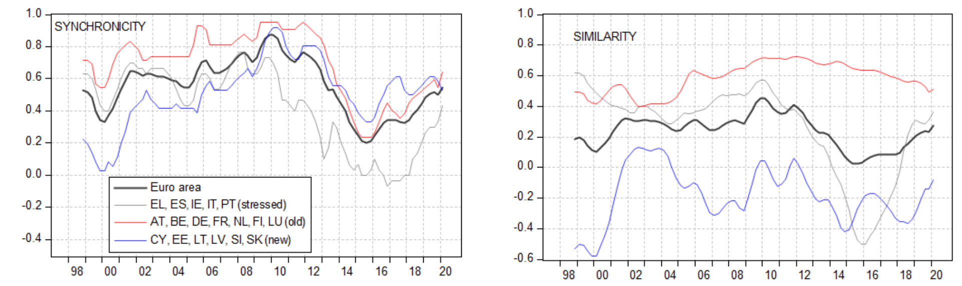
7 Mink, Jacobs and De Haan (2012) provide two simple examples to illustrate how (over-)reliance on correlation coefficients between output gaps can be misleading. Two cycles, for example, may be of the same sign throughout the sample, but at the same time only weakly correlated. Second, two perfectly correlated cycles do not need to have similar amplitudes. In both cases, correlation between business cycles is arguably misleading for the purposes of common monetary policy.

8 The median reference cycle maximises the overall synchronicity and similarity simultaneously (Joag-Dev, 1989).

Chart 12

Synchronicity and similarity of business cycles in the euro area



Source: Authors' calculations.
Notes: Synchronicity and similarity are three-year moving averages.

The synchronicity measure suggests that the phase synchronicity of the business cycles of euro area members increased steadily from the end of the 1990s to the peak of the GFC, around 2008 (**Chart 12**). This synchronicity at aggregate euro area level was driven by all groups of countries: members that were stressed and old members were becoming more synchronised with the overall euro area economy, while new members (then mostly outside the Monetary Union) were rapidly catching up. The synchronicity measure peaked during the GFC, as all countries were hit by the same global shock. Subsequently, during the sovereign debt crisis, business cycle phase synchronicity weakened. Those countries that were under particularly strong stress during the debt crisis were also dominant drivers of decreased coherence between business cycles. Other European countries – both old Member States and new euro area members – also contributed to that trend. Importantly, the decrease in measures of synchronicity observed after 2011 brought the measures in absolute terms to levels lower than those recorded at the start of the EMU in 1998. This indicates the major impact of the sovereign debt crisis in the alignment of macro fluctuations across euro area countries in the context of a visible and persisting divide, mainly between the stressed countries and the rest.

Finally, the trend reversed around 2014-15, largely supported by the recovery dynamics at the euro area level, in particular the launch of the ECB's asset purchase programme (APP). The APP also stabilised financial markets and pushed down borrowing costs for both the private and public sectors, particularly in the stressed countries. Since 2014-15, a recovery in coherence among business cycles within the euro area has been observed. When looking at similarities between cycle amplitudes, the results can be summarised in the same way as for phase synchronicity. Most importantly, the overall divergence between the amplitudes of output gaps was largely driven by the stressed countries but was also present (to a lesser extent) in other euro area countries. Overall, similarity between cycle amplitudes has been recovering since 2015, although it has not yet reached the levels of 2005-06.[9]

9 The main results appear robust, as they remain broadly unchanged when considering alternative output gap measures (e.g. based on a Hodrick-Prescott filter).

Box 4

Business cycles through the lens of an optimum currency area index for the euro area

Prepared by Davor Kunovac, Diego Rodriguez Palenzuela and Yiqiao Sun

Analysis of euro area business cycle drivers can be used to deliver insights on its optimum currency area (OCA) properties. The extent to which the euro area can be considered an OCA depends, inter alia, on the degree to which common shocks have symmetric impact across its regional components (typically countries). Estimating the magnitude (which may change over time) of the symmetric shocks of euro area business cycle fluctuations enables the evolution of the euro area to be characterised with respect to its OCA conditions. Such monitoring of OCA conditions is particularly relevant in a newly established monetary union, as it unfolds and develops. Our starting point is an analysis of OCA conditions based on the identification of three underlying business cycle shocks, namely global shocks, shocks that are non-global but common in the euro area and idiosyncratic country-level shocks. This modelling framework is then employed to gauge the time-varying influence of each type of shock on the euro area and country-level business cycles. This analysis, in turn, delivers an indicator of OCA conditions t.

Even though the OCA properties of the euro area have been at the centre of reflections on the design of the EMU in Europe since its inception, there is no single, consensual way to measure the "optimality conditions" of a monetary union. The early OCA theory in the 1960s defines nominal adjustment flexibility and international mobility of factors as prerequisites for the formation of a currency union (Mundell, 1961). While these criteria are difficult to measure, some "empirical" OCA properties were put forward in the 1990s. Several contributors, including Bayoumi, Eichengreen et al. (1996), Masson and Taylor (1993) and Alesina and Barro (2002), suggested that similarity of economic shocks governing economies in a currency union would qualify for a "catch-all" OCA property incorporating the interaction between several of these characteristics. This idea is also particularly appealing as Frankel and Rose (1998) argued that eligibility for a currency union could be an endogenous process, as the country's economic conditions change after joining and can therefore only be evaluated ex post.

First, country-specific and common shocks are identified, using zero and sign restrictions within an open-economy Structural Vector Autoregression (SVAR) set-up, as shown in Table A.

Table A

Zero and sign restrictions at t = 0

	GDPi	GDPREA	GDPRoW
Country-specific shock	+	0	0
Common shock (euro area)	+	+	0
Common shock (world)	+	+	+

Source: Authors' calculations.
Notes: The endogenous variables included in the SVAR refer to the real GDP growth of a euro area country I, the rest of the euro area (REA) and the rest of the world (RoW). "+" restricts the endogenous variable to react positively to a shock and "0" shuts down any reaction of the endogenous variable to a shock.

Country-specific shocks cannot affect the rest of the euro area (REA) or rest of the world (RoW) at any point in time. In order to identify them, a block exogeneity is imposed. In contrast, common shocks affect the individual country and the REA simultaneously, in the same direction. However, some shocks, common to the entire euro area, may have asymmetric impacts on different euro area Member States. Consequently, asymmetric shocks are defined as including both country-specific (local) shocks and the aforementioned particular type of common shock. Such a definition of asymmetric shocks captures the idea that whenever a country's economy is predominantly driven by country-specific or common shocks with an asymmetric impact, membership of the monetary union is more costly.

We proceed by estimating the SVAR for each of the euro area countries and evaluate the relative importance of country-specific, symmetric euro area and symmetric global shocks based on the historical decomposition of GDP growth. The OCA theory essentially implies that a monetary union is appropriate if common shocks have a certain degree of predominance. On the basis of this idea, we use the estimated shocks identified with the SVAR to construct our OCA measure for the euro area. Specifically, we draw on two specific quantifiable criteria. First, it is preferable from an OCA perspective if the importance of symmetric shocks is high on average, as monetary policy in a currency union is more challenged the more the specific regional shocks predominate. This is a necessary condition for a monetary union to be an OCA and means that the cross-country average of the relative importance of symmetric shocks (μ) is high (Chart A, panel a). Second, it is preferable from the OCA perspective if a high average value of importance of symmetric shocks is attained in a landscape of more homogeneous country structures, i.e. for a given average level of importance of common symmetric shocks, ideally all countries make similar contributions to that average measure. It follows that the cross-country standard deviation of the relative importance of symmetric shocks (σ) should be low (Chart A, panel b) in terms of a sound OCA indicator.

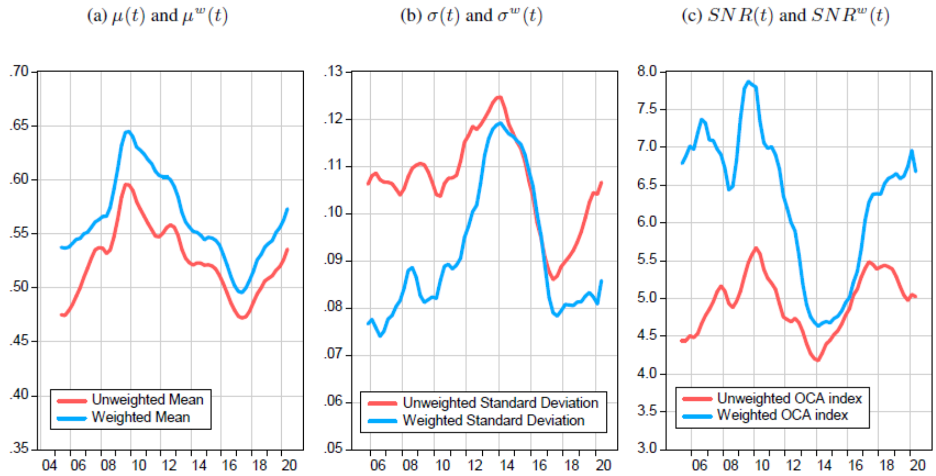
A straightforward candidate for such an intuitive time-varying OCA index, which embeds the two requirements simultaneously, is the signal-to-noise ratio (SNR), μ/σ. Chart A, panel c) compares two versions of that ratio. The first version assumes that equal weight is attached to each country (unweighted OCA index), while the second version uses country GDP to calculate pertaining weights (weighted OCA index) when calculating μ and σ. The weighted index always has a higher value than the unweighted index, indicating that the biggest euro area members have been largely driven by symmetric shocks. The large values of both indices point to a strong signal of average importance of symmetric shocks across countries. The difference between the two versions decreased after the European debt crisis, however, mainly as a result of the closing gap between weighted and unweighted measures of standard deviation σ.

Looking at the resulting OCA indicators in Chart A, the indices started off at a low level and improved in the first decade after the creation of the EMU. Both weighted and unweighted OCA features tended to surge in times of global crises, as cross-country co-movement was generally high. In contrast, the subsequent sovereign debt crisis, which brought considerable fragmentation within the euro area, meant that the OCA features weakened significantly. In the recovery period, approximately from 2014, the OCA indicators broadly picked up. However, this pattern was interrupted again in the run-up to the COVID-19 pandemic. The impact of the pandemic on the divergence between country groups is still uncertain. In terms of levels, overall, the unweighted OCA measure (Chart A, panel a) suggests improved OCA conditions for euro area member countries compared with 20 years ago, albeit in a context of varying trends and speeds of progress across periods. The weighted index (Chart A, panel b) shows very little improvement in OCA conditions after the Monetary Union underwent various headwind episodes. Finally, according to the weighted indicator (Chart A, panel c), the relative importance of symmetric shocks increased for all countries on average, but the differences between the largest countries may have been aggravated following the European sovereign debt crisis, such that the dispersion measure was at a higher level than at the start of the EMU.

Overall, the optimality of the euro area as a currency union is hard to measure. Using a variety of indicators is appropriate. We conclude that SVAR-based measures have synthetic value and provide a useful perspective in monitoring OCA conditions in a multi-country currency union. The latter tends to show gradually strengthening OCA measures in stable periods, notably the first decade of its inception and the 2014-20 period. However, this progress has been challenged in various episodes of major uncertainty and major adverse shocks.

Chart A

Weighted and unweighted OCA index



Source: Authors' calculations.

Overall, these results broadly confirm, from the perspective of a separate methodology, some of the main conclusions in the chapter on the gradual, but uneven, progress observed in terms of the co-movement of country-level business cycles in the euro area and the slowly increasing role of common structural factors behind the trend in business cycle alignment.

2.2.2 The predictive power of euro area GDP

Business cycle synchronisation of countries with the euro area can be examined by tracing to what extent economic cycles in individual Member States can be forecast according to their co-movement with the euro area cycle, as in Giannone, Lenza and Reichlin (2008). This section revisits this approach with an updated dataset (annual data from 1970 to 2018) and an improved Bayesian estimation methodology. The approach consists of three steps. In the first step, an "event" is chosen that could have led to potential disruptions in the synchronisation in GDP growth among euro area countries. This event is used as a breakpoint to split the sample into estimation and projection subsamples (i.e. before and after the event, respectively). The chosen events are the start of the EMU and the GFC. In the second step, a Bayesian vector autoregression (BVAR), containing all countries and a population-weighted aggregate for the euro area, is estimated for the first subsample. In the third step, the estimated model is used to generate, for each country, a forecast of GDP growth conditional on growth in the euro area over the whole sample.[10]

The predictions of the BVAR model remain similar in the pre-EMU period (in-sample) and in the period after the introduction of the euro (out-of-sample) (Chart 13). These results therefore suggest that the introduction of the euro was not associated with an increase in de-synchronisation, confirming earlier findings in Giannone, Lenza and Reichlin (2008). Based on the difference in the tightness of the confidence band for the GDP growth forecasts across countries, there is a cluster of countries (that can be labelled "core") for which the euro area growth cycle is a good predictor (i.e. a narrower confidence band), while others are more desynchronised (i.e. a wider confidence band).

Relating the exercise to the GFC as the sample breakpoint event, the evidence does not point to the GFC as a lasting or significantly disruptive factor for euro area cross-country synchronisation (Chart 14). Although a certain, limited degree of de-synchronisation emerges, euro area GDP growth is still a better predictor for countries within the core of more synchronised Member States, while countries outside the core are less synchronised. Persistent differences in economic growth can be found: some countries within the core (e.g. Germany) consistently outperform the benchmark, while others (e.g. Italy) stay at the lower limit of the range, albeit co-moving well with the euro area. These results qualify some of the indications derived from less sophisticated approaches, such as looking at the sheer correlation of countries' growth rates, suggesting that this method may be more reliable for gauging genuine business cycle synchronicity trends.[11]

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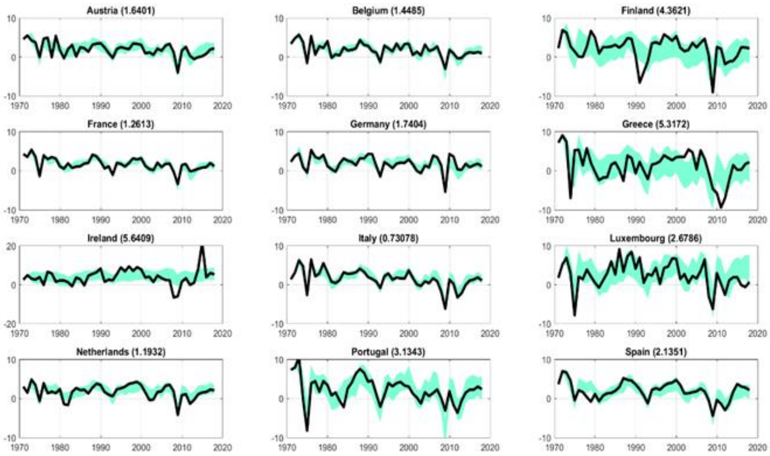
10 Since the forecast covers the whole sample, this is equivalent to performing both an in-sample and out-of-sample exercise at the same time.

11 To check the robustness of the results, the same exercise is performed excluding two statistical outliers, Greece and Ireland, as well as excluding from the estimation sample the period of the 1970s, when there was a steep decline in dispersion that may have contaminated the results. Moreover, the BVAR models are also estimated using quarterly, rather than annual, data. The results in these cases remain broadly consistent with the main findings reported, pointing to the robustness of these findings.

Chart 13

Real GDP growth conditional forecast: estimation period 1970-1998

(percentages)

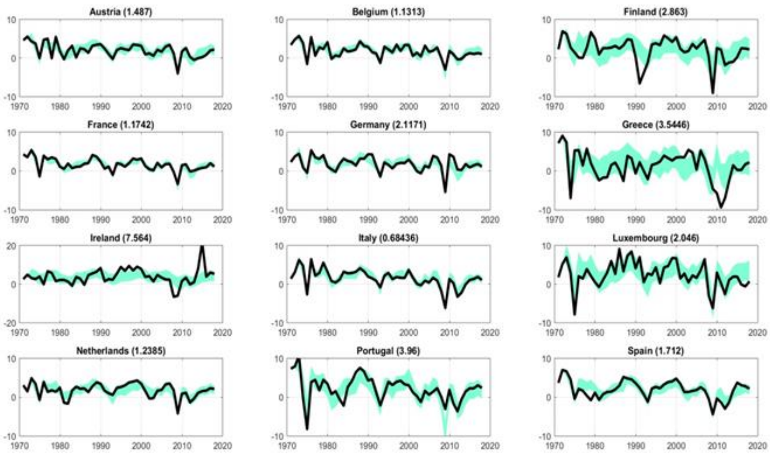


Source: Authors' calculations.
Notes: The black solid line is observed GDP growth in each country. The green area is the confidence interval between the16th and 84th percentile of the forecast GDP growth, conditional on EA GDP growth. The conditional forecasts are computed using the parameters estimated using the sample from 1970 to 1998. The number in parenthesis is the Root Mean Square Error computed between the median forecast and the realised GDP growth for the sample from 1999 to 2018.

Chart 14

Real GDP growth conditional forecast: estimation period 1970-2007

(percentages)



Source: Authors' calculations.
Notes: The black solid line is observed GDP growth in each country. The green area is the confidence interval between the 16th and 84th percentile of the forecast GDP growth conditional on EA GDP growth. The conditional forecasts are computed using the parameters estimated using the sample from 1970 to 2007. The number in parenthesis is the Root Mean Square Error computed between the median forecast and the realised GDP growth for the sample from 2008 to 2018.

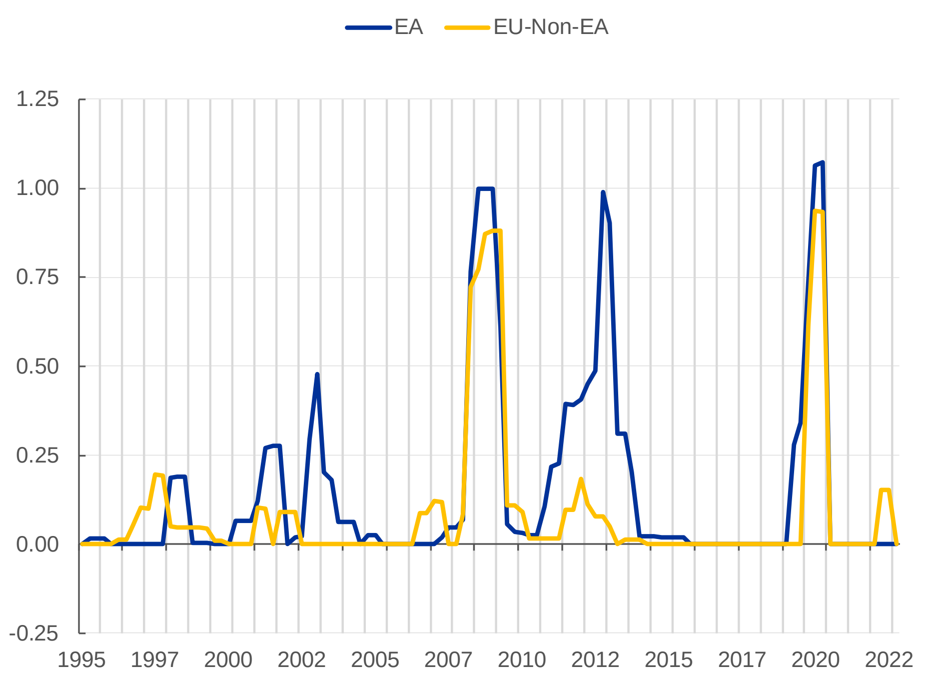
2.3 Synchronisation across the euro area countries

2.3.1 Concordance analysis

A simple measure of synchronisation is the proportion of the time that the cycles of two countries are in the same phase, i.e. the concordance index (Harding and Pagan (2002)). The cyclical phases are defined by the classical turning points described in Chapter 1: an expansion goes from a trough to the following peak, and a recession goes from a peak to the following trough. To investigate the cyclical synchronisation for a group of countries, it is possible to compute a diffusion index, as the proportion of countries in recession at any given time (see Altug and Canova (2014)) and Chang and Hwang (2011)).

According to this analysis, the cycles in the five largest euro area countries spend 80-97% of the time in the same phase as the euro area cycle (Annex 2, Chart A2.1). Spain, France and the Netherlands have somewhat higher concordance with other euro area countries than Germany and Italy. The diffusion index for the EA is somewhat higher than that for the European Union non-euro area countries (EU non-EA), indicating a higher degree of cyclical synchronisation for euro area countries (**Chart 15**). While many of the euro area countries experienced both the financial and the sovereign debt crisis, this was not the case for non-euro area countries. All countries, however, experienced recessions during the pandemic crisis.

Chart 15
Diffusion index for the euro area and the EU non-euro area countries



Source: Authors' calculations. Latest observation: 2022Q2.

The concordance indices for the global economies suggest that the cycles of advanced economies, such as the United Kingdom, Canada and the euro area, are the most correlated with the cycle of the United States (Annex 2, Chart A2.2). Countries such as Brazil have a lower correlation but are in the upper part of the interval. All emerging economies seem mostly correlated with the business cycles of the United States and the United Kingdom and less with the economies of the other advanced countries in the group. The advanced economies seem quite highly correlated among themselves overall, except Japan, which has a low correlation with the rest of the advanced economies. The results are broadly in line with the findings reported in Deutsche Bundesbank (2020).

There was a perfect recession synchronisation at the global level during the GFC, both within the advanced and the emerging groups. During the COVID-19 crisis, there was a perfect recession synchronisation within the emerging markets group, and around 98% synchronisation for the advanced economies (as Sweden did not experience a recession). Regarding expansion periods, the advanced economies seem more synchronised than the emerging markets, which, as also seen in Box 3 in Chapter 1, tend to experience country-specific recessions even in periods of global sustained economic growth.

2.3.2 Vector autoregression analysis of forecast errors

This section investigates pairwise correlations of VAR forecast errors at different horizons as a measure of business cycle synchronisation (as used by Den Haan (2000) and Den Haan and Sumner (2004)).[12] Since business cycles last between four and six years on average, the focus of the analysis is on pairwise correlations of VAR forecast errors 48 months ahead. As in Camacho, Pérez-Quirós and Saiz (2006), the business cycle is proxied by monthly industrial production growth.[13] The sample of countries includes 27 European Union countries and the United Kingdom, and, for comparison, several European and advanced economies (Norway, Turkey, Japan, the United States and Canada). First, the correlations are computed by estimating the VARs over a ten-year rolling window, and, unsurprisingly, a surge in correlations due to the GFC is observed. To prevent the GFC from biasing the analysis, the sample is split into two periods: pre-financial crisis (1990-2007) and post-financial crisis (2009-19).

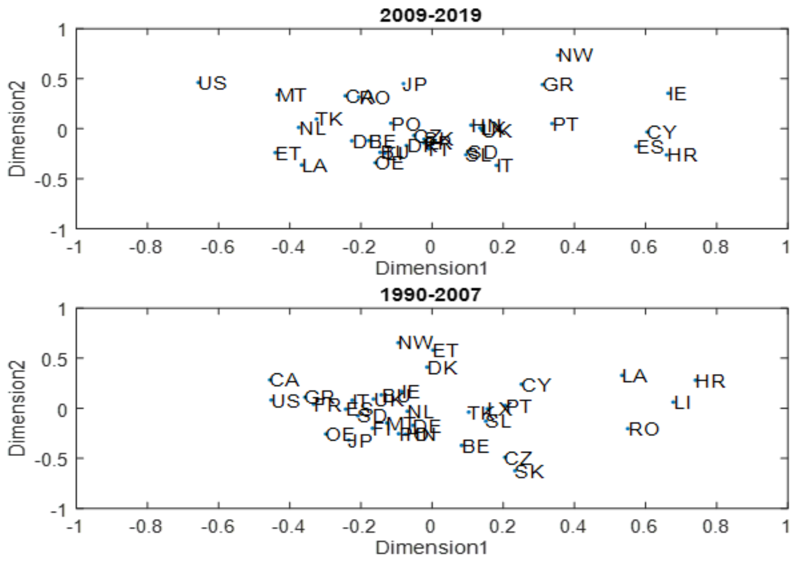
Pairwise correlations are projected onto a plane (after they have been transformed into "distances", defined as one minus the correlation coefficient), in order to create a map (as in Camacho et al. (2006)). The more correlated the countries are, the shorter their distance, and they will therefore appear very close together on the map. In contrast to the heatmap, on the basis of the map

[12] As argued by den Haan (2000), unconditional correlations lose important information about the dynamic aspects of the co-movement between variables. Moreover, since the unconditional correlation coefficient is only defined for stationary variables, it is necessary to first transform the data in some way (with many possible alternatives).

[13] Although this measure does not include the services sector, it has the advantage of wider coverage in terms of countries and a longer sample period than other indicators, such as quarterly GDP. Also, the industry sector, as a tradable sector, is more sensitive to cyclical conditions.

of cyclical distances it is difficult to conclude that countries are closer together (i.e. with more correlated cycles) in the post-financial crisis period (**Chart 16**). Interestingly, while most of the euro area countries were close together in the pre-financial crisis period, in the post-financial crisis period the countries that received financial assistance programmes during the sovereign debt crisis (Greece, Ireland, Portugal, Spain and Cyprus) are less synchronised with the other euro area countries, since they are closer to each other and further away from the rest.

Chart 16
Map of cyclical distances

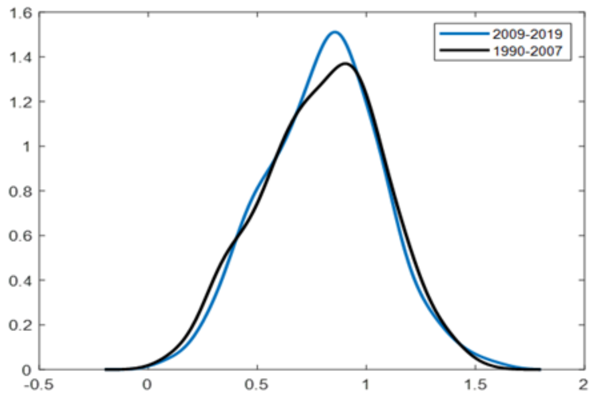


Source: Authors' calculations.
Note: The maps are produced using multidimensional scaling.

No major changes are observed in the distribution of cyclical distances (one minus correlation coefficients) across countries with respect to the pre-financial crisis period (Chart 17). The average and the dispersion are fairly similar in both periods and, if anything, the density of cyclical densities has become slightly more concentrated.

The average distances between the euro area countries, either among themselves or compared with all EU countries, remained broadly unchanged (Table 1). The same is also true for EU countries. For example, the average distance between euro area countries in both the pre- and post-financial crisis periods is 0.76, which is close to the average distance between euro area countries and EU countries (0.76 in the pre-financial crisis period and 0.75 in the post-financial crisis). These average distances are clearly shorter than the distances between euro area (or EU countries) and other non-EU countries. These distances clearly increased in the post-GFC period (e.g. from 0.82 to 0.93 for the euro area). Finally, the cyclical distances for non-EU countries clearly increased among themselves but also with respect to the euro area and EU countries after the GFC.

Chart 17
Distribution of cyclical distances



Source: Authors' calculations.
Notes: Distance are computed as one minus the correlation coefficient.

Table 1
Cyclical distances by groups of countries

(averages)

	Euro area (19 countries)		European Union (28 countries)		Non-European Union countries	
	1990-2007	2009-2019	1990-2007	2009-2019	1990-2007	2009-2019
Euro area (19 countries)	0.76	0.76	0.76	0.75	0.82	0.93
European Union (28 countries)	0.76	0.75	0.74	0.74	0.82	0.92
Non-European Union countries	0.82	0.93	0.82	0.92	0.71	0.82

Source: Authors' calculations.
Note: The average distance is computed using Fisher's transformation, as in Camacho et al. (2006).

Next, the role of macroeconomic imbalances in explaining the pairwise synchronisation changes in the post-financial crisis period with respect to the pre-financial crisis is investigated. The following Macroeconomic Imbalances Procedure (MIP) scoreboard indicators are considered: i) private sector debt (as a percentage of GDP); ii) private sector credit flow (as a percentage of GDP); iii) bank debt growth (consolidated); iv) the average percentage change in the real effective exchange rate; v) the current account (as a percentage of GDP); vi) the average percentage change in the nominal unit labour cost; vii) government debt (as a percentage of GDP); viii) the unemployment rate; and, in addition, ix) the public deficit (as a percentage of GDP) and x) the public primary deficit (as a percentage of GDP).[14] The candidate explanatory variables are computed as the average bilateral differences between pairs of countries for the pre-financial crisis period. Since the number of potential regressors is large, variable selection techniques (LASSO) are used. The selected explanatory variables are the public deficit, bank debt growth, the

[14] House prices, net international investment position and export market shares are not considered, since the series are not available for all the European countries in the pre-financial crisis period.

current account and unit labour cost growth. These results are similar to the findings of Lukmanova and Tondl (2017).[15]

Table 2

Regression results

Dependent variable: distances between 2009 and 2018

Explanatory variables	(1)	(2)
Distances between 1990 and 2007	-	0.223***
Public deficit	0.029***	0.030***
Bank debt growth	0.007***	0.005***
Current account	-0.011***	-0.012***
Unit labour costs growth	-0.0003**	-0.0002**
R-squared	0.088	0.136

Source: Authors' calculations.
Notes: (1) Robust OLS regression coefficients. The explanatory variables are differences in absolute value between the corresponding variable for each country pair and are computed over the period 1990-2007 to avoid endogeneity issues. */**/*** refers to significance levels of 10%, 5% and 1%.

The regression results suggest that pre-crisis national fiscal and macroprudential policies can explain business cycle synchronisation in the post-crisis period to some extent (Table 2). The larger the discrepancies in national fiscal policies (public deficits) and in bank debt growth in the pre-financial crisis period, the less synchronised (or more distant) the countries became in the post-financial crisis period. This result highlights the importance of coordination or complementarity of fiscal and macroprudential policies (Martin and Philippon (2017)).[16] Also, it is in line with Meller and Metiu (2017), who found that synchronisation of bank credit and business cycles go hand in hand. Finally, pre-crisis similarities in current account and unit labour cost growth appear to reduce synchronisation in the post-financial crisis period, rather than increase it.[17] This result is probably due to the fact that changes in relative prices were a key adjustment mechanism, particularly during the sovereign debt crisis, and it is omitted from the regression.[18]

15 Lukmanova and Tondl (2017) showed that differences among euro area members in terms of current account, government deficit, public debt, private debt and unit labour costs (MIP scoreboard indicators) have reduced business cycle synchronisation in the euro area, particularly in the post-crisis period.

16 In a counterfactual exercise, Martin and Philippon (2017) showed that periphery countries could have stabilised employment if they had followed more conservative fiscal policies during the boom and conducted macro-prudential policies to limit the increase in private debt.

17 The effect of current account similarities on synchronisation in the post-crisis period may be related to the fact that persistent current account disequilibria affect the characteristics of expansions. See Camarero et al. (2020).

18 Furceri et al. (2022) find that price flexibility is an important shock absorber in the EMU compared with the United States.

2.4 A granular view of business cycle synchronisation

2.4.1 A sectoral perspective of business cycle synchronisation

This section adds a sectoral perspective to the analysis of business cycle synchronisation in the euro area. The sectoral composition of an economy determines its aggregate business cycle, since different sectors (such as agriculture, construction, real estate and public services) typically follow their own cycles. Differences in sectoral composition across member countries are crucial in explaining the degree of cyclical synchronisation in the euro area. The ECB report on sectoral specialisation (ECB (2004)) found that manufacturing and trade services contributed the most to the overall cyclical co-movement across countries between 1980 and 2002. In this section, the focus is on the co-movement of the quarterly value added in 11 NACE revision 2 sectors (1-digit level) and their contributions to the economy-wide co-movement in the period 1996Q1-2019Q3.[19] The synchronicity and similarity measures (see **Section 2.2.1** and Mink et al. (2012)) are calculated using the median output gap of sector j over all countries as the reference gap. The output gaps are obtained using the Hodrick-Prescott and Baxter-King filters.

Three different trends over time can be observed in the co-movement of the total economy (Chart 18).[20] In the first period, until 2007, business cycle synchronisation (BCS) increased. During the financial crisis and in its aftermath, BCS decreased. In the subsequent years, BCS increased again, but remained below the levels of the 2000s.

Manufacturing, business-related services and trade show the highest degree of co-movement across countries. At the sectoral level, the largest degree of co-movement is observed for manufacturing (average similarity of 0.19), followed by business-related services (0.16) and trade, transport and accommodation (0.16). Real estate activities (0.04), agriculture (0.07), private services (0.07) and public services (0.07) show the lowest similarity of all sectors. The synchronicity measure confirms this ranking of the sectoral co-movement.[21]

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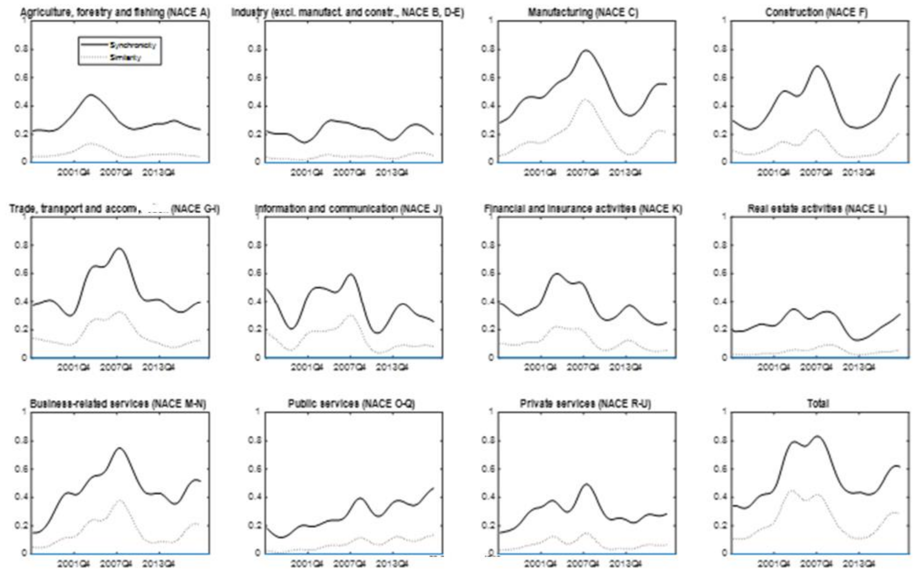
19 The 11 NACE Rev. 2 sectors are: Agriculture, forestry and fishing (NACE A), Industry (excluding manufacturing and construction, NACE B, D-E), Manufacturing (NACE C), Trade, transport and accommodation (NACE G-I), Information and communication (NACE J), Financial and insurance activities (NACE K), Real estate activities (NACE L), Business-related services (NACE M-N), Public services (NACE O-Q) and Private services (NACE R-U).

20 The Bai-Perron test (Bai and Perron, 2003) for multiple breakpoints identified breakpoints in 2007Q4 and 2013Q1 in a regression of the similarity measure on a constant and a trend.

21 These results are, in general, aligned with those of Álvarez et al. (2020) for the main European countries.

Chart 18

Synchronicity and similarity of euro area sectors



Source: Authors' calculations.
Note: The synchronicity and similarity measures have been smoothed using Gaussian smoothing, which is a symmetric moving average with a window length of six years and Gaussian weights.

Next, we analyse how the different sectors of the euro area countries have contributed to aggregate business cycle co-movement. A panel data model is estimated to explain the co-movement measure (i.e. either synchronicity or similarity) at the aggregate level on the measures of the 11 sectors in all euro area countries. For synchronicity, all sectors except agriculture, information and communication and real estate services (which are not significant) have a positive coefficient for the whole sample (1996Q1-2019Q3) (**Chart 19**). As regards similarity, the results are slightly different. Manufacturing plays a more important role, while information and communication, financial and insurance activities and real estate services contribute negatively to overall similarity. Over time, these relationships change slightly. In particular, the coefficient for construction becomes insignificant in the last period. The results for manufacturing and trade remain positive and significant in all periods.

The last part of the analysis investigates how the sectoral co-movement contributes to the aggregate co-movement. To that end, the sectoral co-movement measures are aggregated using the estimated regression coefficients as weights. For the whole sample, both measures show that manufacturing, trade and business-related services explain the bulk of the co-movement (**Annex 2, Chart A2.3**). In contrast, agriculture and most of the other service sectors do not play an important role. What differs between the measures is the relative role of the sectors. The similarity measure shows that manufacturing is the single most important contributor to overall co-movement.

Chart 19

Coefficients of sectoral co-movements to overall business cycle co-movement

	96Q1-19Q3		99Q1-07Q4		08Q1-13Q1		13Q2-19Q3	
	Sync	Sim	Sync	Sim	Sync	Sim	Sync	Sim
Agriculture, forestry and fishing (NACE A)	0	0	+	0	+	0	0	-
Industry (excl. manufact. and constr., NACE B, D-E)	+	-	0	0	-	+	-	-
Manufacturing (NACE C)	+	+	+	+	+	+	+	+
Construction (NACE F)	+	+	+	+	+	+	0	0
Trade, transport and accommodation (NACE G-I)	+	+	+	+	+	+	+	+
Information and communication (NACE J)	0	-	0	+	+	-	-	-
Financial and insurance activities (NACE K)	+	-	+	0	-	0	+	0
Real estate activities (NACE L)	0	-	0	0	0	-	0	0
Business-related services (NACE M-N)	+	+	+	+	-	+	+	+
Public services (NACE O-Q)	+	-	+	+	-	+	+	+
Private services (NACE R-U)	+	+	0	+	+	+	+	-

Source: Authors' calculations.
Notes: The entries in the table are based on the estimated coefficients of a panel data model with fixed effects for the countries where we have regressed the co-movement at the aggregate level on the co-movement of the different sectors. We have done this separately for synchronicity and similarity.
+: Sector contribution to overall business cycle convergence is significant at the 5% level.
-: Sector contribution to overall business cycle divergence is significant at the 5% level.
0: No significant contribution at the 5% level.

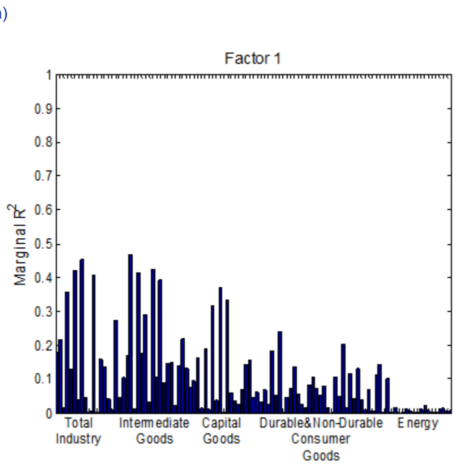
2.4.2 Industrial business cycles

This section focuses on the industrial production sectors and addresses the following two research questions: i) which industrial sectors are leading the business cycle in the euro area and euro area countries? and ii) how has the importance of common shocks changed over time for industrial production across euro area countries? To answer the first question, rather than using simple correlation analysis with different leads and lags, the methodology proposed by Parker and Sul (2016) is used to identify the "dominant leader" industrial sectors. An approximate dynamic factor model separates the impact of common and idiosyncratic shocks on the five main industrial groups (intermediate goods, capital goods, durable consumer goods, non-durable consumer goods and energy) in the EU countries, the United Kingdom and Norway in the period 2000-19.

Evidence of the existence of two common factors is found. Looking at the percentage variance explained by each factor (marginal R-squared) (**Chart 20**), the first factor is very important for the total industries, intermediate and capital goods sectors, while the second factor is more relevant for the energy sector. Since some instability in the loadings of the dynamic factor model are found, the analysis is split into two sub-periods, i.e. before and after the financial crisis (2000-08 and 2009-19, respectively).

Chart 20

Importance of the common factors for the main industrial groups



Source: Authors' calculations.

According to the method used by Parker and Sul (2016), the candidate "leader" industrial sectors are identified as follows. The ten sectors in which the goodness of fit (R-squared) of the regressions of the two estimated common factors (the first two principal components) on the production growth of that specific sector is the highest (**Table 3**). For the first sub-period, total industry and the intermediate goods sector in several large euro area countries and the French capital goods sector are selected as potential leaders. In the second sub-period, while total industry and intermediate goods sectors remain leaders, the novelty is the inclusion of the energy sector in France, Italy and Germany. This could be the result of a shift towards more efficient and cleaner domestic energy production and efforts to reduce oil import dependency.

Whether the importance of common shocks has changed over time is also investigated. Comparing the percentage of variance explained by the common factors in the two sub-periods, the importance of common shocks decreased after the financial crisis (**Annex 2, Chart A2.4**). This finding suggests that common shocks were a more important source of fluctuations before 2009. Moreover, the proportion of forecast error variance explained by common shocks also declined over time (**Annex 2, Chart A2.5**).[22] Taken together, while the importance of common shocks decreased after 2009, these shocks nevertheless explain a large proportion of the variation in sectoral production growth rates.

[22] The forecast error variance decomposition is based on the moving average representation of the dynamic factor model. The dynamic factor model is estimated over a rolling window of 81 months (around six years).

Table 3
Ten industrial sectors as potential "leaders"

2000-08		2009-19	
Variable	R-squared	Variable	R-squared
Euro area		Euro area	
Total industry	0.83	Total industry	0.73
Intermediate goods	0.70	Energy	0.67
Country – sector		Country – sector	
Spain – Total industry	0.64	France – Total industry	0.50
France – Total industry	0.64	Germany – Total industry	0.43
Belgium – Intermediate goods	0.56	France – Energy	0.41
Italy – Total industry	0.53	Belgium – Intermediate goods	0.41
France – Intermediate goods	0.52	Germany – Intermediate goods	0.38
Germany – Intermediate goods	0.48	Italy – Energy	0.36
France – Capital goods	0.48	France – Intermediate goods	0.36
Italy – Intermediate goods	0.47	Germany – Energy	0.36

Source: Authors' calculations.
Notes: The common factors are estimated using production for the five main industrial groups or, if this is not available for a specific European country, it is included the total industry aggregate. In any case, the common factor estimates do not include euro area aggregates and total industry for the largest euro area countries.

2.4.3 Can firm-level idiosyncratic shocks explain aggregate fluctuations?

This section investigates whether idiosyncratic shocks to large firms (the "granular residual") can explain GDP fluctuations in euro area countries. Gabaix (2011) found that idiosyncratic movements in the largest 100 firms in the United States explain one-third of the variation in real GDP growth. More recently, Carvalho and Grassi (2019) developed a quantitative theory of aggregate fluctuations in which the firm size distribution plays a key role. The main findings are: i) large firm dynamics drive aggregate growth and, hence, the business cycle (in line with Gabaix (2011)); and ii) cross-sectional dispersion in firm size drives aggregate volatility (Bloom et al. (2018)). Finally, Ebeke and Eklou (2017) investigated the granular hypothesis for a panel of firms in a selected group of euro area countries using data from Orbis. In this section, a similar analysis is conducted using firm-level data at annual frequency from the iBach database. The dataset is assembled by the Bank for the Accounts of Companies Harmonized Working Group (BACH WG). It covers six euro area countries, starting from different years: Belgium, Spain (2008), France (2003), Italy (2006), Portugal (2003) and Slovakia (2011). The analysis uses information until 2018, and Slovakia is excluded given the short sample.

When the distribution of firm size in an economy is more skewed or heavy-tailed (i.e. many small firms and very few large firms) idiosyncratic shocks are more likely to influence the entire economy. As a first approach, visual inspection of kernel density indicates that the firm size (proxied by net turnover and number of employees) distributions are highly skewed and show long tails in all countries and years. A power-law distribution is fitted to the empirical data and their parameters are estimated (Clauset et al. (2009)). The power-law parameter quantifies the degree of heterogeneity of the firm size distribution.[23] The estimated power-law coefficients range between 1.9 and 2.3 for the country-year pairs.

Chart 21

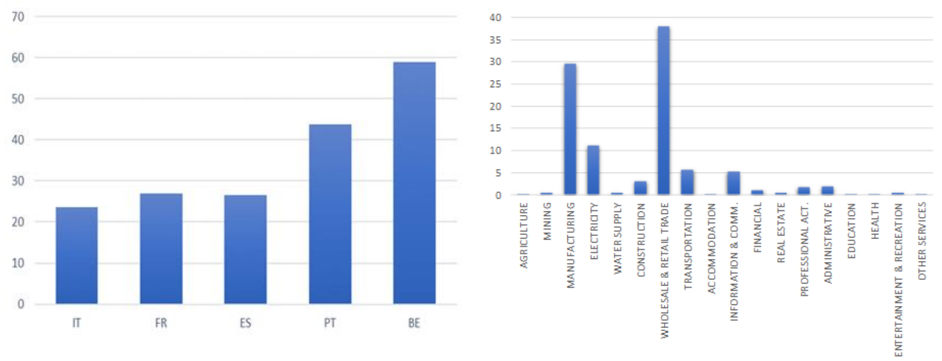
Relevance of the top 100 firms

a) Sales of top 100 firms by country

(percentage of GDP)

b) Sales of top 100 firms by sector

(percentage of value added)



Sources: iBach database, Eurostat, authors' calculations.

On average, sales in the top 100 largest firms account for around 25% of GDP in France, Italy and Spain, around 40% in Portugal and 60% in Belgium. Most firms belong to the wholesale and retail trade and manufacturing sectors (**Chart 21**). Interestingly, these sectors are precisely those that in Section 2.4.1 were found to be the main drivers of aggregate co-movement. For comparison, Gabaix (2011) found that the sales of the top 100 firms in the United States represent 30% of GDP.

The granular residual is a parsimonious measure of idiosyncratic shocks to the top 100 firms. The idiosyncratic shocks are calculated as the difference between the real sales per employee growth (proxy for productivity growth) of an individual firm, minus the average for the industry in the sample considered or differentiating by year and/or country. These idiosyncratic shocks are then aggregated, using as weights the share of the firm's sales over total GDP, so that shocks to larger firms are assigned a higher weight.

[23] In general, a higher value of the coefficient signals a lower degree of heterogeneity, which is reflected in a less skewed shape of the distribution. A power law function with a coefficient of more than 1 is characterised by a very large or non-finite variance.

A simple regression analysis shows that the granular residual is statistically significant and can explain at least one-third of GDP fluctuations in France, Italy, Spain, Belgium and Portugal (Table 4). This result is independent of the definition of the granular residual considered.[24] Also, when including additional explanatory variables to control for oil price, monetary policy and fiscal policy shocks, the granular residual remains statistically significant (**Annex 2, Table A2.1**). These results are broadly in line with those of Ebeke and Eklou (2017), although our regression coefficients of the granular residuals are more stable over different specifications.[25]

Table 4

Regression analysis: granular residual

Dependent variable: real GDP growth

Explanatory variables	(1) Demeaned (country-sector)	(2) Demeaned (sector)	(3) Demeaned (country-year)	(4) Demeaned (country-sector-year)
Granular residual	0.27**	0.27**	0.14*	0.17
Constant	1.73***	1.71***	1.86***	1.93***
Observations	69	69	69	69
R-squared	0.46	0.46	0.32	0.33
Adj. R-squared	0.37	0.37	0.21	0.21

Source: Authors' calculations.
Notes: Significance levels: * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$. All the regressions include country fixed effects and country-specific trends. Robust standard errors are clustered at country level.

Overall, this section has shown that idiosyncratic shocks to large firms directly contribute to aggregate fluctuations in several euro area countries. Nonetheless, as discussed by Di Giovanni, Levchenko and Mejean (2014), aggregate fluctuations may also arise from idiosyncratic shocks due to input-output linkages across the economy whose effect may be three times as large.

24 As in Ebeke and Eklou (2017), four definitions of granular residuals are considered: i) demeaning firm-specific productivity growth using the sector-country average; ii) demeaning using average productivity growth for the sector worldwide, to control for structural differences in productivity growth across sectors that may arise due to specific technological shocks; iii) demeaning using the average productivity growth in the sector in a given year, to control for time-varying worldwide technological shocks; and iv) demeaning using the average productivity growth of all firms in the same sector, in the same country, in a given year to control for sector-specific shocks that may vary between countries and over time.

25 The results are also robust when the granular residual is computed excluding firms in the financial and energy sectors.

3 Business cycle drivers

This chapter provides an overview of selected analytical projects conducted by the expert team on Business Cycle Drivers of the Eurosystem Working Group on Forecasting (WGF), focusing on analysing key forces of euro area business cycle dynamics. While analysing and forecasting the business cycle, and conducting basic growth accounting, is typically a data-driven exercise and thus does not necessarily involve fully fledged structural models, the identification of the shocks driving the business cycle requires models that can identify the independent forces of the business cycle, given the data and theory-based assumptions about the co-movements of the relevant variables.

The business cycle drivers have been analysed from several perspectives.

- Growth accounting approach: the results point to the TFP cycle – which captures temporary technology shocks but also changes in capacity utilisation – as well as the labour market adjustment via the intensive margin (via hours worked per person) having a key role in the euro area business cycle.
- Financial sector dimension: the financial sector, in addition to amplifying fluctuations arising from shocks originating elsewhere, may itself be a source of business cycle fluctuations. This aspect is analysed with a dynamic stochastic general equilibrium (DSGE) model approach.
- International perspective: foreign shocks – both demand and supply – may also be sources of fluctuations in open economies. Key findings from an estimated two-country DSGE model with endogenous growth are reported below.
- Domestic demand: expenditures on durable goods, due to their specific cyclical features, are responsible for a large proportion of private consumption fluctuations.
- The COVID-19 pandemic posed an extraordinary challenge to business cycle analysis, given the sheer magnitude and the unusual nature of the shocks to economic activity it generated. While the economic implications of the pandemic have been analysed by many studies in the last few years, early modelling results, including the ones reported below, highlighted the likely heterogenous impact of the shock across sectors, demand components and countries.

Selected analytical results are presented below.

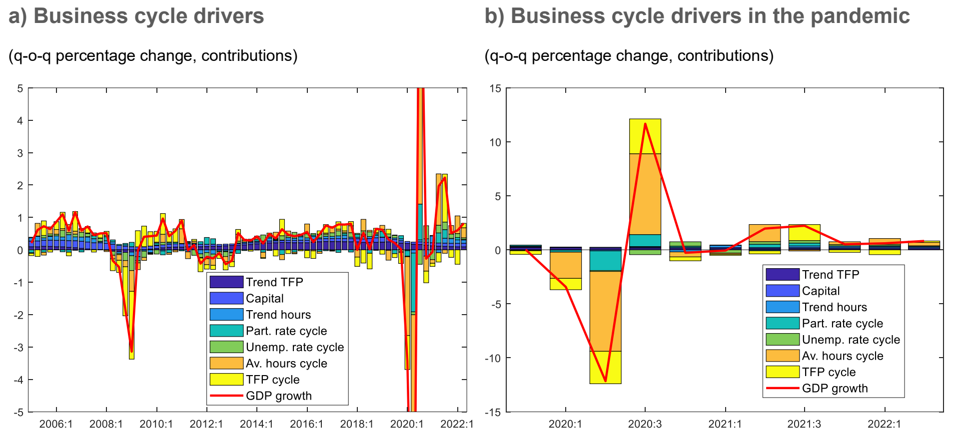
3.1 Growth accounting in the deviation cycle approach

The deviation cycle approach used in Chapter 1 is applied to analyse the drivers of the business cycle from a growth accounting perspective, via a decomposition of GDP growth into trend and cyclical components through the

lens of a standard Cobb-Douglas production function, as in Tóth (2021). According to this approach, the TFP cycle was the most important contributor to quarterly changes in euro area real GDP before the pandemic (i.e. in the period 1999-2019), particularly around major recessions and the subsequent rebounds. The second most important contributor was the cyclical component of hours worked per person (**Chart 22**, panel a). This implies that adjustment to business cycle shocks took place to a large extent via changes in the utilisation of production factors that went beyond the traditional adjustment channels via the extensive (employment) or intensive (hours worked per person) margins of the labour market. In contrast, during the pandemic period, the intensive margin of the labour market clearly played the most important role (**Chart 22**, panel b), as job retention schemes were widely implemented by governments to cushion the impact of lockdowns and other containment measures on employment, corporate liquidity and bankruptcies.

Chart 22

Business cycle drivers in the deviation cycle approach



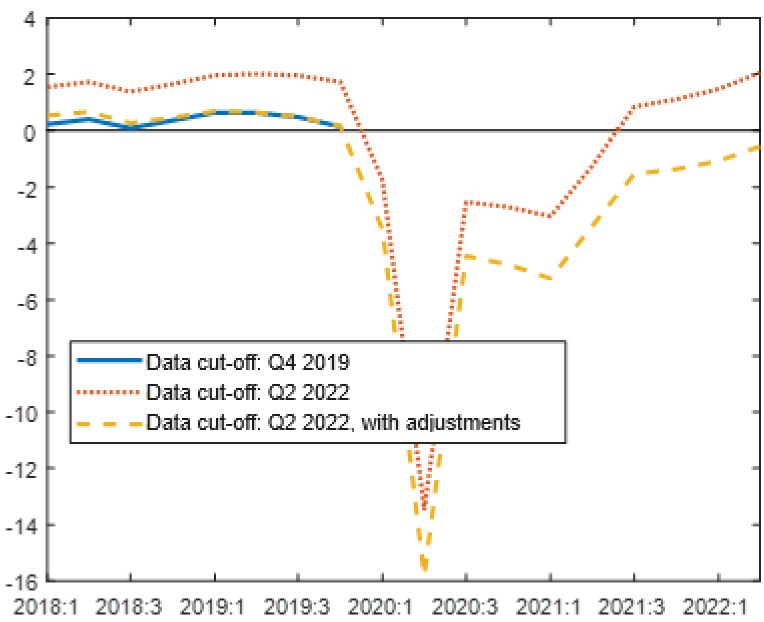
Source: Authors' calculations.
Notes: The cycle refers to the deviation from the estimated long-term trend, given observed data. Latest observation: 2022Q2.

Due to the unprecedented magnitude and nature of the COVID-19 shock, given the available data samples, trend-cycle decomposition methods that are based on two-sided filters (or smoothers) tend to revise the history of business cycle measures, particularly in periods directly preceding the shock. This phenomenon can be illustrated using the deviation cycle approach. When extending the estimation sample to include data after the fourth quarter of 2019, the deviation cycle approach tends to revise the GDP cycle upwards significantly in 2018 and 2019 (**Chart 23**). To prevent this from contaminating the estimation of the business cycle and its decomposition, adjustments to the covariance matrix of the model shocks can be introduced in the quarters affected by COVID-19 containment, allowing for a substantial deviation of the variance of the relevant shocks from their values estimated on a pre-pandemic sample. These adjustments relate, in particular, to allowing for a significantly higher variance for the shock of the equation linking the cyclical components of GDP and the unemployment rate cycle, and also introducing a measurement error on the extremely volatile nominal wage developments over the pandemic period, in the light of job retention schemes and various income support measures introduced in euro area countries. This approach is similar in spirit to the suggestion of Lenza and Primiceri (2021), who considered estimating vector autoregressions (VARs) on data that include the pandemic shock. After this adjustment, the subsequent retrospective revisions to the path of the business cycle compared with an estimate that ends in Q4 2019 become much smaller.

Chart 23

Revisions to the GDP cycle due to the COVIDCOVID-19 pandemic shock

(percentage deviations from trend)



Source: Authors' calculations.
Note: Latest observation: 2022Q2.

3.2 Financial drivers of the euro area business cycle

The shocks driving business cycles are often analysed through the lens of DSGE models. In these models, fluctuations arise due to decisions made by optimising agents responding to exogenous shocks, given budget constraints and a range of possible market imperfections or frictions. As the GFC of 2008-09 indicated, imperfections related to the financial system may have important implications for business cycle fluctuations. The financial system may be a source of shocks in itself or may act as an amplification mechanism for shocks that originate elsewhere. To tackle this perspective, one of the papers in focus – Hirschbühl, Krustev and Stoevsky (2020) – extends the financial business cycle model of Iacoviello (2015), used to disentangle the drivers underlying the GFC. Iacoviello (2015) finds that financial shocks accounted for two-thirds of the observed collapse in output in the United States during the Great Recession. An important extension in Hirschbühl, Krustev and Stoevsky (2020) is the introduction of capital reallocation inefficiencies, which delivers a more realistic response of activity to an entrepreneurial default shock by eliminating positive income effects by augmenting the depreciation rate, as outlined by Ramey and Shapiro (2001). The results for the United States are updated based on a dataset up to 2018. The model is also applied to the euro area.

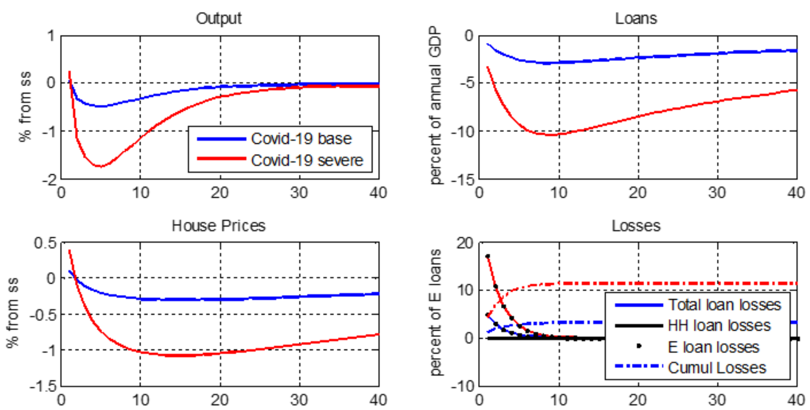
The key findings of the paper can be summarised as follows: (i) the incorporation of capital reallocation inefficiencies improves the response of economic activity to entrepreneurial defaults in the model; (ii) extending the estimation of the model by several years of data entails a slightly weaker, but still close to two-thirds contribution of financial factors to US GDP in 2008-09, while these shocks also made a substantial contribution to the subsequent recovery; (iii) in contrast to the United States, the estimation results for the EA point to a much smaller role of financial factors in driving the business cycle, with only one-fifth to one-quarter of the double-dip recession in the EA being explained by adverse financial shocks. However, they played a bigger role in the subsequent recovery, contributing more than two-fifths of output growth in 2014-18. On the basis of these results, we can conclude that financial factors seem to have played a smaller role during the double-dip recession in the EA than during the GFC in the United States.

The model is applied to study potential financial amplification effects during the COVID-19 episode, in particular stemming from losses on bank loans resulting from the reduction in household income and non-financial corporations' cash flows. Such losses could trigger deleveraging needs and/or a credit crunch as banks attempt to restore capital adequacy in the aftermath of widespread simulated defaults. The effects reported below (**Chart 24**), evaluated through the lens of the model, are based on estimates reported in the May 2020 ECB Financial Stability Report, namely losses on non-financial corporation (NFC) loans amounting to slightly more than 3% (or almost 12%) as a ratio of total NFC loans under a base (or severe) scenario in terms of NFC cash flows. The simulations imply a drop in output of 0.5% (or 1.7%) at the trough, five quarters after the initial shock, highlighting second-round amplification risks to economic activity.

Chart 24

Effects of estimated losses on NFC loans in FBC_EA model

(percentage deviation from steady state)



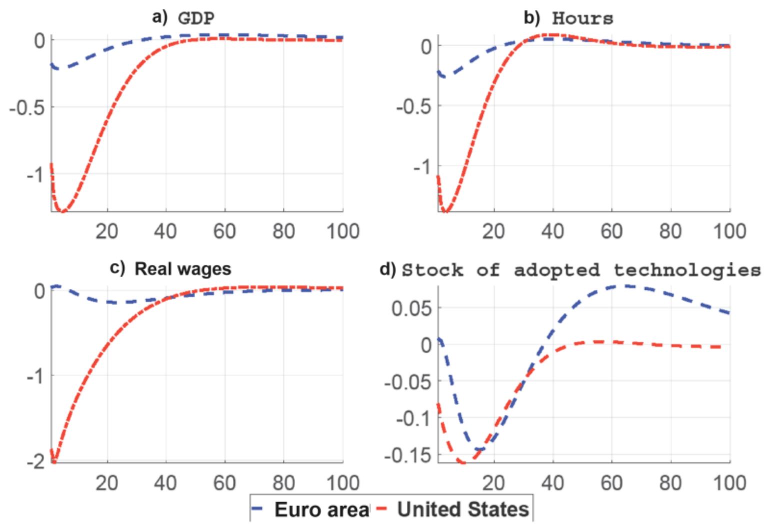
Source: Hirschbühl, Krustev and Stoevsky (2020).

3.3 International medium-term business cycles

There is a debate over the role of foreign-driven medium-term business cycles that arise from fluctuations at the technological frontier (United States) in macroeconomic developments in the EA. To disentangle domestic and foreign drivers of the EA business cycle, the study of Hirschbühl and Spitzer (2021) developed a two-economy medium-scale DSGE model with endogenous growth, based on the mechanism proposed by Anzoategui, Comin, Gertler and Martinez (2019). The model is estimated for the United States and the EA over the period between the first quarter of 1984 and the fourth quarter of 2017. Results from a Bayesian estimation suggest that financial shocks affecting innovation dynamics may increase international spillovers and contribute to pro-cyclicality in real variables (**Chart 25**).

Chart 25
Shock to US liquidity preference

(percentage deviation from steady state)



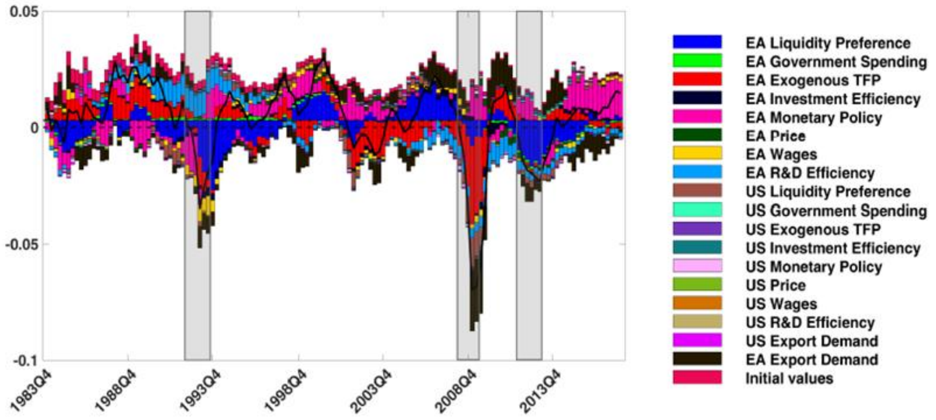
Source: Hirschbühl and Spitzer (2021).

The results suggest that EA business cycle dynamics are more dependent on US developments than vice versa. In particular, foreign-driven medium-term oscillations are found in the EA in the years leading up to the GFC. Moreover, the substantial negative contribution of the exogenous TFP shock in the GFC period may indicate financial contagion effects that are not well captured by the model. The model unveils the non-neutral effects of monetary policy, contributing substantially to growth and driving output, consumption and investment dynamics in the EA since 2014. It is also notable that domestic financial shocks played a major role during the sovereign debt crisis in the euro area, while their contribution was more limited in the GFC phase (**Chart 26**). The negative contribution of domestic financial shocks persisted after the sovereign debt crisis: thus, these shocks and their propagation were at least partly responsible for the sluggish recovery that followed.

Chart 26

Historical decomposition of euro area real GDP growth

(percentages)



Source: Hirschbühl and Spitzer (2021).

3.4 Cyclical drivers of consumption: the role of durable goods

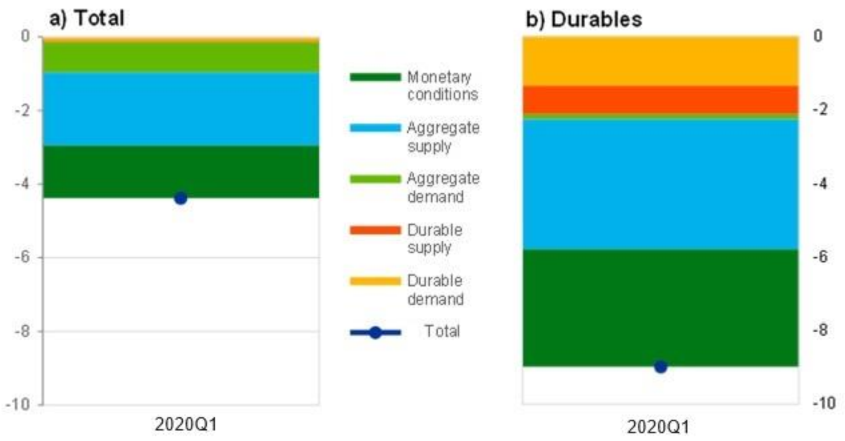
Expenditure on consumer durables – such as cars, furniture and electronics – makes up a small proportion of total consumption, but accounts for a disproportionately large fraction of its overall fluctuation in the euro area. Durable goods have specific characteristics that complicate substantially the task of a modeller when they enter into a consumption function. First, a durable good provides utility over multiple periods and (in the same way as capital) is subject to depreciation. This allows consumers to postpone purchases of durables in times of economic duress, while still benefiting from the service flow from the accumulated stock, and to catch up with upgrades to the desired stock when the economy is doing better. Second, durables can often be financed with credit and may also serve as collateral to secure the claim of a lender. This characteristic makes them more exposed to fluctuations in credit conditions and lending rates.

The cyclical dynamics of consumption in the EA and the large EA countries are analysed by distinguishing durable from non-durable expenditures. A theoretical partial equilibrium framework is adopted to justify the identification strategy of an empirical model: a time-varying parameter structural vector autoregression (TVP-SVAR). Following the main insight from the theoretical model, i.e. that liquidity constraints bring about important interactions between durables and non-durables, durable-specific demand and supply shocks are distinguished, also taking into account monetary and credit conditions.

The main findings are as follows: (i) durables react faster and more strongly than non-durables after monetary shocks in the EA and in the largest EA countries, confirmation of an outcome commonly reported for the United States; (ii) there is a high degree of cross-country heterogeneity in the way that different factors (including durable-specific ones) explain consumption; and (iii) the extent of spillovers from durable to non-durable consumption, as predicted by the theory, is empirically correlated with the share of liquidity-constrained households across countries.

Chart 27
Historical decomposition of total and durable consumption in the euro area

(percentages)



Source: Authors' calculations.
Notes: The decomposition is based on a time-varying parameter Bayesian VAR (TVP-BVAR) model of consumption featuring durable goods as described in Casalis and Krustev (2020). The model parameters are estimated up to 2019Q4.

A decomposition of the decline in consumption (both total and durable) into structural factors during the initial COVID-19 shock (in 2020Q1) can be performed based on the TVP-SVAR model. According to this model, distinguishing durable and non-durable goods, a large share of the contraction in consumption in 2020Q1 is attributable to adverse supply shocks, and to a lesser extent to demand shocks (**Chart 27**). This reflects the steep drop in quantities and the relative stability in prices in that quarter. About one-third of the fall in consumption is also attributed to the observed tightening of credit conditions for households at the time.

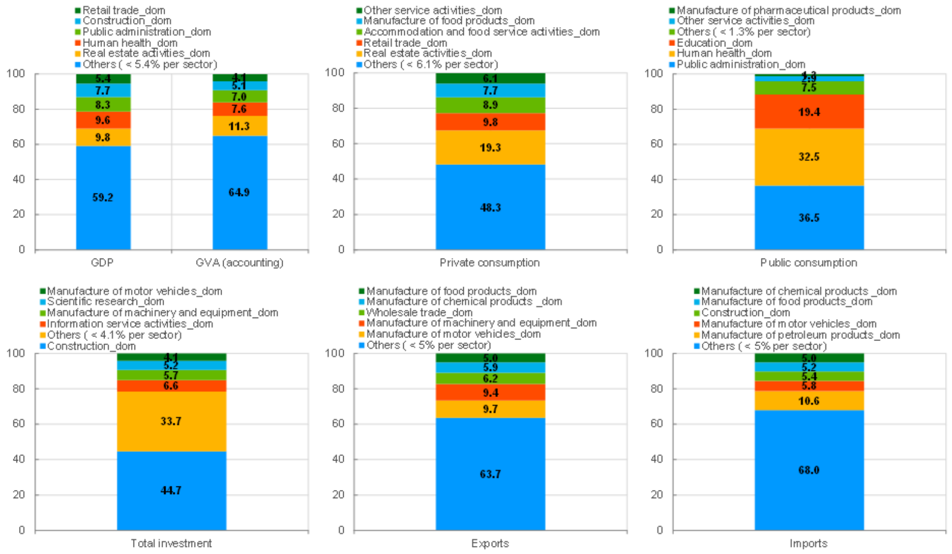
3.5 Short-term impact of COVID-19 containment

The initial impact of the COVID-19 containment was also analysed with a framework that embeds a production network, based on input-output tables, in a dynamic agent-based model (ABM). This approach was used in the early phase of the pandemic to identify the short-term impact of lockdown measures on demand components. This impact was assessed for the euro area and for its five largest countries. **Chart 28** shows the impact of a symmetric multi-sector shock on GDP and demand components in the euro area. It first contrasts the sector-specific contributions to GDP, as implied by the underlying structure of the economy, with the sector-specific contributions to gross value added (GVA), as implied by a pure accounting approach. Once input-output linkages are considered, the contribution of each sector to GDP is different from its contribution to GVA, with some sectors being relatively more important (e.g. construction, from 5% in GVA to 8% in GDP) and others relatively less important (e.g. real estate, from 11% in GVA to 10% in GDP) due to production network effects. Moreover, the concentration of the top five contributing sectors varies significantly across demand components, with public consumption relatively more concentrated (where the top contributor is public administration, at 37%), followed by total investment (with construction, at 45%), private consumption (with real estate, at 19%), exports (with motor vehicles, at 10%) and imports (with petroleum products, at 11%).

Chart 28

Symmetric multi-sector shock: contributions to losses in euro area demand

(percentages)



Source: WIOD (2016) and authors' calculations.
Note: Each (domestic) sector is assumed to be hit by the same (percentage) reduction in production and use of domestic and foreign inputs.

Chart 29 illustrates the heterogeneous impact of an asymmetric multi-sector shock – broadly reflecting the cross-sector impact of lockdown measures – across demand components and countries. Looking at the results across demand components, the implementation of lockdown measures would imply relatively larger losses for exports (19-20%), followed by private consumption (14-17%), total investment (11-17%) and public consumption (7-8%), only partly offset by losses in imports (12-13%). Across countries (**Chart 29**), these lockdown measures entail relatively larger GDP losses for Spain (17.2%) and Italy (16.8%), with smaller losses for Germany (15.9%), the Netherlands (15.8%) and France (15.3%). Moreover, Germany, Spain and the Netherlands record relatively larger losses in private consumption, while France and Italy suffer higher losses in total investment. Re-opening scenarios were also implemented, but with expert judgement needed to quantify the shocks to sectors.

Chart 29

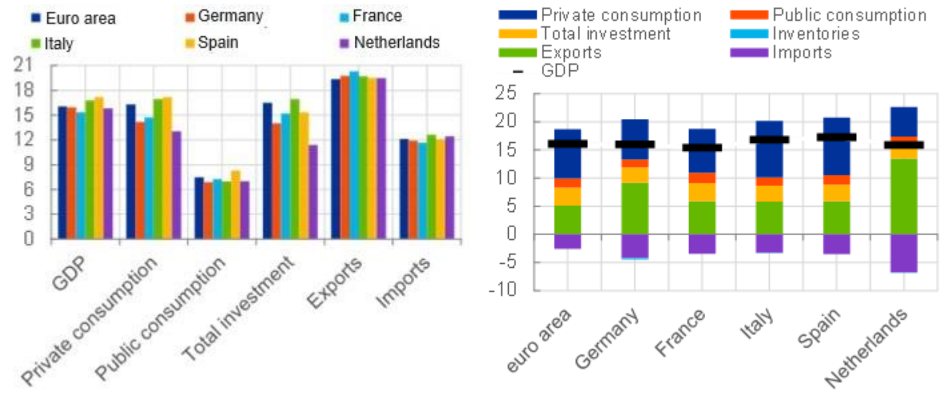
GDP and component losses in the euro area and five largest euro area countries

a) Losses

(percentage deviation from steady state)

b) Contributions

(contribution to GDP deviation from steady state.)



Source: WIOD (2016) and authors' calculations.
Notes: The initial sectoral losses for domestic sectors are in line with those in Box 1 of the Economic Bulletin Issue 3 2020. The shock to production and use of domestic and foreign inputs of each sector is applied between 17 March and 15 May 2020 and gradually decreases thereafter, with a daily compound rate of 0.01%.

Subsequent developments largely confirmed the implications of these initial model simulations. Despite the behavioural responses, gradual adaptation and learning during the sequence of pandemic waves and their containment, the contact-intensive services activities were the most affected sectors throughout 2020-21 across the euro area countries.[26]

[26] For further details see the box entitled "Economic developments and outlook for contact-intensive services in the euro area", *Economic Bulletin*, Issue 7, ECB, 2021.

4 Conclusions

This paper has presented findings on business cycle dating and characteristics, based on a number of alternative methods, according to the classical and growth cycle approaches. The results are based on transparent and automated procedures, producing comparable findings across the EU countries and the euro area aggregate indicators. The tools incorporate the possibility of implementing expert judgement, which has been used in exceptional cases, e.g. for truncated phases or if the turning point is not supported by other evidence, to achieve a consistent and plausible representation of the state of the business cycle.

The results from utilising the developed tools complement the chronologies provided by official business cycle dating committees. The presented analysis is based on timely and reliable signals, as well as a rich cross-country and cross-indicator perspective. The latter is also the basis for more in-depth investigations of the specific characteristics of the different episodes of the business cycle.

Among the main findings when dating the euro area business cycle at a monthly frequency is that the augmented Bry-Boschan procedure correctly identifies the relatively long recession in the early 1980s, as also dated by the CEPR. The algorithm also correctly dates the GFC and the sovereign debt crisis in the euro area, and points to a pre-pandemic peak in October 2019, followed by a trough in activity in April 2020.

The business cycle chronology for the euro area and the EU countries, based on the quarterly univariate MBBQ algorithm, highlights three major episodes of contractions, being relatively widespread across the EU countries. Regarding the pandemic period, the algorithm identified the last economic peak in 2019Q4, and the onset of a recession from 2020Q1 onwards. The analysis of the business cycle statistics across countries points to the high diversity of average durations of expansions, in contrast to the more homogenous average durations of recessions.

Deriving global business cycle chronologies based on the MBBQ algorithm also suggests three episodes of relatively synchronised recessions. The latter two contractions, namely the GFC and the COVID-19 related slump, are widespread across both advanced and emerging countries, and across global and country-specific macroeconomic aggregate indicators.

Based on a rich set of euro area aggregate indicators, the results point to varying cyclicality across economic measures and sectors. For example, there is a relatively high volatility of sentiment indicators and measures for the manufacturing sector. The results also point to the lead/lag properties of some indicators: for example, industrial production excluding construction tends to lead the turning points of the GDP cycle, although caution is required, given false signals in the more distant past. One key finding in this section is that the labour market variables tend to show the least cyclicality, whereas sentiment and confidence indicators are among the most cyclical.

The multivariate MBBQ applications provide complementary information and help better approximate the state of the economy. They utilise the cross-sectional information for countries or macroeconomic aggregates. The results from several average-then-date methods, while consistently identifying the latest three widespread recessionary episodes, also point to the weakness in the euro area economy in the early 2000s. These findings are further supported by the clusters identified in the date-then-average methods, which also point to some weakness in 2001-02.

The deviation cycle method provides an alternative approach to the business cycle chronology, identifying four distinct phases. The findings with this method suggest a broadly similar pattern across the euro area countries in the run-up to the GFC and its aftermath. One conclusion from the UCM-based analysis is that the euro area business cycle has primarily reflected fluctuations in the TFP cycle and the (un)employment cycle over the last two decades.

Some refinements of the presented automated tools could also be envisaged. First, incorporating additional rules within the algorithms for the classical business cycle dating (e.g. improving the reliability of the classifications when growth fluctuates around zero) could be useful. Second, extra restrictions could be implemented in the tools for time series exhibiting very high (low) volatility of economic cycles, so that periods currently requiring the implementation of expert judgement could be properly and automatically classified by the algorithms. Third, calculating and automatically reporting additional business cycles statistics, for example over rolling or non-overlapping samples, could also be considered.

This paper also investigated the evolution of business cycle synchronisation in the euro area over the last 20 years. Given the mixed results in the literature, several synchronisation measures, following different approaches, were presented. Apart from the pandemic crisis, over the past 20 years two major events have affected the evolution of the degree of synchronicity and the level of heterogeneity among the European economies: i) the inception of EMU and ii) the GFC. The introduction of the euro was associated with some (albeit small) increase in synchronisation, given relatively unchanged average cross-country dispersion. Indeed, synchronicity increased among the euro area countries in the early years of EMU, followed by a sharp increase around the GFC. Overall, the evidence does not point to the GFC as a significantly disruptive factor for euro area cross-country synchronisation. Instead, it was during the sovereign debt crisis when business cycle phase synchronicity across the euro area countries weakened. In addition, the amplitude of the business cycles increased. In a regression analysis we find an explanatory role for the pre-financial crisis macroprudential and fiscal policies for this divergence.

The euro area cycle is an important factor in explaining the variability of domestic business cycles, although with different levels of sensitivity. Furthermore, the global business cycle plays a major part in explaining the euro area business cycle. At regional level, business cycle synchronisation across regions within the euro area also increased in the years before the pandemic, but there is evidence of a strong national border effect. Similarities in sectoral composition mainly explain regional business synchronisation. By sector, manufacturing, business-related services and trade show the highest degree of co-movement across countries and explain most of the aggregate co-movement. Within the industrial sector, the production of intermediate goods explains most of the cyclical fluctuations in the industry, regardless of the period considered, but since the GFC, energy production has become more relevant. Nevertheless, since the financial crisis, common shocks appear less important for explaining fluctuations in industry output. At a more granular level, idiosyncratic shocks at the top 100 large firms have some explanatory power for business cycle fluctuations in euro area countries.

The paper also provided a selection of analytical results focused on the drivers of the euro area business cycle from different perspectives. Based on diverse approaches and theory-based assumptions, the analytical studies identified orthogonal factors driving the business cycle fluctuations, utilising a growth accounting perspective or stemming from the financial sector, the international dimension or the cyclicality of demand for specific products. This part also provided an early assessment of the economic implications of COVID-19 containment, based on a framework embedding a production network within a dynamic agent-based model. As the pandemic period was an extraordinary economic event (in terms of size, characteristics and duration), posing specific challenges to the business cycle analysis, a more comprehensive assessment of its features and economic implications was deemed outside of the scope of this paper.[27]

[27] The economic implications of the pandemic have been analysed by numerous research studies. Examples of early studies include Jorda, Singh and Taylor (2020) and Eichenbaum, Rebelo and Trabandt (2021). For an initial assessment of the economic impact in the euro area, see the box entitled "Alternative scenarios for the impact of the COVID-19 pandemic on economic activity in the euro area", *Economic Bulletin*, Issue 3, ECB, 2020.

5 Annexes

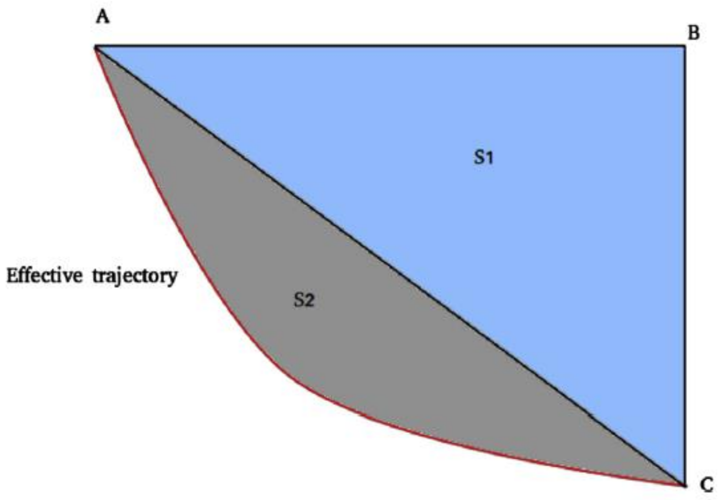
5.1 Annex 1. Business cycle statistics

As noted by Grigoraș et al. (2016), and Harding and Pagan (2002), several statistics can be calculated to describe the business cycle.[28] Chart A1.1 illustrates a stylised recession for the log level of economic activity, from point A, the peak, to point C, the trough, with AB being the time in quarters. The standard business cycle measures are as follows.

- Duration of the phase: the number of quarters of the phase (segment AB).
- Amplitude: the magnitude of the decline (in % of initial level; segment BC).
- Slope: steepness of the decline (amplitude/duration, the ratio of segments: BC/AB).
- Cumulative gain/loss: compared with a no-growth counter-factual scenario (sum of areas: S1+S2).
- Excess: asymmetry of the economic trajectory compared with a linear decline (the ratio of areas: S2/S1).

For recessions, the amplitude, slope and gain are reported with a negative sign.

Chart A1.1
A stylised recession

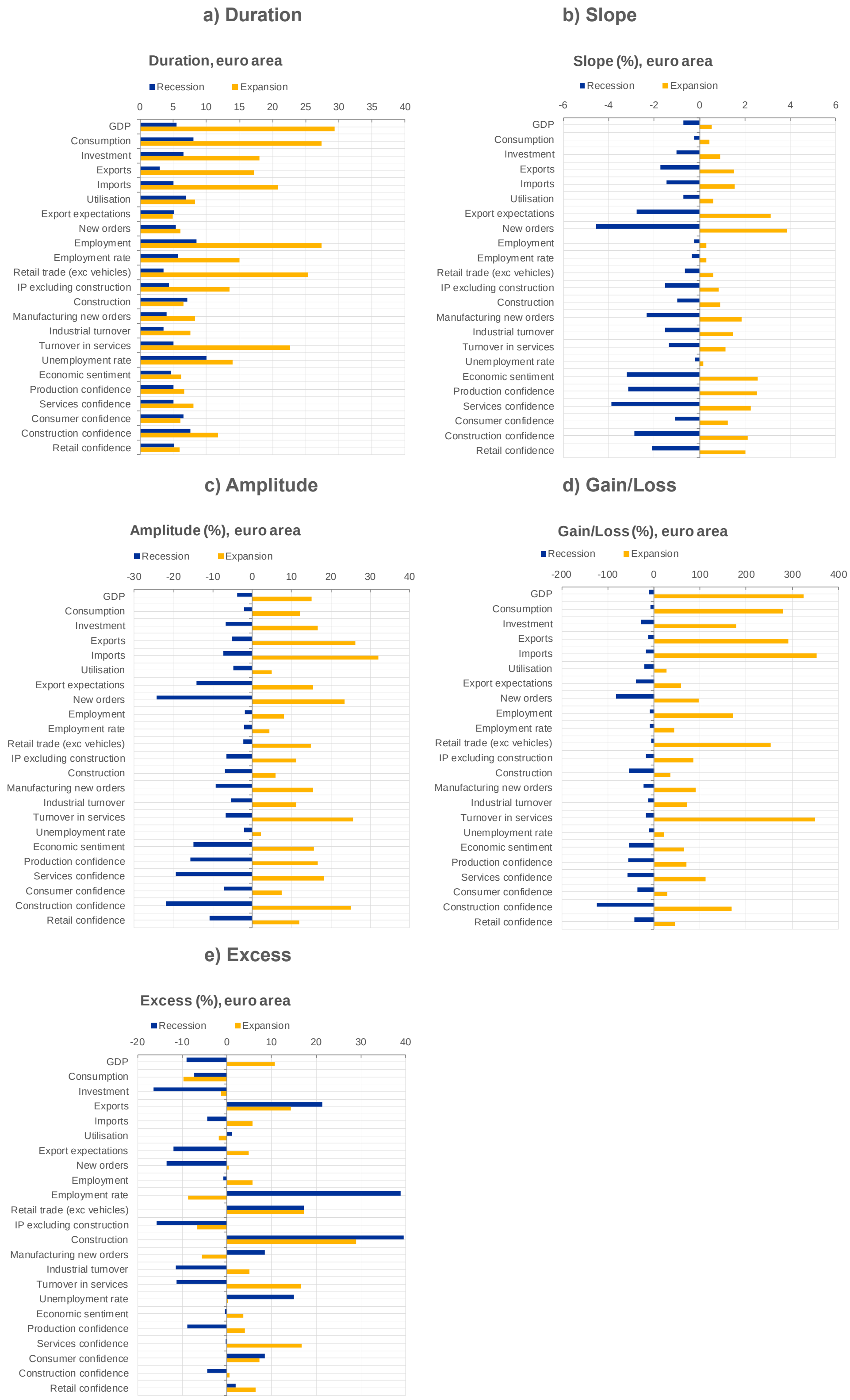


Source: Grigoraș et al. (2016).

[28] Gadea et al. (2017) also propose a set of new quantitative measures to characterise more carefully the features of economic recoveries. In addition, Camarero et al. (2021) apply these measures to a wide set of 46 countries, including developed and developing economies.

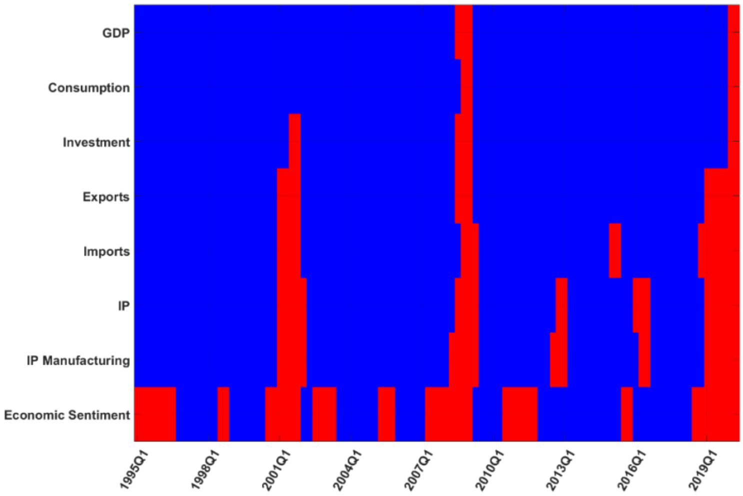
Chart A1.2

Statistics for the euro area business cycle



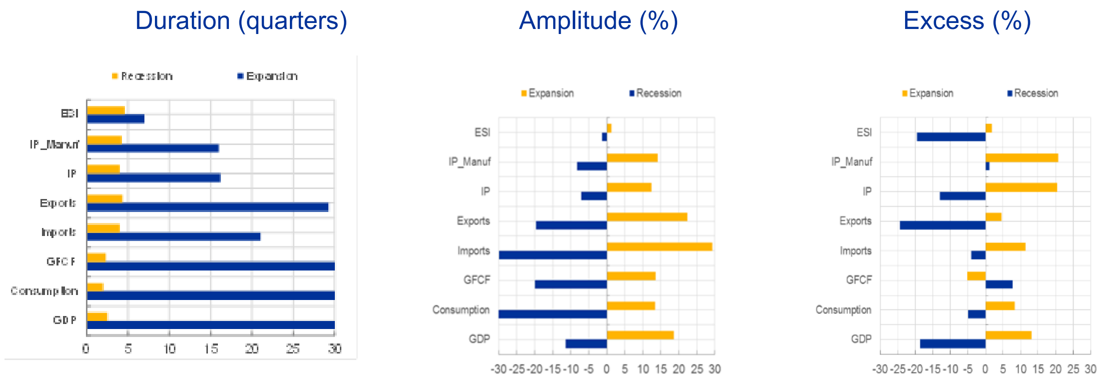
Source: Authors' calculations.

Chart A1.3
Heatmap of global business cycle dating



Source: Authors' calculations.

Chart A1.4
Statistics for the global business cycle



Source: Authors' calculations.

Table A1.1
Business cycle phases under the deviation cycle approach

	Cycle < 0	Cycle > 0
Δ Cycle > 0	Recovery	Expansion
Δ Cycle < 0	Slowdown	Downturn

Source: Authors' calculations.
Note: The cycle is defined as the log deviation of the observable variable from its trend.

5.2 Annex 2. Business cycle synchronisation

Chart A2.1

Concordance index for the EU countries

	EA	AT	BE	BG	HR	CY	CZ	DK	EE	FI	FR	DE	EL	HU	IE	IT	LV	LT	LU	MT	NL	PL	PT	RO	SK	SI	ES	SE
EA	1.00	0.95	0.93	0.79	0.86	0.90	0.93	0.86	0.79	0.86	0.93	0.87	0.82	0.90	0.92	0.80	0.80	0.87	0.84	0.81	0.95	0.88	0.90	0.83	0.91	0.94	0.95	0.97
AT	0.95	1.00	0.93	0.79	0.84	0.86	0.89	0.82	0.77	0.83	0.93	0.86	0.78	0.88	0.86	0.78	0.78	0.87	0.82	0.86	0.92	0.92	0.85	0.83	0.91	0.90	0.91	0.92
BE	0.93	0.93	1.00	0.77	0.80	0.85	0.87	0.84	0.79	0.79	0.93	0.89	0.75	0.88	0.85	0.77	0.80	0.89	0.86	0.86	0.92	0.88	0.85	0.83	0.95	0.88	0.89	0.90
BG	0.79	0.79	0.77	1.00	0.70	0.77	0.84	0.68	0.73	0.68	0.76	0.70	0.65	0.80	0.75	0.74	0.74	0.81	0.68	0.84	0.76	0.77	0.69	0.91	0.79	0.78	0.77	0.78
HR	0.86	0.84	0.80	0.70	1.00	0.86	0.81	0.77	0.72	0.83	0.84	0.73	0.87	0.83	0.83	0.75	0.80	0.80	0.71	0.73	0.88	0.76	0.85	0.76	0.80	0.92	0.89	0.86
CY	0.90	0.86	0.85	0.77	0.86	1.00	0.88	0.77	0.77	0.87	0.83	0.79	0.76	0.84	0.86	0.85	0.72	0.81	0.76	0.74	0.89	0.82	0.86	0.78	0.85	0.89	0.92	0.89
CZ	0.93	0.89	0.87	0.84	0.81	0.88	1.00	0.83	0.74	0.80	0.85	0.83	0.76	0.84	0.86	0.76	0.76	0.81	0.79	0.82	0.92	0.84	0.84	0.88	0.87	0.90	0.91	0.90
DK	0.86	0.82	0.84	0.68	0.77	0.77	0.83	1.00	0.74	0.77	0.87	0.77	0.73	0.85	0.83	0.71	0.73	0.80	0.77	0.75	0.84	0.74	0.81	0.74	0.84	0.83	0.82	0.86
EE	0.79	0.77	0.79	0.73	0.72	0.77	0.74	0.74	1.00	0.73	0.83	0.79	0.67	0.78	0.80	0.70	0.83	0.85	0.79	0.77	0.79	0.78	0.71	0.78	0.81	0.77	0.77	0.82
FI	0.86	0.83	0.79	0.68	0.83	0.87	0.80	0.77	0.73	1.00	0.81	0.74	0.79	0.77	0.82	0.83	0.67	0.74	0.70	0.67	0.85	0.75	0.80	0.69	0.77	0.84	0.88	0.86
FR	0.93	0.93	0.93	0.76	0.84	0.83	0.85	0.87	0.83	0.81	1.00	0.87	0.78	0.90	0.85	0.75	0.84	0.91	0.87	0.86	0.90	0.85	0.85	0.81	0.95	0.88	0.87	0.92
DE	0.87	0.86	0.89	0.70	0.73	0.79	0.83	0.77	0.79	0.74	0.87	1.00	0.71	0.81	0.79	0.69	0.84	0.82	0.95	0.82	0.88	0.81	0.83	0.76	0.87	0.81	0.82	0.85
EL	0.82	0.78	0.75	0.65	0.87	0.76	0.76	0.73	0.67	0.79	0.78	0.71	1.00	0.76	0.85	0.68	0.75	0.73	0.69	0.64	0.80	0.70	0.79	0.70	0.73	0.85	0.82	0.83
HU	0.90	0.88	0.88	0.80	0.83	0.84	0.84	0.85	0.78	0.77	0.90	0.81	0.76	1.00	0.87	0.74	0.83	0.90	0.83	0.82	0.89	0.82	0.82	0.80	0.90	0.91	0.86	0.91
IE	0.92	0.86	0.85	0.75	0.83	0.86	0.86	0.83	0.80	0.82	0.85	0.79	0.85	0.87	1.00	0.74	0.76	0.86	0.76	0.71	0.89	0.84	0.84	0.80	0.83	0.91	0.88	0.93
IT	0.80	0.78	0.77	0.74	0.75	0.85	0.76	0.71	0.70	0.83	0.75	0.69	0.68	0.74	0.74	1.00	0.68	0.68	0.68	0.67	0.77	0.70	0.76	0.70	0.71	0.76	0.80	0.77
LV	0.80	0.78	0.80	0.74	0.80	0.72	0.76	0.73	0.83	0.67	0.84	0.84	0.75	0.83	0.76	0.68	1.00	0.82	0.86	0.82	0.80	0.72	0.76	0.79	0.82	0.81	0.77	0.81
LT	0.87	0.87	0.89	0.81	0.80	0.81	0.81	0.80	0.85	0.74	0.91	0.82	0.73	0.90	0.86	0.68	0.82	1.00	0.82	0.85	0.86	0.85	0.79	0.86	0.91	0.88	0.84	0.88
LU	0.84	0.82	0.86	0.68	0.71	0.76	0.79	0.77	0.79	0.70	0.87	0.95	0.69	0.83	0.76	0.68	0.86	0.82	1.00	0.84	0.86	0.77	0.83	0.72	0.87	0.79	0.78	0.83
MT	0.81	0.86	0.86	0.84	0.73	0.74	0.82	0.75	0.77	0.67	0.86	0.82	0.64	0.82	0.71	0.67	0.82	0.85	0.84	1.00	0.85	0.87	0.78	0.82	0.92	0.80	0.81	0.80
NL	0.95	0.92	0.92	0.76	0.88	0.89	0.92	0.84	0.79	0.85	0.90	0.88	0.80	0.89	0.89	0.77	0.80	0.86	0.86	0.85	1.00	0.87	0.93	0.79	0.92	0.96	0.95	0.94
PL	0.88	0.92	0.88	0.77	0.76	0.82	0.84	0.74	0.78	0.75	0.85	0.81	0.70	0.82	0.84	0.70	0.72	0.85	0.77	0.87	0.87	1.00	0.80	0.80	0.90	0.84	0.85	0.86
PT	0.90	0.85	0.85	0.69	0.85	0.86	0.84	0.81	0.71	0.80	0.85	0.83	0.79	0.82	0.84	0.76	0.76	0.79	0.83	0.78	0.93	0.80	1.00	0.73	0.85	0.89	0.90	0.89
RO	0.83	0.83	0.83	0.91	0.76	0.78	0.88	0.74	0.78	0.69	0.81	0.76	0.70	0.80	0.80	0.70	0.79	0.86	0.72	0.82	0.79	0.80	0.73	1.00	0.83	0.84	0.79	0.82
SK	0.91	0.91	0.95	0.79	0.80	0.85	0.87	0.84	0.81	0.77	0.95	0.87	0.73	0.90	0.83	0.71	0.82	0.91	0.87	0.92	0.92	0.90	0.85	0.83	1.00	0.88	0.87	0.90
SI	0.94	0.90	0.88	0.78	0.92	0.89	0.90	0.83	0.77	0.84	0.88	0.81	0.85	0.91	0.91	0.76	0.81	0.88	0.79	0.80	0.96	0.84	0.89	0.84	0.88	1.00	0.94	0.95
ES	0.95	0.91	0.89	0.77	0.89	0.92	0.91	0.82	0.77	0.88	0.87	0.82	0.82	0.86	0.88	0.80	0.77	0.84	0.78	0.81	0.95	0.85	0.90	0.79	0.87	0.94	1.00	0.92
SE	0.97	0.92	0.90	0.78	0.86	0.89	0.90	0.86	0.82	0.86	0.92	0.85	0.83	0.91	0.93	0.77	0.81	0.88	0.83	0.80	0.94	0.86	0.89	0.82	0.90	0.95	0.92	1.00

Source: Authors' calculations.

Chart A2.2

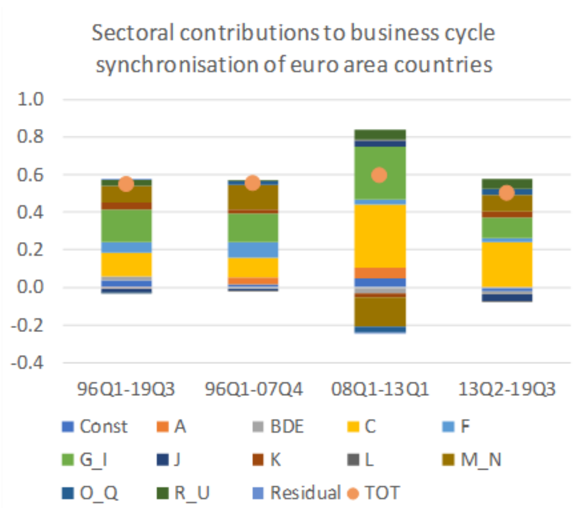
Concordance index for selected advanced and emerging economies

	EA	US	UK	JP	CA	MX	RU	AU	NZ	IN	BR
EA	1.00	0.91	0.94	0.81	0.91	0.83	0.63	0.90	0.81	0.88	0.71
US	0.91	1.00	0.95	0.77	0.95	0.86	0.80	0.94	0.87	0.92	0.75
UK	0.94	0.95	1.00	0.82	0.95	0.89	0.74	0.95	0.85	0.94	0.76
JP	0.81	0.77	0.82	1.00	0.77	0.78	0.59	0.78	0.76	0.77	0.72
CA	0.91	0.95	0.95	0.77	1.00	0.88	0.80	0.95	0.83	0.93	0.80
MX	0.83	0.86	0.89	0.78	0.88	1.00	0.65	0.87	0.78	0.87	0.74
RU	0.63	0.80	0.74	0.59	0.80	0.65	1.00	0.76	0.85	0.72	0.78
AU	0.90	0.94	0.95	0.78	0.95	0.87	0.76	1.00	0.84	0.98	0.77
NZ	0.81	0.87	0.85	0.76	0.83	0.78	0.85	0.84	1.00	0.81	0.68
IN	0.88	0.92	0.94	0.77	0.93	0.87	0.72	0.98	0.81	1.00	0.77
BR	0.71	0.75	0.76	0.72	0.80	0.74	0.78	0.77	0.68	0.77	1.00

Source: Authors' calculations.

Chart A2.3

Sectoral contributions to aggregate co-movement

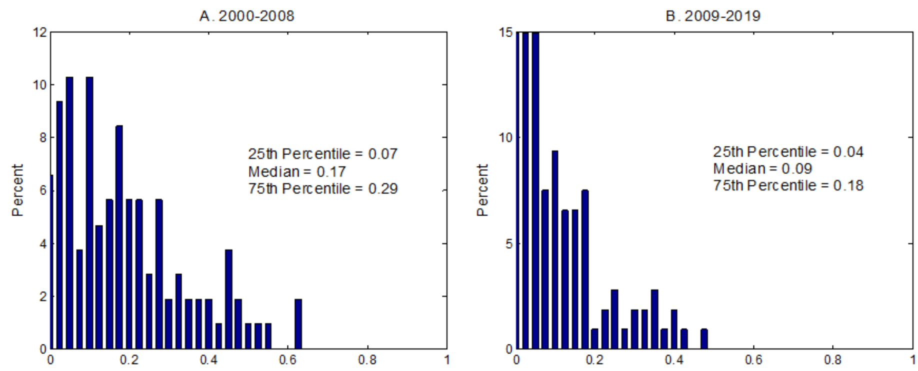


Source: Authors' calculations.

Chart A2.4

Distribution of R-squared for industrial sectors

(percentages)

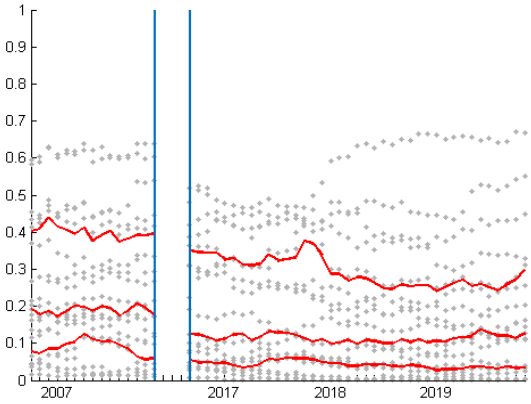


Source: Authors' calculations.
Note: R-squared is the proportion of variance of production in each industrial sector explained by common factors.

Chart A2.5

Forecast error variance explained by common shocks

(proportion)



Source: Authors' calculations.
Notes: The dotted lines are 81-month rolling estimates of the proportion of forecast error variance of industrial production growth rates for euro area countries due to common shocks over a horizon of one year. The median, 25th and 75th percentiles of the 19 forecast error decompositions are in solid red lines.

Table A2.1

Regression analysis: granular residual controlling for other factors

Dependent variable: real GDP growth

Explanatory variables	(1) Basic	(2) Demeaned (country-sector)	(3) Demeaned (sector)	(4) Demeaned (country-year)	(5) Demeaned (country-sector-year)
Oil prices	-0.04*	-0.04*	-0.04*	-0.04*	-0.04*
Interest rates	0.73**	0.35	0.35	0.46	0.54*
Public spending	-0.05	-0.04	-0.04	-0.08	-0.05
Granular residual	-	0.29**	0.29**	0.20**	0.21**
Constant	1.54***	2.54***	2.51***	2.32***	1.93**
Observations	85	69	69	69	69
R-squared	0.32	0.60	0.60	0.48	0.49
Adj. R-squared	0.20	0.51	0.51	0.36	0.36

Source: Authors' calculations.
Notes: Significance levels: * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$. All the regressions include country fixed effects and country-specific trends. Oil prices correspond to Brent oil prices in euro, interest rates refer to the Euro Overnight Index Average (EONIA) and all variables are deflated using the GDP deflator for each country. Robust standard errors are clustered at country level.

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