DEUTSCHE
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# Discussion Paper

Deutsche Bundesbank
No 04/2018

## Financial cycles in euro area economies: a cross-country perspective

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Internet http://www.bundesbank.de



ISBN 978–3–95729–430–2 (Printversion)
ISBN 978–3–95729–431–9 (Internetversion)

# Non-technical summary

## Research Question

We investigate the cross-country synchronization in cycles in credit, house prices, equity prices and interest rates between six euro area countries. Medium-to-longer-term cycles in these variables are commonly interpreted as representations of financial cycles. We study whether evidence for cross-country cyclical co-movements can be found in the data, whether they differ across variables and whether these co-movements have changed over time.

## Contribution

Our most important contribution is the application of different empirical approaches to measure and assess cross-country co-movements of cycles in financial variables to a harmonized data set. Some of these methods allow for changes in the cross-country relationships over time. Due to the range of these methods we can make robust assessments about statistical properties of the financial cycle in euro area economies.

## Results

We find that cycles in equity prices and interest rates are more strongly synchronized across countries than cycles in real economic activity whereas the synchronization of credit cycles and, in particular, cycles in house prices is weaker than for real GDP. Among credit variables only medium-term cycles in bank lending to non-financial firms display marked and stable cross-country co-movements.

# Nichttechnische Zusammenfassung

## Fragestellung

Wir untersuchen für sechs Länder des Euroraums, ob länderübergreifende gemeinsame Zyklen in Krediten, Immobilienpreisen, Aktienkursen oder Zinsen vorliegen. Mittel- bis langfristige Zyklen in diesen Variablen werden häufig mit dem Finanzzyklus in Verbindung gebracht. Wir analysieren, ob die Daten Hinweise auf das Vorliegen gemeinsamer, länderübergreifender Zyklen in diesen Daten liefern, ob es Unterschiede zwischen den verschiedenen Variablen gibt und ob sich diese Zusammenhänge im Laufe der Zeit verändert haben.

## Beitrag

Unser Beitrag besteht in der Anwendung verschiedener empirischer Ansätze zur Analyse gemeinsamer, länderübergreifender Zyklen in Finanzmarktvariablen und Vermögenspreisen auf Grundlage eines harmonisierten Datensatzes. Einige der Ansätze erlauben es, Veränderungen der Zusammenhänge in den Daten über die Zeit zu untersuchen. Die Bandbreite der verwendeten Ansätze erlaubt es uns, relativ robuste Aussagen über Eigenschaften von Finanzzyklen im Euroraum zu machen.

## Ergebnisse

Unsere Ergebnisse zeigen, dass Aktienkurse und Zinsen im Vergleich zur realen Aktivität stärkere länderübergreifende Zyklen aufweisen. Dagegen spielen länderübergreifende Zyklen für die Kredite und insbesondere die Immobilienpreise eine geringere Rolle als für das reale BIP. Unter den Kreditvariablen zeigen nur die Kredite an nichtfinanzielle Unternehmen ausgeprägte und stabile gemeinsame zyklische Schwankungen über die Länder hinweg.

DEUTSCHE BUNDESBANK DISCUSSION PAPER NO 04/2018

# Financial cycles in euro area economies: a cross-country perspective*

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**Abstract**

We study the cross-country dimension of financial cycles for six euro area countries using three different methodologies: principal component analysis, synchronicity and similarity measures and wavelet analysis. We find that equity prices and interest rates display synchronization across countries similar to or exceeding that of real GDP. In contrast, our estimates show much lower cross-country synchronization of credit variables and house prices - bank lending to non-financial firms being an exception with relatively large cross-country co-movements. These results are robust across the different estimation methodologies. Concerning time-variation we find evidence for a decline in the extent of co-movements in house prices over time while co-movements in the term spread have increased with the introduction of the European monetary union.

**Keywords:** financial cycles, band-pass filter, principal components, wavelet analysis

**JEL-Classification:** C32, C38, E44, E51.

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* This paper is a substantially extended version of Section 4 in Rünstler et al. (2018). We are indebted to Gerhard Rünstler for helpful comments and discussions. The views expressed in this paper are those of the author(s) and do not necessarily co-incide with the views of the Deutsche Bundesbank, the Hrvatska Narodna Banka or the Eurosystem.

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# 1 Introduction

In the aftermath of the financial crisis the concept of the financial cycle as a potential source of macroeconomic and financial instability has drawn much interest from policymakers and researchers alike.

Financial cycles are interpreted as representing the build-up of imbalances in the financial system and being at the root of financial boom and bust cycles (eg. Borio, 2014). In fact, various studies have presented evidence on the predictive power of financial cycle proxies for financial crises (eg. Alessi and Detken, 2009; Borio and Drehmann, 2009; Drehmann and Juselius, 2014; Schüler, Hiebert and Peltonen, 2017; Voutilainen, 2017). An understanding of financial cycles, their manifestations, causes and implications is important for policymakers since macroprudential policy measures have been tied to proxies for the financial cycle. For example, Basel III regulations link counter-cyclical capital buffers to the deviation of the credit-to-GDP ratio from its long-run trend (eg. Drehmann and Tsatsaronis, 2014). There is also some evidence that the effectiveness of macroprudential policy tools depends on the state of the financial cycle (Cerutti, Claessens and Laeven, 2017). In Europe, the cross-country dimension of financial cycles has important implications for policy co-ordination. First, the degree of coherence of national financial cycles is important for whether common policies should be applied across countries. Dissimilar cycles might require country-specific policies in order to cope with national idiosyncrasies.[1] Second, national macro-prudential authorities may want to integrate both domestic and foreign developments in their decision-making. If cycles are sufficiently synchronised across (clusters of) countries, looking at international developments might be informative for policies at the national level as well (Hubrich et al., 2013).[2]

Empirically, financial cycles represent common movements in financial variables, most prominently credit or the credit-to-GDP ratio and property prices (eg. Borio, 2014; Drehmann, Borio and Tsatsaronis, 2012). In this paper we focus on the cross-country dimension of the financial cycle among euro area economies, ie. we analyse cross-

[1] Within the current European macroprudential framework, the responsibility for activating macroprudential instruments, such as the counter-cyclical capital buffer, lies with the national designated authorities, although the ECB issues warnings and recommendations.

[2] In addition, international spill-overs might also have domestic repercussions, for example if foreign banking or financial crises affect the economy through banks' foreign exposures (Drehmann et al., 2012).

country correlation and synchronicity in cycles in various financial time series using a range of different empirical approaches.

Many studies use univariate time-series approaches to extract cyclical components from financial time series, such as turning-point analysis (eg. Claessens, Kose and Terrones, 2011; Drehmann et al. 2012; Hubrich et al., 2013; Stremmel, 2015) or band-pass filters (eg. Aikman, Haldane and Nelson, 2015; Drehmann et al., 2012; Meller and Metiu, 2017).[3] Compared to business cycles, cycles in credit and house prices are typically found to operate on lower frequencies (eg. Borio, 2014; Drehmann et al., 2012; Rünstler et al., 2018; and, for credit cycles, Aikman et al., 2015) and to have a higher amplitude (eg. Drehmann et al., 2012; Galati, Hindrayanto, Koopman and Vlekke, 2016; Rünstler et al., 2018).

Aikman et al. (2015) analyse medium-term cycles in real bank lending in 14 industrialized economies using the empirical distribution of pairwise correlation coefficients and show that post-1980 this distribution has shifted towards higher cross-country correlations. Nevertheless, on average they find the absolute level of correlation to be relatively low. Meller and Metiu (2017) study cycles in bank lending using the Schularick and Taylor (2012) data set. The results of their cluster analysis and tests for breaks in the cycles' cross-country phase synchronisation indicate changes in the cross-country relationship between credit cycles over time. They also show that in the post-Bretton-Woods period countries with more synchronized business cycles also tend to experience more synchronized credit cycles. Anguren-Martin (2011) estimates credit regimes in 12 OECD countries using a Markov-switching framework and finds a high synchronisation of credit regimes during the recent financial crisis. Claessens et al. (2011) analyse cycles in credit, house prices and equity prices in 21 OECD countries using turning-point analysis. Based on a concordance index (Harding and Pagan, 2002) they show cross-country synchronisation to be highest for credit cycles and lowest for cycles in house prices. Moving beyond credit and house prices, Rünstler et al. (2018) extract cyclical components from credit aggregates, house prices, equity prices and interest rates for a number of EU countries using a band-pass filter. Applying principal components analysis to the filtered series within each country they show credit, house prices, term spread and real GDP to contain an important common cyclical component. While long-term interest rates and equity prices share a common component, cycles in these two variables exhibit little correlation with the other variables.

[3] De Bonis and Silvestrini (2014) estimate a trend-cycle decomposition for the Italian credit-to-GDP ratio) using a structural time series model (Harvey, 1989).

Other analyses use multivariate approaches and extract the common component in multiple financial time series, thus, directly taking into account that the financial cycle should be present in multiple financial data. Strohsal, Proaño and Wolters (2015) analyse interaction of the common component in credit and house prices between the U.S. and the U.K. and find that they have become more closely related in the post-1985 period. Furthermore, the frequency range of the relationship has shifted from business-cycle frequencies in the pre-1985 sample to lower frequencies. Galati et al. (2016) estimate multivariate structural time series models for house prices and credit or the credit-to-GDP ratio for the U.S. and the euro area and, for each country, extract common components from the time series. Rünstler and Vlekke (2016) extend this model to allow for common cyclical components in credit, house prices and real GDP. They find a high cross-country synchronisation of major peaks in the estimated cycles in these variables for the U.S., the U.K., Germany, France, Italy and Spain. While the previous literature treats business and financial cycles as distinct phenomena, they present evidence of important common medium-term cycles in credit, house prices and real GDP.

Schüler, Hiebert and Peltonen (2015) construct country-specific financial cycle measures that capture common cyclical components in credit, house prices, equity prices and bond yields. For these measures they find high pairwise concordance between a large subset of 14 European economies with the notable outlier of Germany and, to some extent, Austria. Their financial cycle indicators turn out to be less synchronised across countries than similarly derived business cycle indicators. For the G7 Schüler et al. (2017) extract the common component of the country-specific composite financial cycle indicators, constructed as in Schüler et al. (2015) as the first principal component across countries. They estimate correlation between this global financial cycle proxy and the country-specific financial cycles to exceed the correlation between national and global business cycle proxies except for Germany and Japan.

Using a data set for 24 countries with about 350 time series Breitung and Eickmeier (2016) estimate that global factors on average explain about 40 percent of movements in financial variables with common components being particularly important in "fast-moving" variables, such as stock prices and interest rates, but less so for monetary and credit aggregates as well as for house prices. Miranda-Agrippino and Rey (2015) analyse a global data set of more than 300 asset prices and estimate that more than 60 percent of the covariance matrix can be explained by a single global factor.

In this paper, we use three different and diverse methods to assess the cross-country dimension of the financial cycle in the euro area with the aim of providing a robust assessment by collecting results from different approaches which are based on a harmonised data set. As in Rünstler et al. (2018) we include a broad set of financial indicators such as different credit aggregates, property prices, equity prices, long- and short-term interest rates. The methods we apply are principal component analysis (PCA), measures of synchronicity and similarity, and cohesion measures derived from wavelet analysis.

The PCA approach extracts cross-country common components from country-specific filtered time series. By studying the factor loadings we analyse the extent to which the individual countries participate in common financial cycles. In contrast to the PCA, the synchronicity and similarity measures allow for time-variation in the cross-country relationship of the filtered series. The wavelet-based cohesion measures go even beyond this by not only allowing for time variation in synchronisation but also for synchronisation being frequency dependent. Furthermore, the wavelet-based approach is not based on a pre-filtering of time-series, ie. is a direct instead of a two-step methodology. To our knowledge, our paper is the first to pull together evidence on the cross-country dimension of financial cycles from such a diverse set of methods.

Our results show that the synchronicity of credit and house prices across euro area countries is moderate and lower than for real GDP. In contrast, the synchronicity of equity prices and interest rates is very high. Wavelet analysis further suggests that the co-movement between cycles of loans to households has been rising after the introduction of the euro, while it has decreased over time for house prices. Both principal component analysis and the analysis of phase synchronisation show Germany standing out with small cycles that appear largely independent from the other countries. For some variables, the first principal component in the cycle estimates seems to capture a North-South divide.

The paper is structured as follows: section 2 provides information on the data, section 3 explains the different empirical methodologies used to assess the cross-country dimension of the financial cycle together with the empirical results for each empirical approach. Section 4 provides an overall discussion of the results across the different empirical approaches and concludes.

## 2 Data

The data set is based on an update of the database used in Hubrich et al. (2013). We consider eight time series of quarterly data: real loans of monetary financial institutions (MFIs) to private households (LHH), real MFI loans to non-financial corporations (LNF), real bank credit to the non-financial private sector (BCN), real residential property prices (RPP), real equity prices (EQP), nominal long-term interest rates (LTN) and the nominal term spread (SPN). We use real GDP (YER) to compare the cross-country dimension of cycles in the financial variables to that of cycles in real activity. Specifics on data and data sources are given in the appendix. Nominal data is deflated using the GDP deflator. The data set initially included 17 EU member states with data availability differing substantially across countries. Since a reliable analysis of financial cycles requires sufficiently long time series we select from this data set six countries for which we have all the series starting at least in 1980: BE, DE, ES, FR, IT and NL. All time series end in 2016Q4.

## 3 Empirical analysis

Principal component and phase synchronization analyses use pre-filtered series of log levels of the variables as inputs while wavelet analysis is based on their annual growth rates, except for the long-term interest rate and for the term spread. For filtering the Christiano and Fitzgerald (2003) band-pass filter is applied.

In many studies the frequency range on which the financial cycle operates has been selected as exceeding eight years. For example, Drehmann et al. (2012) choose eight to 30 years, Meller and Metiu (2017) eight to 20 years. This a-priori specification excludes the possibility of co-movements in financial variables at other frequency ranges. In order to be more agnostic about the financial cycle frequencies we follow Aikman et al. (2015) and use a frequency range between eight and 80 quarters for the band-pass filter. The extracted cyclical components are shown in Appendix B. Using a very similar data set Rünstler et al. (2018) show that within this frequency range the standard deviation of cycles in credit aggregates and house prices is about three times the standard deviation of cycles in real GDP and that the standard deviation of the cyclical component in equity prices is about ten times that for real GDP.[4] Using turning point analysis they

[4] These results refer to those for the "long data sets" in Table 3 in Rünstler et al. (2018). Their data set includes BE, DE, DK, ES, FI, FR, IT, LU, NL and PT. The main difference to our data set is that our sample does not include DK, FI, LU and PT because one or more time series for these countries are too short for the application of the wavelet analysis. Another difference concerns the deflation of the nominal

show the length of these cycles in credit aggregates to exceed that of cycles in real GDP while equity prices, long-term interest rates and the term spread display shorter cycles than real GDP. Both average cycle lengths and standard deviations are estimated to be similar across countries.

## 3.1 Principal component analysis

The principal component analysis (PCA) is the first method we use to address the coherence between financial cycles among countries under analysis. The principal components are defined recursively as uncorrelated linear combinations of the extracted cycles having the maximal variance. Constructed in this way they represent the common dynamics underlying the movement of the group of series of interest.

**Table 1:** Eigenvalues and fraction of total variance explained by principal components

| PC | BCN | LHH | LNF | RPP | EQP | SPN | LTN | YER |
|---|---|---|---|---|---|---|---|---|
| | **Eigenvalues** | | | | | | | |
| 1. | 3.27 | 3.70 | 4.40 | 3.47 | 5.01 | 4.19 | 5.02 | 4.78 |
| 2. | 1.57 | 0.99 | 0.82 | 1.81 | 0.44 | 1.01 | 0.49 | 0.58 |
| 3. | 0.49 | 0.78 | 0.47 | 0.42 | 0.28 | 0.53 | 0.31 | 0.33 |
| 4. | 0.39 | 0.29 | 0.15 | 0.15 | 0.15 | 0.14 | 0.11 | 0.14 |
| 5. | 0.18 | 0.16 | 0.09 | 0.10 | 0.10 | 0.09 | 0.05 | 0.10 |
| 6. | 0.11 | 0.07 | 0.08 | 0.04 | 0.03 | 0.05 | 0.02 | 0.08 |
| | **Fraction of total variance explained** | | | | | | | |
| 1. | 0.54 | 0.62 | 0.73 | 0.58 | 0.83 | 0.70 | 0.84 | 0.80 |
| 2. | 0.26 | 0.17 | 0.14 | 0.30 | 0.07 | 0.17 | 0.08 | 0.10 |
| 3. | 0.08 | 0.13 | 0.08 | 0.07 | 0.05 | 0.09 | 0.05 | 0.05 |
| 4. | 0.06 | 0.05 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 |
| 5. | 0.03 | 0.03 | 0.02 | 0.02 | 0.02 | 0.01 | 0.01 | 0.02 |
| 6. | 0.02 | 0.01 | 0.01 | 0.01 | 0.00 | 0.01 | 0.00 | 0.01 |

**Note**: The following abbreviations are used: real loans of monetary financial institutions to private households (LHH), real MFI loans to non-financial corporations (LNF), real bank credit to the non-financial private sector (BCN), real residential property prices (RPP), real equity prices (EQP), nominal long-term interest rates (LTN), the nominal term spread (SPN) and real GDP (YER).

When applied to address the concordance among cycles, the PCA may be used in two distinct ways. First, one can be interested in estimating the overall financial cycle represented by the common component in different cycles within a country as, eg. in section 2 in Rünstler et al. (2018). In contrast, the focus of this paper is on the co-movement of the extracted cycles in each of the series between countries. For that purpose, for each of the seven filtered financial variables we estimate the between-country principal components and study the evidence they provide about the

time series for which we consistently use the GDP deflator while Rünstler et al. (2018) use a mix of GDP deflator and CPI.

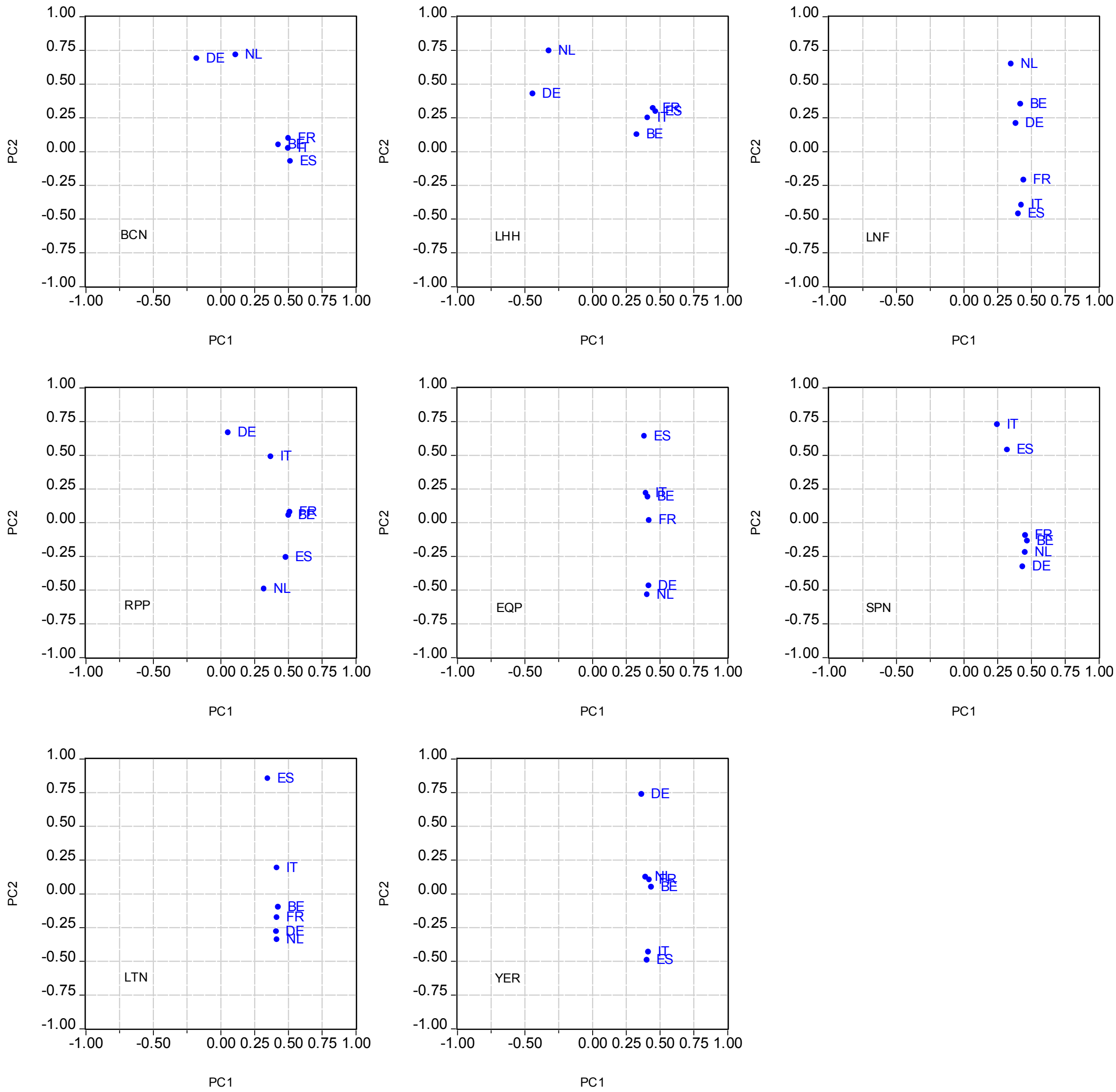
synchronicity of extracted cycles. For comparing the concordance among financial cycles to that of cycles in real activity we perform the same analysis for real GDP.

Table 1 shows the eigenvalues and the relative contributions of each of the six principal components to the overall variance for each series. Generally, for all the series under analysis there exists a fairly large degree of commonality among the countries – the first two principal components together always explain no less than 80% of the total variance. The first principal component alone explains a large share of total variance for the long term nominal interest rates (84%) and equity prices (83%). This result is consistent with the literature finding that financial series such as interest rates and equity prices co-move more compared to other types of series (Breitung and Eickmeier, 2014). Extracted cycles in real GDP also seem to share a strong common component – the first principal component explains 80% of the overall variance. In contrast, cycles in real property prices and credit aggregates seem to be less correlated across countries and to have somewhat stronger idiosyncratic components – the first principal components account for only 54% of overall variance in total bank credit series and 58% for real house prices.

It may seem surprising that the first principal component for bank credit to the non-financial private sector (BCN) explains less of the total variance across countries (54%) compared to the principal components of the main credit sub-aggregates – loans to households, LHH (62%), and loans to non-financial corporations, LNF (73%). This is largely due to different sources and definitions of credit aggregates we rely on throughout the analysis. MFI loans to households (LHH) and to non-financial corporations (LNF) are based on a narrower definition and include only loans while bank credit to the non-financial private sector includes not only bank loans but other sources of bank financing, eg. corporate bonds purchased by banks, as well.[5]

[5] Data on bank loans is taken from the Eurosystems' BSI (balance sheet indicators) statistics while the source for the bank credit data is the BIS. See the appendix for details.

**Figure 1**: Relative importance of each country (ie. loadings) in the first two principal components (PC1 vs PC2)




In order to investigate further whether the group of countries under analysis has synchronized cycles and also to have an initial look at possible groupings of countries within clusters, we study the weights of the first two principal components pertaining to each country – the loadings.[6] For example, the case when all countries load strongly and similarly on the first principal component is consistent with the existence of a single common cycle among countries – we can broadly conclude that their cycles are highly correlated and share a strong common component. This is illustrated in Figure 1,

[6] The term *loadings* is borrowed from factor analysis and refers to weights (i.e. eigenvectors of the correlation matrix) of the principal components. Factor analysis and PCA are different methodologies. Even though, they both deal with reducing the dimensionality of potentially large data sets. Under certain assumptions, however, the parameters of a factor model can be estimated using principal components analysis (Johnson and Wichern, 1998; Stock and Watson, 1998; Kunovac, 2007).

plotting the loadings on the first principal component against those on the second component. Summarized in this way, results of the PCA offer a simple visual test for the existence of an important common component – in case when the dots on the graph approximately lie on the same vertical and/or horizontal line there is evidence of a strong cyclical co-movement among countries. According to that particular (informal) criterion, cycles in equity prices, long term interest rates, term spread, loans to non-financial corporation and real activity seem to share a common cyclical component – all the countries load similarly on the first principal component. In contrast, cycles extracted from total bank credit, real loans to households and real house prices seem to have stronger underlying idiosyncratic components. In those cases Germany stands out – it has close to zero or negative loadings on the first principal component for the three series.[7] Similar results, albeit with somewhat smaller degree of asynchronicity, are also found in the Netherlands.

For some of the variables for which countries load similarly on the first principal component the loadings on the second principal component, nevertheless, suggest a country grouping. For the long-term interest rate (LTN) and for the term spread (SPN) the second PC suggests a north-south divide with positive loadings for ES and IT and negative loadings for the other countries. For real output (YER) ES and IT load negatively on the second PC while the loadings for the other countries are estimated to be positive or close to zero with DE standing out with a strongly positive loading.

## 3.2 Synchronicity and similarity of cycles across countries

In this subsection we study synchronicity and similarity of estimated cycles, ie. filtered series. This analysis complements the principal component analysis, or any other assessment based on correlation coefficients, as it has been well recognized that such approaches may fail to result in a proper assessment of the concordance among cycles. Simple correlations, for example, need not reflect accurately those occasions when two cycles have the same sign or amplitude. Indeed, two cycles may have the same signs throughout the sample, but at the same time display only a modest correlation. Or, two perfectly correlated cycles may have very different amplitudes, depending on their standard deviations (Mink, Jacobs and De Haan, 2012; Belke, Domnick and Gros, 2017). Taking these considerations into account, for each series under analysis we first

[7] In order to investigate how these idiosyncrasies governing the German cycles affect our general conclusions we repeat the exercise with Germany excluded from our sample. Our results prove to be highly robust to this exclusion – principal components constructed from a smaller set of countries point to equivalent conclusions as in our baseline specification.

define measures of synchronicity and similarity for the extracted medium-term fluctuations as proposed by Mink et al. (2012).[8] After that, we look at the overall cross-country synchronization and similarity between cycles. In contrast to the PCA this type of analysis allows for changes in synchronisation and similarity over time. Once we have calculated measures of cycle synchronicity we test for the existence of a unique financial cycle among EU countries. To do so we rely on a simple OLS-based test proposed by Meller and Metiu (2017).

### 3.2.1 Synchronicity

For each variable and each country under analysis (indexed by *i=1,...,n*) we calculate a binary measure of synchronicity indicating whether the sign of cycle in country $i$ at time $t$, $c_i(t)$, coincides with that of a *reference* cycle, $c_r(t)$:

$$\varphi_{ir}(t) = \frac{c_i(t)c_r(t)}{|c_i(t)c_r(t)|}. \quad (1)$$

Note that $\varphi_{ir}(t)$ is either 1 (if $c_i(t)$ and $c_r(t)$ are of the same sign) or -1 (if $c_i(t)$ and $c_r(t)$ are of the opposite sign). Once a time series of $\varphi_{ir}(t)$ for $t = 1, \ldots, T$ is obtained, one can compute the average synchronicity between the cycle in country *i* and the reference cycle over time: $-1 \leq \frac{\sum_{t=1}^{T} \varphi_{ir}(t)}{T} \leq 1$. If the average synchronicity measure is 1, then country *i*'s cycle is perfectly synchronised with the reference cycle.

The overall synchronicity of a group of n countries with the reference cycle is calculated at time $t$ by averaging over countries:

$$\varphi(t) = \frac{1}{n} \sum_{i=1}^{n} \frac{c_i(t)c_r(t)}{|c_i(t)c_r(t)|}. \quad (2)$$

### 3.2.2 Similarity

For each variable and country under analysis (indexed by *i=1,...,n*) we also calculate a similarity measure taking into account the absolute difference of the cycle in country i and a reference cycle (ie. the difference of cycle *elongations*):

$$\gamma_{ir}(t) = 1 - \frac{|c_i(t) - c_r(t)|}{\sum_{i=1}^{n} |c_i(t)|/n}. \quad (3)$$

Again, we calculate the overall similarity for a group of countries by averaging the measure over all countries:

$$\gamma(t) = 1 - \frac{\sum_{i=1}^{n} |c_i(t) - c_r(t)|}{\sum_{i=1}^{n} |c_i(t)|}. \quad (4)$$

[8] A similar measure of the cyclical synchronization is used by Harding and Pagan (2006). Both Harding and Pagan (2006) and Mink et al. (2012) apply their methodology to measure business cycle concordance, but with an important difference - the former paper considers the levels of the time series and the latter studies the extracted cycles.

The reference cycle we use is the median of the cycles in the variable under consideration across all countries (ie. median computed at each point in time). Calculated in this way, our reference cycle maximizes the overall synchronicity and similarity simultaneously in the two corresponding equations above (Joag-Dev, 1989). Taking the median as a reference, these measures are now normalised to lie between zero (minimal cycle coherence) and unity (maximal cycle coherence). For details on the methodological framework see Mink et al. (2012).

**Results on synchronicity and similarity**

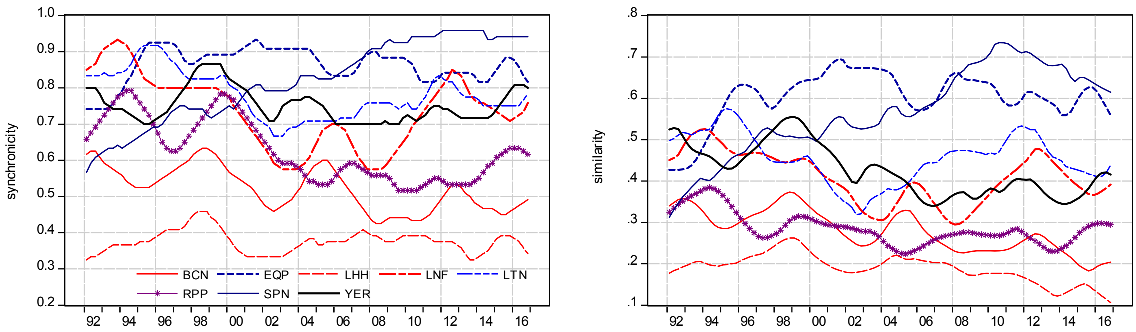
Figure 2 compares measures of overall synchronicity and similarity of extracted cycles for each series across countries. Both measures are shown as moving averages over the last 40 quarters in order to abstract from highly erratic movements governing the movements of both indicators in the short run. Our focus is therefore on the trends underlying the evolution of cycle concordance among countries.

The reported time-varying measures of cycle coherence point to several conclusions: First, regarding synchronicity, it turns out that cycles extracted from loans to households (LHH) are the least synchronized among countries. This is also reflected in very small synchronicity of total bank credit cycles (BCN). A very similar pattern is found for cycles in real residential property prices (RPP) which also contain a strong idiosyncratic component.

The group of more synchronized indicators includes nominal long-term interest rates (LTN), loans to non-financial corporations (LNF) and the two indicators with the strongest concordance of cycles, very close to unity – real equity prices (EQP) and the nominal term spread (SPN). Compared to financial series in our sample, cycles extracted from the real GDP are relatively strongly synchronized – just below the two indicators with the highest cycle concordance as measured by the overall synchronicity. Interestingly, the time-varying measures of overall similarity among cycles are generally lower compared to those for synchronicity, but point to largely the same conclusions. The results from the synchronicity and similarity measures are consistent with those from the PCA: Equity prices, long-term interest rates and term spreads show high commonality comparable or higher to that of real output while the credit variables and real house prices are less synchronized.

The synchronicity and similarity analysis, however, has the additional benefit of providing some information on changes in the cross-country co-movements over time. For real property prices and real bank credit to the non-financial private sector estimates indicate a decline in synchronicity and similarity over time. This decline is also visible for loans to non-financial corporations but is reversed around the onset of the global financial crisis. Total bank credit (BCN), bank lending to non-financial corporations (LNF), long-term interest rates (LTN) and residential property prices (RPP), as well as real GDP (YER) exhibit a marked decline in synchronicity following the introduction of the European Monetary Union. However, this reduction in synchronicity is persistent only for RPP while for real GDP it only compensates for an increase in synchronicity in the late 1990s. The only variable for which there is a continuing increase in synchronicity and similarity through the sample period is the term spread which might be a reflection of the common monetary policy of the Eurosystem. Both the synchronicity and similarity measures for the long-term interest rate increase towards the end of the sample period, probably to some extent due to the Eurosystem's unconventional monetary policy measures, such as the asset purchase programme which strongly affected long-term yields.

**Figure 2:** Overall synchronicity and similarity of extracted cycles




**Note**: Both measures are transformed to 10-year moving averages. The following abbreviations are used: real loans of monetary financial institutions to private households (LHH), real MFI loans to non-financial corporations (LNF), real bank credit to the non-financial private sector (BCN), real residential property prices (RPP), real equity prices (EQP), nominal long-term interest rates (LTN), the nominal term spread (SPN) and real GDP (YER).

### 3.2.3 Testing for phase synchronisation – is there a common cycle?

In order to test for phase synchronisation in each of the analysed series we rely on the methodological framework proposed by Meller and Metiu (2017). In short, for each series we first calculate an average measure of phase synchronisation between cycles of each country pair. A formal statistical test is then conducted to assess the statistical significance of the estimated average phase synchronicity measures. Finally, we summarise the information in the form of *multidimensional scaling maps*. More formally, the procedure is outlined in the following steps:

1. We first map the extracted cycles into a binary indicator reflecting the sign of the cycle:

$$B_i^{gap}(t) = \frac{c_i(t)}{|c_i(t)|}, \tag{5}$$

where $c_i(t)$ denotes cycle $i$ at time $t$. After that we obtain a time series of *synchronization measure* between countries $i$ and $j$ as before: $S_{ij}^{gap}(t) = B_i^{gap}(\mathrm{t})B_i^{gap}(\mathrm{t})$.

2. We define three *extreme* concepts of phase synchronization between two countries:
   - Perfect Positive Synchronization (PPS) ⟺ The two cycles are in the same phase *almost surely* (with probability one)
   - Perfect Negative Synchronization (PNS) ⟺ The two cycles are in the opposite phase *almost surely* (with probability one)
   - Non-Synchronization (NonS) ⟺ Two cycles are in the same phase or in the opposite phase with the same probability

   It can be easily verified that the expected value of our synchronization measures ($\mathrm{E}[S_{ij}(t)]$) may be rewritten in terms of different concepts of phase synchronization:
   - Perfect Positive Synchronization (PPS) ⟺ $\mathrm{E}[S_{ij}(t)] = 1$
   - Perfect Negative Synchronization (PNS) ⟺ $\mathrm{E}[S_{ij}(t)] = -1$
   - Non-Synchronization (NonS) ⟺ $\mathrm{E}[S_{ij}(t)] = 0$.

3. In order to determine whether two countries have synchronised cycles we perform a statistical test of the null hypothesis that cycles are either not or negatively synchronised on average,

$$H_0\colon \mathrm{E}[S_{ij}(t)] \leq 0,$$

against the one-sided alternative of positively synchronised cycles,

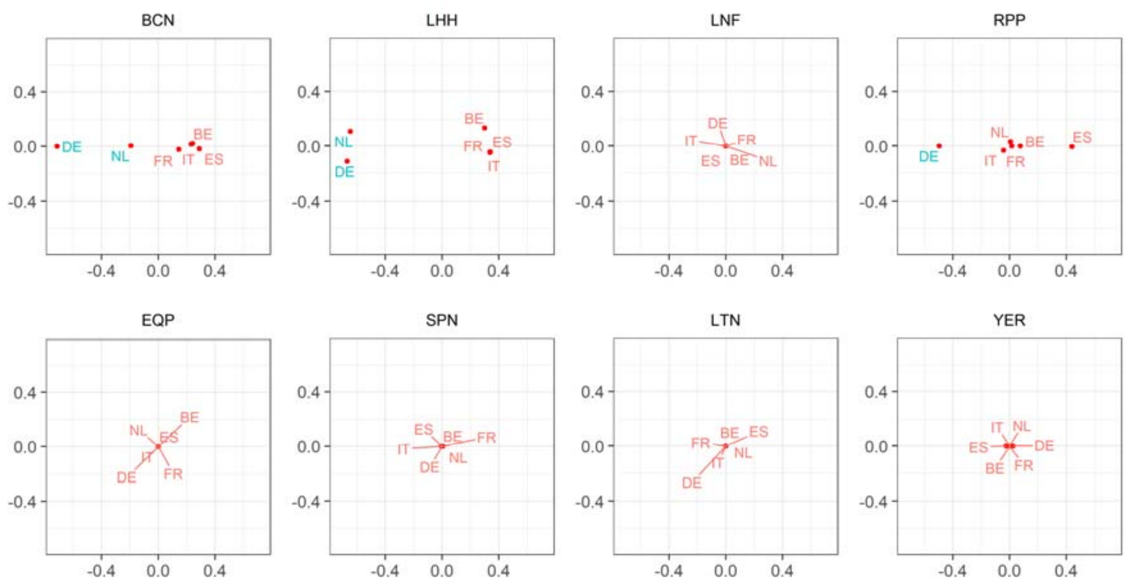
$$H_1\colon \mathrm{E}\big[S_{ij}(t)\big] > 0.$$

If the null is rejected using a one-sided t-test, there is evidence that the cycle phases are positively synchronized. Meller and Metiu (2017) propose a simple OLS regression of the time series $S_{ij}(t)$ for $t = 1, \ldots, T$ on an intercept to estimate $\mathrm{E}[S_{ij}(t)]$ and obtain the associated *p*-values to perform the t-test above (they propose to use Newey-West standard errors).

4. Once, for each variable, we constructed bilateral synchronization measures for all country pairs and tested for their statistical significance, we construct a matrix of *dissimilarities* between countries based either on bilateral estimates of

E[$S_{ij}$], ie. $\boldsymbol{D}_{NxN} = [D_{ij}]$=[1- E[$S_{ij}$]], or based on the associated $p$-values. Based on the dissimilarity matrix we can construct a *multidimensional scaling map*. A multidimensional scaling map in our case is a two-dimensional representation of a group of country cycles that (approximately) *preserves pairwise distances between countries given in a dissimilarity matrix*. For example, if dissimilarities between two countries are based on $p$-values from the statistical test above, a small (Euclidian) distance for any country pair on the scaling map is reflecting a small associated $p$-value. Consequently, this is pointing to a significant synchronization between the two cycles and the existence of a common cycle for that country pair.

**Figure 3:** Scaling maps




**Note**: *i)* The following abbreviations are used: real loans of monetary financial institutions to private households (LHH), real MFI loans to non-financial corporations (LNF), real bank credit to the non-financial private sector (BCN), real residential property prices (RPP), real equity prices (EQP), nominal long-term interest rates (LTN), the nominal term spread (SPN) and real GDP (YER). *ii)* Small (Euclidian) distance for any country pair on the scaling map is pointing to a significant synchronization between the two cycles and the existence of a common cycle for that country pair. *iii)* All the countries within a same cluster are shown in the same colour.

### Results: multidimensional scaling maps and clustering

Figure 3 shows scaling maps for medium-term components in the eight series under analysis with the matrix of dissimilarities (ie. distances) constructed from bilateral $p$-values from the statistical test outlined before.

The results point to several main conclusions: first, the extracted cyclical components in real equity prices (EQP), nominal long-term interest rates (LTN) and the nominal term spread (SPN) are strongly synchronised for all country pairs and share a common cycle. Beside the three financial series, extracted cycles in real GDP appear to be highly synchronized as well. In contrast, real house prices and credit aggregates diverge much more across countries with lending to non-financial firms again as the exception with strong synchronisation. These results are consistent with those from the PCA (Figure 1).

Finding indications for possible *groupings* of countries into separate clusters is complicated by the relatively small sample of countries under analysis. Nonetheless, we follow Camacho, Perez-Quiros and Saiz (2006) and Meller and Metiu (2017) and use *the hierarchical clustering algorithm* to visualise possible clusters of (real and) financial cycles among the six countries. When identifying clusters of countries, the distance between any pair of cycles is the *p*-value from a statistical test with a null hypothesis that cycles *are either not or negatively synchronised*, as outlined above. The farthest-neighbour clustering algorithm ensures that the null is rejected for each pair of cycles within a cluster, that is, all the cycles within the same cluster are characterized by significantly positive synchronization. The cut-off points of *p*-values for the clustering algorithm are set at 10% (see Meller and Metiu, 2017).

Based on this methodology, we identify separate clusters of countries in Figure 3. For visualisation purposes, all the countries within a cluster are shown in the same colour. Consistent with our previous findings, house prices and credit variables (except for LNF) are grouped in more than a single cluster. Specifically, for cycles in the total bank credit (BCN) and loans to households (LHH) the algorithm indicates two separate clusters – Germany and Netherlands form the first one, while other countries in the sample belong to the second. We obtain a similar grouping for cycles in real house prices – now only Germany does not belong to the same cluster as the rest of the countries under analysis. For the other financial variables - real loans to non-financial corporations (LNF), real equity prices (EQP), nominal long-term interest rates (LTN) and the nominal term spread (SPN) – the null hypothesis that their cycles are either not or negatively synchronised is strongly rejected for each combination of country pairs and, thus, all the countries belong to the same cluster and form a single common cycle. This is also the case for cycles in real GDP.

## 3.3 Wavelet Analysis

Wavelet analysis is another, highly flexible method to assess cyclical properties of time series. In essence, wavelet analysis is an extension of spectral analysis that allows for time variation. Spectral analysis interprets a time series as the weighted sum of cycles with specific periodicities and estimates the contribution of these cycles to the overall variance of the series. Wavelet analysis allows for inspecting time-variation in these contributions. It can therefore distinguish the case that a series is the sum of several cycles at different frequencies from the case that the series is characterized by structural change, ie. consists of a single cycle with a frequency that shifts across subsamples.[9]

Specifically, wavelet analysis decomposes a time series into periodic functions (waves) with only finite support, which allows for locating changes in the importance of specific cyclical frequencies in time (Cazelles et al., 2008). Its advantage compared to rolling window Fourier analysis is the use of efficient windowing, as the window width is adjusted endogenously dependent on the frequency as the wavelet is stretched or compressed.

Wavelet analysis does not rely on filtering, but is applied directly to (annual) growth rates. The transformation into annual growth rates is in itself the application of a filter that eliminates cycles at annual frequencies. For the cycles of two years and longer on which we focus in this paper the transformation into annual growth rates is not neutral with respect to the spectrum of the time series. It emphasizes cycles at business cycle frequencies relative to longer cyclical components. However, (i) as will be shown later, most of the additional insights from the wavelet analysis apply to frequencies below business cycle frequencies and (ii) as our analysis concerns co-movements in time series at identical frequencies and not the comparison of the relative importance of cycles at different frequencies this transformation is unlikely to distort our results.

The continuous wavelet transformation (CWT) is obtained by projecting the time series $x(t)$ onto wavelet functions $\psi$ (Aguiar-Conraria and Soares, 2014)[10]

$$W_x(\tau, s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{|s|}} \psi^* \left( \frac{t-\tau}{s} \right) dt, \qquad (6)$$

[9] For an introduction to wavelet analysis, see Aguiar-Conraria and Soares (2014) and Rua (2012).

[10] For estimation we used the AST-toolbox for MATLAB by Aguiar-Conraria and Soares (https://sites.google.com/site/aguiarconraria/joanasoares-wavelets/) which has been extended to estimate cohesion.

where s represents the scale (which is inversely related to frequency) and $\tau$ the location in time. It is calculated for all combinations of scales and time and gives information simultaneously on time and frequency.

Specifically, the empirical analysis in this paper is based on the Morlet wavelet

$$\psi_{\omega_0}(t) = \pi^{-\frac{1}{4}} e^{i\omega_0 t} e^{-\frac{t^2}{2}}. \tag{7}$$

It can be described as a Gaussian modulated sine wave. In its centre it behaves like a sine wave, but towards its tails it dies out quite fast (finite support). The Morlet wavelet with $\omega_0 = 6$ has optimal time-frequency localization and a direct relation between scale and frequency ( $\omega \approx 1/s$ ).

The wavelet power spectrum measures the relative contribution to the variance of the time series at each scale and at each point in time. It is defined as

$$WPS_x(\tau, s) = \left|W_x(\tau, s)\right|^2. \tag{8}$$

The greater the power spectrum $WPS_x(\tau_i, s_i)$, the higher the correlation of the time series around $\tau_i$ and the wavelet of scale $s_i$, ie. the more important the fluctuations at the specified frequency for the overall series.

The assessment of the cross-country co-movements in the variables will use a measure of cohesion. It is based on estimated dynamic correlation defined as

$$\rho_{x_i x_j} = \frac{\Re\left(W_{x_i x_j}(\tau, s)\right)}{\sqrt{\left|W_{x_i}(\tau, s)\right|^2}\sqrt{\left|W_{x_j}(\tau, s)\right|^2}}, \tag{9}$$

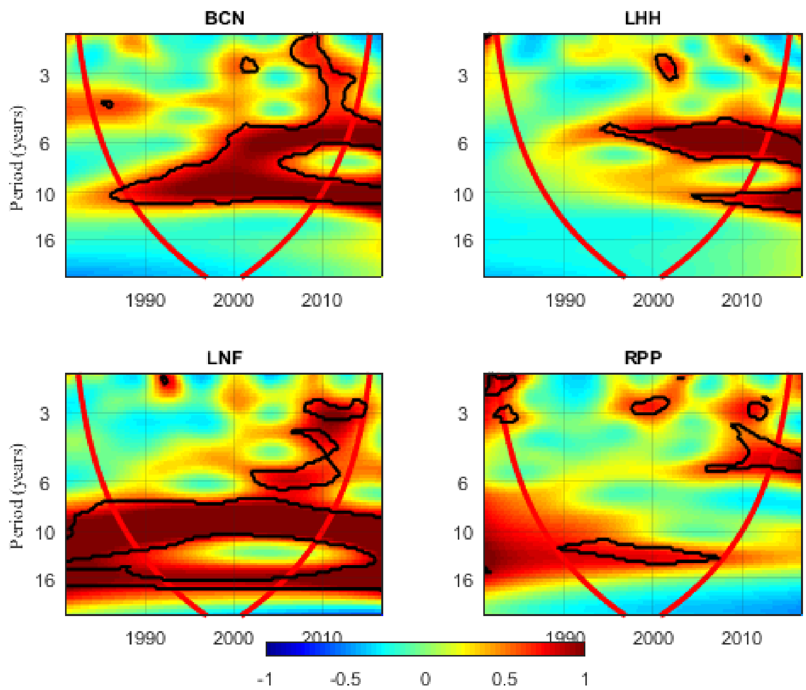
where $\Re$ denotes the real part of the cross-wavelet transform $W_{x_i x_j}$. The latter represents the local covariance between $x_i$ and $x_j$ at each time and frequency. Based on dynamic correlation, Rua and Silva Lopes (2015) propose a measure of cohesion, which is a weighted average of all pairwise dynamic correlations with $w_i$ and $w_j$ representing weights

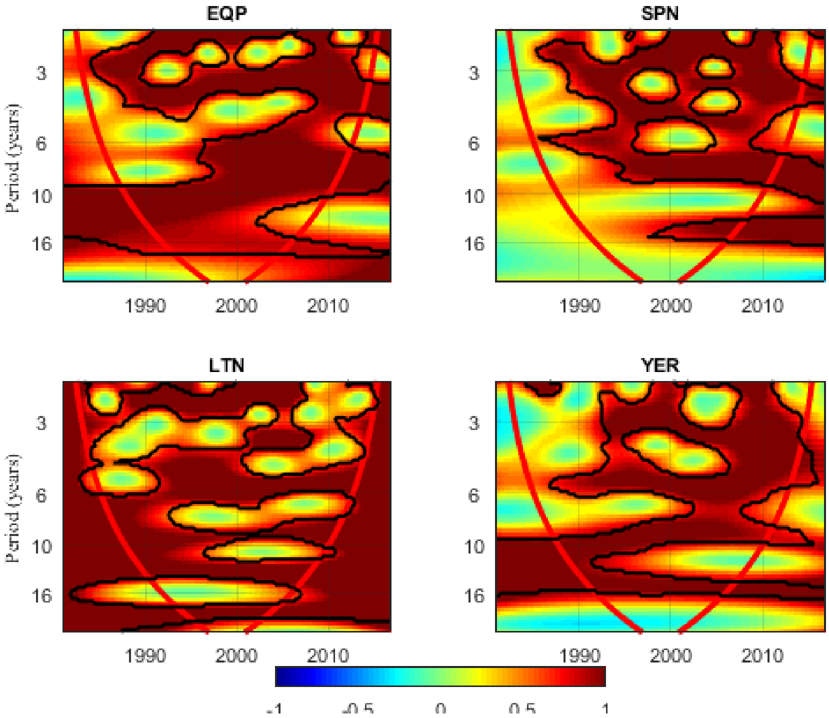
$$\mathrm{coh}(\tau, s) = \frac{\sum_{i \neq j} w_i w_j \rho_{x_i x_j}(\tau, s)}{\sum_{i \neq j} w_i w_j}. \tag{10}$$

In this application we use weights based on real GDP. Significance of cohesion is tested by parametric bootstrap. Based on estimated uncorrelated autoregressive processes, a number of simulated replications for each series are generated. Using the dynamic correlations for these replications the simulated distribution of cohesion under the null hypothesis of unrelated time series can be derived.

So far, wavelet analysis has been applied to the analysis of financial cycles in only a few papers. Verona (2016) estimates wavelet power spectra of U.S. credit, house prices, equity prices and real GDP using the continuous wavelet transform and concludes that the dominant cycles in credit and house prices operate on lower frequencies than those in real GDP. Voutilainen (2017) constructs for 13 EU countries financial cycle proxies out of credit, house prices and equity prices using the discrete wavelet transform and selection of weights based on an early-warning exercise for financial crisis.

**Figure 4:** A heat map of cohesion at different frequencies






The x-axis represents time, while the periodicity of the cycles is given in years along the y-axis. Cohesion is represented by colour. Dark red indicates cohesion close to +1, while dark blue indicates cohesion close to -1. Black lines indicate regions with statistically significant positive cohesion. The left and right red lines in each plot represent the cone of influence. The area outside the red lines should not be interpreted.

Figure 4 shows the estimated cohesion for the seven financial variables and for real GDP growth. By construction, cohesion is restricted to the interval between minus one (dark blue) and plus one (dark red). Green indicates cohesion around zero, ie. no contemporaneous correlation on average across countries. The red lines mark the border of the cone of influence. Results outside the time-frequency combinations between the red lines should not be interpreted.[11]

For total bank credit to the non-financial private sector (BCN, upper left panel) we estimate significant cohesions close to one for fluctuations with duration of about ten years over the full subsample for which the results can be interpreted, ie. between about 1990 and the late 2000s. The frequency range for which we find strong co-movements widens over time and includes cycles between six and ten years in the 2000s. This

[11] If there is only an insufficient number of past or future observations available to apply the wavelet transform at a given point in time the algorithm extends the sample backwards or forward by ”reflecting” the first/last observations. The red lines separate the time-frequency combinations for which cohesion is based on this “reflecting” and thus, should not be interpreted, from those for which we can interpret the results. The region of usable estimates becomes smaller as cycles become longer since the flexible determination of the observation window length that enters the wavelet transform implies broader windows and hence, the use of more observations for extracting lower frequency components.

narrow band for co-movements in the first part of the sample might be an explanation why the previous methods did not indicate strong cross-country co-movements for this series. Loans to households (LHH, upper right panel) display a very weak cohesion close to zero up to the late 1990s when cohesion increases markedly for cycles with duration of between four to six years around the time of the introduction of the euro. In comparison, cohesion for loans to non-financial corporations (LNF, second row, left panel) is close to one for cycles of length between about six and ten years over the full sample suggesting a stable common cycle among euro area countries. Cohesion for BCN, which includes both lending to firms and households, reflects the stable significant cohesion in LNF for cycles of about ten years and the significant cohesion for LHH at higher frequencies in the later part of the sample. For LNF we also find evidence for strong co-movements for even longer cycles. For both lending to non-financial firms and households results from wavelet analysis are consistent with the results from the other empirical approaches. All credit variables (BCN, LHH and LNF) show significant cohesion for cycles with duration of six years or less in the late 2000s. This is probably linked to the global financial crisis which led to a contraction in credit across all countries in the sample.

For real house prices (RPP) cohesion is overall decreasing in the six-to-16 years frequency band over the sample period. The estimates indicate significant cross-country co-movements for cycles with periods of about twelve to 14 years up. The significant cohesion estimated for the late 2000s for fluctuations with length of about four years is likely to reflect common declines in house prices at the onset of the global financial crisis.

The bottom half of Figure 4 contains the variables real equity prices, long-term interest rates and the term spread for which we estimate significant cohesion over a broad frequency range. For the term spread co-movements extend to lower frequencies as time progresses. Co-movements in equity prices (EQP, second row, right column) are significant across almost the full sample period and all frequencies and, hence, operate on a much broader frequency spectrum than for the credit variables. This is even more so for the long-term interest rates (LTN, third row, right column) while for the term spread (SPN) cohesion starts out lower but increases over time and is significant over most of the frequency spectrum after the introduction of the single monetary policy. For comparison we estimate the cohesion measure also for real GDP growth (bottom right panel). For this variable, cross-country co-movements occur over a similarly broad frequency range as for equity prices and interest rates.

Overall, the results from the wavelet analysis suggest common cycles across countries in long-term interest rates, the term spread and real equity prices at least covering a frequency range similar to that for real GDP. For the real credit variables and real house prices, cross-country co-movements are confined to much narrower frequency ranges and for loans to households and house prices are not stable over time. Concerning time-variation, the results indicate that the cross-country co-movements in the term spread have become stronger over time, extending to a broader frequency range. There is also some evidence of stronger common cycles in total bank credit and bank lending to private households. At least for the term spread the most reasonable explanation for this change over time might be the introduction of the European Monetary Union which implied identical short-term interest rates in all countries. For loans to households the stronger co-movements also occur in the EMU period. In contrast, cross-country commonalities in real house prices have become weaker over time.

# 4 Discussion and Conclusions

The results from the three different empirical methodologies on cross-country dimension of the financial cycle in euro area countries overall are quite consistent. We find that those variables which represent financial asset prices or returns (long-term interest rates, the term spread and real equity prices) are characterised by a high degree of cross-country synchronization that is at least as strong as that of cycles in real GDP. For real property prices and credit variables the results overall show a comparatively weaker cross-country synchronization. In particular, real property prices but also real bank loans to private households, of which loans for house purchases are the by far most important component, display relatively weak cross-country co-movements. Thus, we find no evidence of a marked common cycle related to the real estate sector. Among the credit variables, we estimate relatively strong common cycles across countries for real bank loans to non-financial corporations. A possible explanation for this result is that, as shown in Scharnagl and Mandler (2016) for the four large euro area countries, bank loans to non-financial firms exhibit common cycles with real activity, e.g. with real GDP, real investment etc. also at frequencies beyond standard business cycle frequencies. Thus the common cycles and bank lending to firms across countries are likely to reflect the common cycles in real activity.[12]

The relatively high synchronicity in the cycles in financial asset prices and returns compared to cycles in credit and real property prices is consistent with euro area

[12] See also Rünstler et al. (2016) for similar results on co-movements between real activity and credit.

financial markets being more integrated than retail banking activity (eg. European Central Bank, 2017).

Among the methods applied in this analysis the synchronicity and similarity measures and wavelet analysis allow for the analysis of time variation in the cross-country co-movements of the variables while the principal component analysis and the scaling maps and cluster analyses which are based on the average synchronicity measures do not consider time variation. For some of the variables we find that allowing for time-variation provides additional insights: cycles in real property prices have become less synchronized over time while cycles in the term spread have become more similar over time, probably due to the European Monetary Union.

While the other approaches rely on pre-filtered series, the wavelet analysis shows at which frequencies – if any – the variables move together across countries. For example, wavelet analysis shows that cross-country co-movements in the credit variables and real house prices are limited to a much more narrow frequency spectrum than the assumed two-to-twenty years cycle length for the band-pass filter. This might be a reason why the other methods, in contrast to wavelet analysis, do not indicate strong common cyclical components in total bank credit to the non-financial private sector.

Overall, the comparison of results from the different approaches shows the merits of applying different methodologies to the analysis of financial cycles in order to arrive at a more robust assessment and to gain additional insights from different perspectives.

To conclude, the overall results of our analysis can be summarized as follows: cycles in financial asset prices and interest rates are highly synchronized among euro area countries. Real property prices and credit aggregates are much less synchronized across countries, in particular, our results do not indicate important stable cross-country cycles in both lending to households and house prices. The exception is bank lending to non-financial firms for which we estimate a high degree of synchronization which is likely to be linked to real activity.

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# Appendix A: Data

**Real GDP:**

Data sources: ECB Statistical Data Warehouse (SDW) and IMF International Financial Statistics (IFS)

| **Country** | **Data source 1** | **Data source 2** | **Data source 3** | **start date** |
|---|---|---|---|---|
| BE | SDW: MNA | IFS | | 1980Q1 |
| DE | SDW: MNA | SDW: ESA | | 1970Q1 |
| ES | SDW: MNA | IFS | | 1970Q1 |
| FR | SDW: MNA | | | 1970Q1 |
| IT | SDW: MNA | SDW: ESA | IFS | 1980Q1 |
| NL | SDW: MNA | SDW: ESA | IFS | 1977Q1 |
| Backward extension of data from data source 1 with annual growth rates of data source 2 and data source 3. | | | | |

The **GDP deflator** is computed using nominal and real GDP. Data sources for nominal GDP are the same as above.

**MFI loans to households** and **MFI loans to non-financial corporations** are from the BSI statistics (ECB Statistical Data Warehouse). All series start in 1980Q1. Series are deflated using the GDP deflator.

**Bank credit to the non-financial private sector** is taken from the BIS "Long series of total credit to the non-financial sectors" (Total bank credit to domestic private non-financial sector, total market value, adjusted for breaks). Series are deflated using the GDP deflator.

| Country | start date |
|---|---|
| BE | 1970Q4[a] |
| DE | 1970Q1 |
| ES | 1970Q1 |
| FR | 1970Q1 |
| IT | 1974Q4[a] |
| NL | 1970Q1[a] |
| [a] Availability of GDP deflator restricts starting point of real equity price series to 1980Q1 (BE and IT) and 1977Q1 (NL). | |

**Equity prices:**

Data sources: OECD Main Economic Indicators (MEI) downloaded from ECB Statistical Data Warehouse (SDW: MEI), IMF International Financial Statistics (IFS). All series are deflated with the GDP deflator.

| Country | Data source 1 | Data source 2 | start date |
|---|---|---|---|
| BE | SDW: MEI | IFS | 1970Q1 [a] |
| DE | SDW: MEI | | 1970Q1 |
| ES | SDW: MEI | IFS | 1970Q1 |
| FR | SDW: MEI | | 1970Q1 |
| IT | SDW: MEI | | 1970Q1 |
| NL | SDW: MEI | | 1970Q1 [a] |
| Backward extension of data from data source 1 with annual growth rates of data source 2.<br>[a] Availability of GDP deflator restricts starting point of real equity price series to 1980Q1 (BE and IT) and 1977Q1 (NL). | | | |

**Residential property prices**

Residential property prices are taken from the BIS ("Long-term series of residential property prices") and deflated with the GDP deflator.

| Country | start date |
|---|---|
| BE | 1970Q1 [a] |
| DE | 1970Q1 |
| ES | 1971Q1 |
| FR | 1970Q1 |
| IT | 1970Q1 [a] |
| NL | 1970Q1 [a] |
| [a] Availability of GDP deflator restricts starting point of real equity price series to 1980Q1 (BE and IT), 1977Q1 (NL) and 1978Q1(PT). | |

**Long-term interest rates**

Data source: IMF International Financial Statistics.

| Country | start date |
|---|---|
| BE | 1970Q1 |
| DE | 1970Q1 |
| ES | 1980Q1 |
| FR | 1970Q1 |
| IT | 1970Q1 [a] |
| NL | 1970Q1 [a] |

**Short-term interest rates**

Short-term interest rates were obtained from the IMF International Financial Statistics as interest rates on Treasury Bills or comparable instruments. For some countries the series were extended backwards using money market rates.

| Country | start date |
|---|---|
| BE | 1980Q1 |
| DE | 1970Q1 |
| ES | 1980Q1 |
| FR | 1970Q1 |
| IT | 1970Q4 |
| NL | 1978Q1 |

The **nominal term spread** (SPR) is computed as difference between long-term and short-term interest rates.

# Appendix B: Filtered time series