Financial cycles in European 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 components analysis, synchronicity and similarity measures and wavelet analysis. We find that financial asset 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 with bank lending to non-financial firm being an exception with relatively large cross-country co-movements. House prices show little cross-country synchronization. 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 currency union.

Keywords: financial cycles, bandpass filter, principal components, wavelet analysis

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

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* Discussion Papers represent the authors' personal opinions and do not necessarily reflect the views of the Deutsche Bundesbank, the Hrvatska Narodna Banka or their staff.

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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 et al., 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 in Europe 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 European economies, i.e. 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/financial crises affecting 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.

In the literature, most cross-country analyses of financial cycles predominantly have been performed in a two-step approach: in the first step cyclical components are extracted from individual financial time series while their cross-country co-movements are investigated in the second step. However, there are also approaches which directly extract measures of the financial cycle as common components from cross-country data sets including multiple financial variables by using factor models (Breitung and Eickmeier, 2016; Miranda-Agrippino and Rey, 2015).

Most of the estimates of financial cycles are based on univariate time-series approaches, 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). 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).

In contrast, multivariate approaches extract the common component in multiple financial time series and directly take into account that the financial cycle should be present in multiple financial data. Galati, Hindrayanto, Koopman and Vlekke (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, thus, for each country extract common components from the time series. Rünstler and Vlekke (2016) extend this model to allow for common cyclical components in financial time series and real GDP.

Using these country-specific financial cycle proxies or estimates, cross-country co-movements in financial cycles have been studied using a broad range of statistical approaches, such as pairwise correlation coefficients (Aikman et al., 2015), or concordance indices (Claessens et al., 2011, Drehmann et al., 2012, Schüler, Hiebert and Peltonen, 2015, 2017). Meller and Metiu (2017) assess synchronisation in credit cycles across countries using cluster analysis and develop a test for positive bilateral phase synchronisation between two countries' credit cycles.[3] Stremmel (2015) uses the cross-country standard deviation of a composite financial cycle indicator as measure of synchronicity.

[3] Part of the literature aims at constructing composite financial cycle measures at the country level which capture co-movements in various financial indicators, eg. Drehmann et al., 2012, Stremmel, 2015, Schüler et al., 2017 and Voutilainen, 2017.

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

The PCA approach is a two-step approach which 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. The synchronicity and similarity measures follow Mink (2012) and, in contrast to the PCA, 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, i.e. 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.

Concerning the characteristics of financial cycles, in the literature they are typically found to operate on lower than conventional business cycles frequencies (eg. Borio, 2014; Drehmann et al., 2012 and, for credit cycles, Aikman et al., 2015) and to have a higher amplitude (eg. Drehmann et al., 2012; Galati et al., 2016). While the previous literature treats business and financial cycles as distinct phenomena, Rünstler and Vlekke (2016) present evidence of important common medium-term cycles in credit, house prices and real GDP.

Turning to the available evidence on the cross-country dimension of financial cycles, Claessens et al. (2011) analyse cycles in credit, house prices and equity prices in 21 OECD countries using turning-point analysis. Using a concordance index (Harding and Pagan, 2002) they show that cross-country synchronisation is highest for credit and lowest for house prices. Schüler et al. (2015) find high pairwise concordance in their composite financial cycle measure between a large subset of 14 European economies with the notable outlier of Germany and, to some extent Austria, for which concordance with the other countries financial cycle proxies is relatively low. They also show cross-country synchronisation of financial cycles to be lower than business cycle synchronisation. For the G7 Schüler et al. (2017) extract the common component of the country-specific composite financial cycle indicators as the first principal component and estimate high correlation between this global financial cycle proxy and the country-specific financial cycles. With the exception of Germany and Japan, correlation of national financial cycles with the global cycle is greater than correlation of the national business cycle with the global one. Rünstler and Vlekke (2016) show major peaks in financial cycle estimates for the U.S., the U.K., Germany, France, Italy and Spain to be highly synchronised across countries. Strohsal, Proaño and Wolters (2015) analyse interaction of the U.S. and U.K. financial cycles using VAR models and find that the relation has become stronger 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. Aikman et al. (2015) study 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 in the second part of their sample period. Nevertheless, on average they find the absolute level of correlation to be relatively low. Meller and Metiu (2017) analyse cycles in bank lending using the Schularick and Taylor (2012) data set. The results of their cluster analysis indicate changes in the cross-country relationship between credit cycles over time. In the post-1973 period their results put Canada, the Netherlands and Sweden into one cluster and all other countries in another cluster, except for Germany which represents a cluster of its own. 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) studies credit regimes in 12 OECD countries using a Markov-switching framework and finds a high synchronisation of credit regimes during the recent financial crisis. Breitung and Eickmeier (2016) using a data set for 24 countries with about 350 time series 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.

Our results on financial cycle synchronisation from all three approaches 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 cohesion of loans to households has been rising after the introduction of the euro area, while cohesion among house prices has decreased over time. Both principal component analysis and the analysis of phase synchronisation show that credit and house prices are subject to relatively low cross-country synchronisation with Germany standing out with small cycles that appear largely independent from the remainder of the euro area. For some variables, the first principal component 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 (SPR). We use real GDP (YER) to compare the cross-country dimension of the financial cycles 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. Data availability differs 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 (see Table 1). All time series end in 2016Q4.

Principal components 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 etc. 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 bandpass filter, the lower upper bound being due to our relatively short sample period.

3 Empirical analysis

3.1 Principal components analysis

The principal components 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.

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. 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 first estimate a full set of the between-country principal components and study the evidence they provide about the 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.

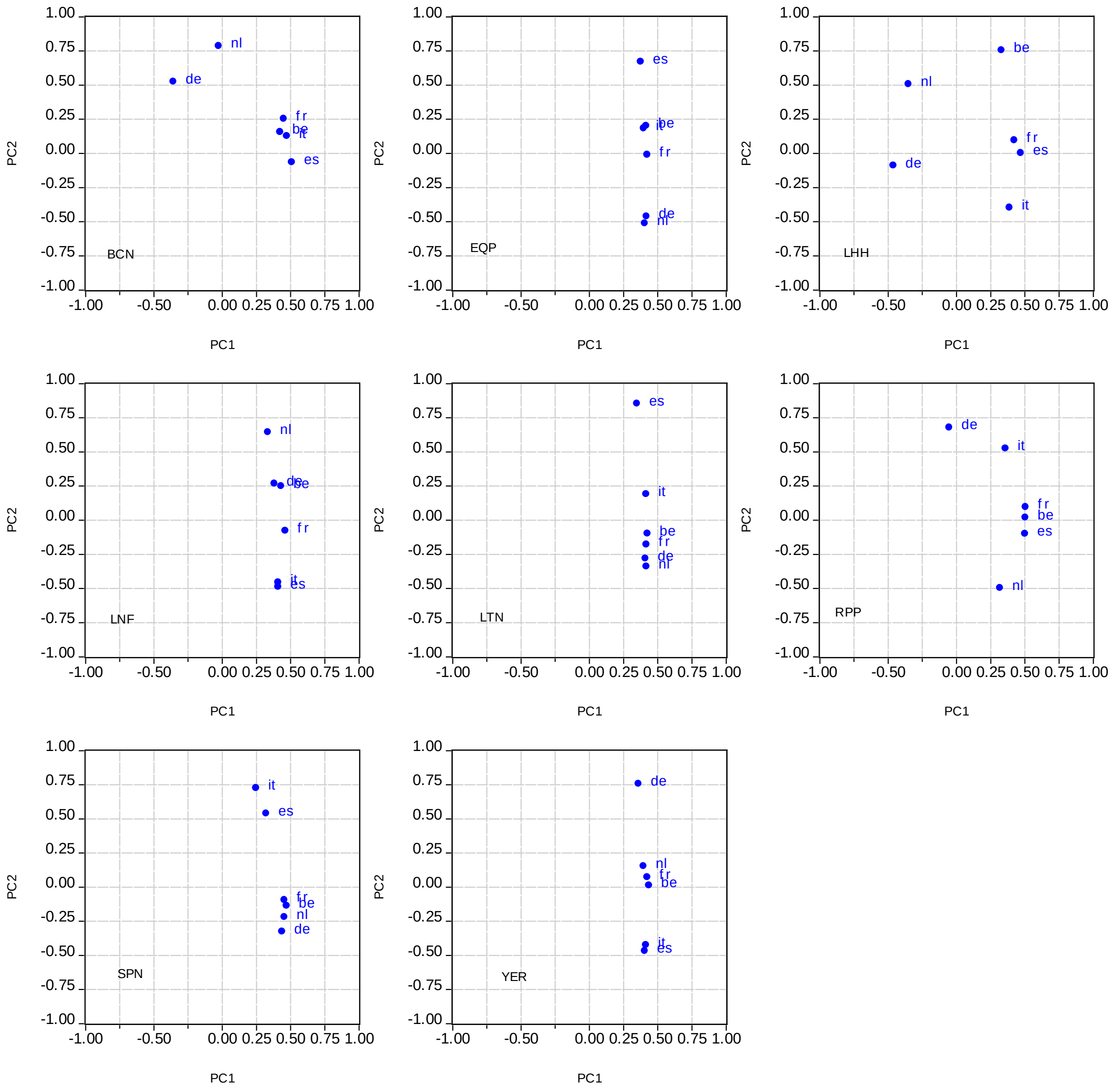
Table 1: Fraction of total variance explained by principal components

BCN	LHH	LNF	RPP	EQP	SPN	LTN	YER
0.56	0.67	0.68	0.58	0.82	0.70	0.84	0.79
0.24	0.14	0.17	0.27	0.09	0.17	0.08	0.10
0.08	0.11	0.08	0.09	0.05	0.09	0.05	0.05
0.05	0.05	0.03	0.03	0.03	0.02	0.02	0.02
0.04	0.02	0.02	0.02	0.02	0.01	0.01	0.02
0.02	0.02	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).

Table 1 compares the relative contributions of each of the first six principal components to overall variance for each series. Generally, for all the series under analysis there exists a fairly large degree of commonality among six countries – the first two principal components 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 (82%). 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 almost 80% of the overall variance. In contrast, cycles in real property prices and credit aggregates seem to be less correlated and to have somewhat stronger idiosyncratic components – the first principal components account for only 56% of overall variance in total bank credit series and 58% for real house prices.

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



It may seem surprising that the first principal components for series representing "total bank credit" - bank credit to the domestic non-financial private sector, BCN – explains less of the total variance across countries (56%) compared to principal components of the main credit sub-aggregates – loans to households, LHH (67%) and loans to non-financial corporations, LNF (68%). 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 made by monetary financial institutions while bank credit to the domestic non-financial private sector includes not only bank loans but other sources of bank financing, e.g. corporate bonds purchased by banks, as well.[4]

Now, 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 principal components pertaining to each country – the loadings.[5] The case when all countries load 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, 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 line there is an 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 to the first principal component. In contrast to that, cycles extracted from overall bank credit series, 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 in the first principal component for the three series. Similar results, albeit with somewhat smaller degree of asynchronicity, are also found in the Netherlands.

For some of the variables for which the specific countries load similarly on the first principal component the loadings on the second principal component 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

[4] 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.

[5] 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.).

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

Here we study synchronicity and similarity of estimated cycles, i.e. filtered series. This analysis largely 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 et al., 2012; Belke et al. 2017.). Taking these considerations into account, for each series under analysis we first define measures of synchronicity and similarity for the extracted medium-term fluctuations as proposed by Mink et al. (2012).[6] After that, we look at the overall cross-country synchronization/similarity between financial 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 i at time t, $c_i(t)$, coincides with that of a *reference* cycle, $c_r(t)$:

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

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 for two variables, one can compute the average synchronicity between these two series

[6] 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.

over time: $-1 \leq \frac{\sum_{t=1}^{T} \varphi_{ir}(t)}{T} \leq 1$. If the average synchronicity measure is 1, then the two series are perfectly synchronised.

The overall synchronicity of a group of n countries with the reference cycle is calculated at time t as:

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

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 of a country i and a reference cycle (i.e. the difference of cycle *elongations*):

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

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

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

The reference cycle we use is the median of the cycles in the variable under consideration across all countries (i.e. 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

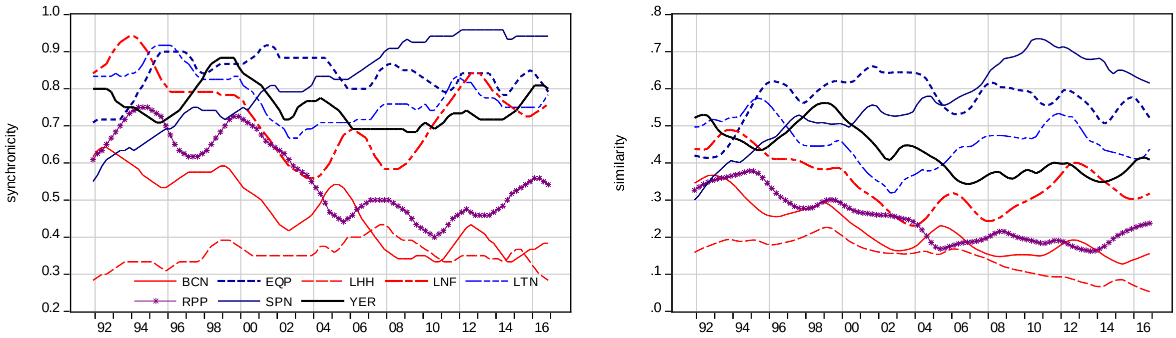
Figure 2 compares measures of overall synchronicity and similarity of extracted cycles for each series across countries. Both measures are shown as moving averages over the last 40 quarters in order to abstract from highly erratic movements governing the movements of both indicators in the short run. 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 seems that cycles extracted from loans to households (LHH) are the least synchronized among countries. This is also reflected in overall 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 the term spread 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 marked 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 BCN and 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 we rely on and related conceptual issues are 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) $\Leftrightarrow$ The two cycles are in the same phase *almost surely* (with probability one)
   - Perfect Negative Synchronization (PNS) $\Leftrightarrow$ The two cycles are in the opposite phase *almost surely* (with probability one)

- Non-Synchronization (NonS) $\Leftrightarrow$ 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) $\Leftrightarrow$ $\mathrm{E}[S_{ij}(t)] = 1$
- Perfect Negative Synchronization (PNS) $\Leftrightarrow$ $\mathrm{E}[S_{ij}(t)] = -1$
- Non-Synchronization (NonS) $\Leftrightarrow$ $\mathrm{E}[S_{ij}(t)] = 0$.

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

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

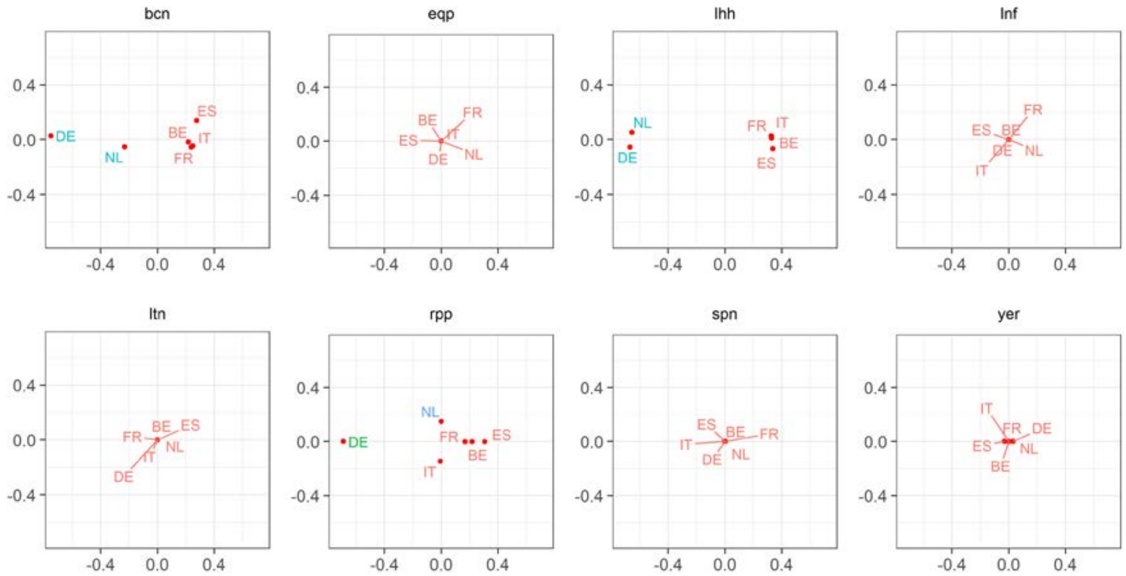
against the one-sided alternative of positively synchronised cycles:

$$H_1: \mathrm{E}\left[S_{ij}(t)\right] > 0.$$

If the null is rejected using a one-sided t-test, there is evidence that the credit 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 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 $\mathrm{E}[S_{ij}]$, i.e. $\boldsymbol{D}_{NxN} = [D_{ij}]$=[1- $\mathrm{E}[S_{ij}]$], 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 compares scaling maps for medium-term components in the eight series under analysis with matrix of dissimilarities (i.e. 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 unique 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 at medium-term frequencies. 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 et al (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 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 at which clusters 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 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 – Germany and Netherlands again do not belong to the same cluster as the rest of the countries under analysis. However, house price cycles in the two countries do not belong to the same cluster neither. 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, i.e. consists of a single cycle with a frequency that shifts across subsamples.[7]

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

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

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 an annual frequency. 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) 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 ψ (Aguiar-Conraria and Soares, 2014).[8]

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

where s represents the scale (which is inversely related to frequency) and τ 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

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

[8] 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.

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

The assessment of the cross-country co-movements in the financial 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. In this application we use weights based on real GDP

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

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 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, i.e. 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.[9]

Total bank credit to the non-financial private sector (upper left panel) we estimate significant cohesions close to one for fluctuations with duration of about ten years for a the full subsample for which the results can be interpreted, i.e. between about 1990 and the late 2000s. The frequency range for which we find the strong co-movements is quite narrow for most of the time. Its shorter end changes from close to ten years to about eight years in the 2000s. This quite narrow band for co-movements 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, loans to non-financial corporations (LNF, second row, left panel), cohesion 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. We also find evidence for strong co-movements for even longer cycles. The significant cohesion at higher estimated for the late 2000s is probably related to the financial crisis when bank lending to firms dropped markedly throughout the euro area. 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.

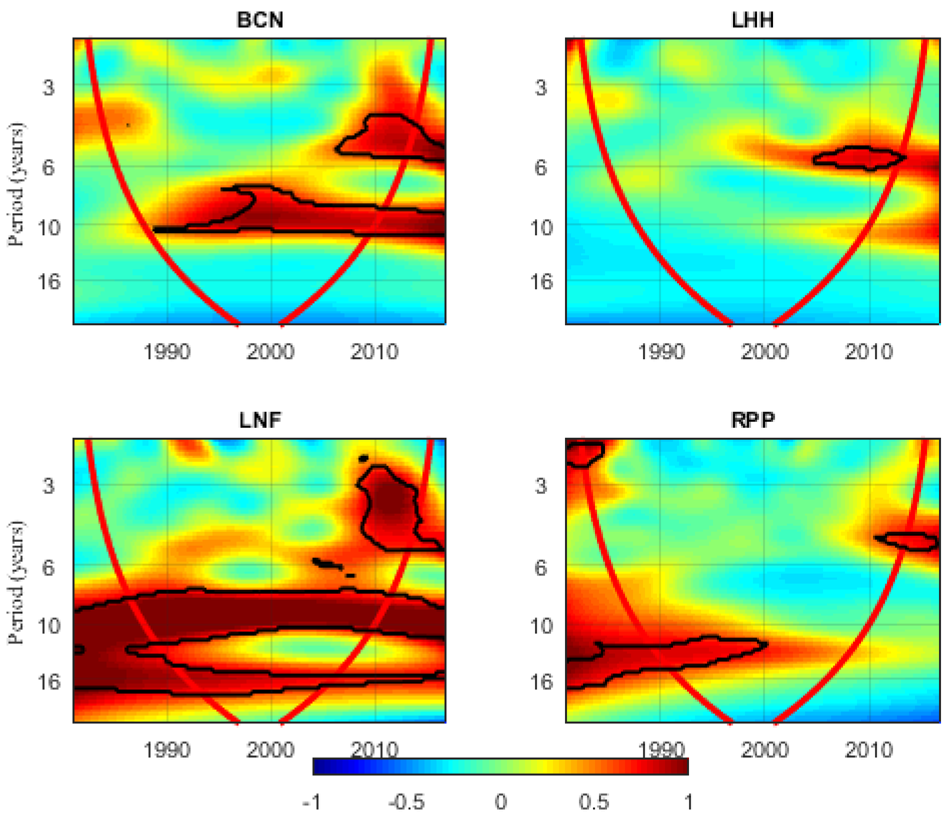
For real house prices (RPP) cohesion is overall decreasing over the sample period. The estimates indicate significant cross-country co-movements for cycles with periods of about twelve to 14 years up to around 2000 which weaken as time progresses. The significant cohesion estimated for the late 2000s 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

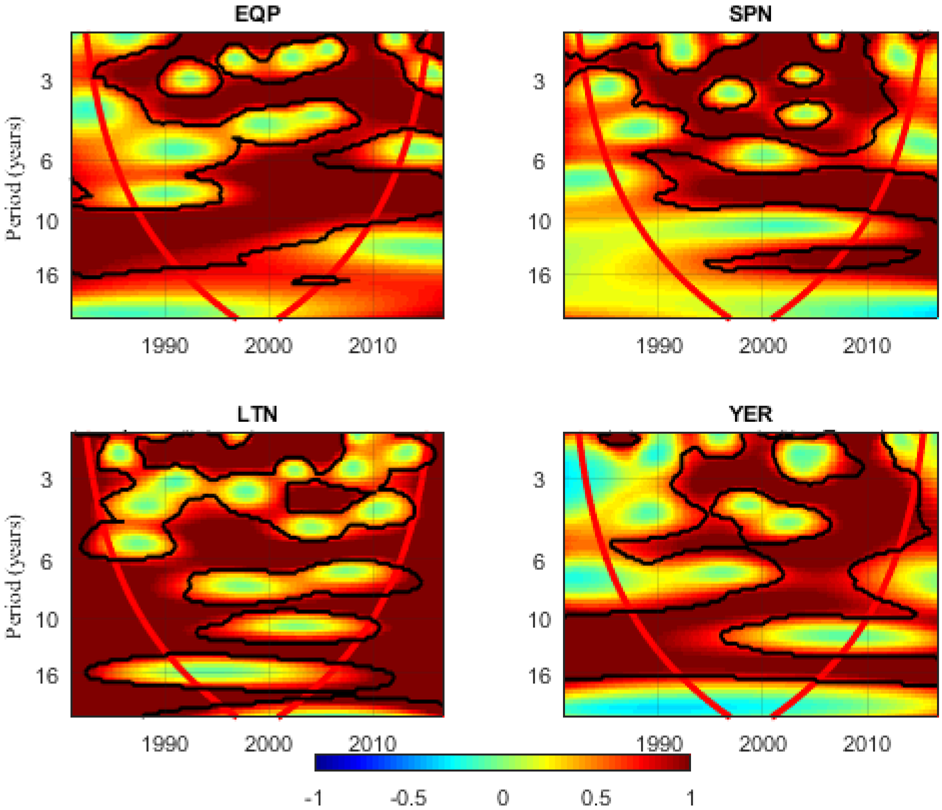
[9] If there is only an insufficient number of past or future observations available to apply the wavelet transform at a given point in time the algorithm extends the sample backwards or forward by ”reflecting” the first/last observations. The red lines separate the time-frequency combinations for which 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.

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 the credit variables. This is even more so for the long-term interest rates (LTN, third row, right column) while for the term spread (SPR) 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 at lower frequencies. 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.

Figure 4: A heat map of cohesion at different frequencies





The x-axis represents time, while the periodicity of the cycles is given along the y-axis in annual terms. Cohesion is represented by colour. Dark red indicates high cohesion, while dark blue indicates low cohesion. Black lines indicate regions with statistically significant 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.

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, except for loans to non-financial firms, 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 for stronger common cycles in total bank credit and bank lending to private households although these remain confined to relatively narrow frequency bands. 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 and turn out to be insignificant in the EMU-period.

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) a high degree of cross-country synchronization that is similar to 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 for a common cycle related to the real estate sector. Among the credit variables, we estimate relatively strong common cycles across countries only 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.

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 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 EMU.

While the other approaches rely on pre-filtered series, the wavelet analysis shows at which frequencies the variables move together – if any – 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 and twenty years for the bandpass 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: medium- to longer-term 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, i.e. our results to not indicate an important cross-country credit cycle. 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	SDW: ESA	IFS	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 domestic 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	1980Q1
DE	1970Q1
ES	1970Q1
FR	1970Q1
IT	1980Q1
NL	1977Q1

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. [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	1980Q1 [a]
NL	1977Q1 [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	1980Q1 [a]
DE	1970Q1
ES	1977Q1
FR	1970Q1
IT	1980Q1 [a]
NL	1977Q1 [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 [a]
DE	1970Q1
ES	1980Q1
FR	1970Q1
IT	1980Q1 [a]
NL	1977Q1 [a]

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

Appendix B: Filtered time series