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Financial Cycles in Euro Area Economies: A Cross-Country Perspective Using Wavelet Analysis*

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Abstract

We study the cross-country dimension of financial cycles for six euro area countries using wavelet analysis. Estimated wavelet cohesions show that cycles in equity prices and interest rates display stronger synchronization across countries than real output cycles, whereas credit variables and house prices show lower cross-country synchronization. We propose a wavelet-based extension to the spectral envelope that is similar to a frequency-based time-varying principal component analysis. The country loadings show that, contrary to all other variables, cycles in loans to households and house prices in Germany and the Netherlands are negatively or less strongly correlated with the common cycles.

I. 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. The concept of macroprudential policies which aims at preventing the build-up of imbalances in the financial system is closely linked to the notion of financial cycles.¹ In the literature 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 (e.g. Borio, 2014). In fact, various studies have presented evidence on the predictive power of financial cycle proxies for financial crises (e.g. Alessi and Detken, 2009; Borio and Drehmann, 2009; Drehmann and

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¹For example, Basel III regulations link counter-cyclical capital buffers to a financial cycle proxy, the deviation of the credit-to-GDP ratio from its long-run trend (e.g. Drehmann and Tsatsaronis, 2014).

Juselius, 2014; Voutilainen, 2017; Schüler, Hiebert and Peltonen, 2020). Empirically, financial cycles represent common movements in financial variables, most prominently credit or the credit-to-GDP ratio and property prices (e.g. Drehmann, Borio and Tsatsaronis, 2012; Borio, 2014).

In this paper we focus on the cross-country dimension of the financial cycle and apply tools from wavelet analysis to a harmonized data set to assess cross-country correlation in cycles in property prices and various financial time series across euro area economies. 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. Compared to more standard methods that rely on prefiltering the data, wavelet analysis does not require the ex-ante specification of the frequencies on which the financial cycle is assumed to operate. Instead, these frequencies are selected endogenously and can vary over time.

In the euro area, the degree of coherence of national financial cycles is crucial for whether *common* macroprudential policies should be applied across countries. Dissimilar cycles might require country-specific policies in order to cope with national idiosyncrasies. 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 European Systemic Risk Board (ESRB) issues warnings and recommendations.

In our analysis we investigate whether there are common cross-country cycles in house prices, credit and other financial variables across euro area economies, whether their properties change over time, and whether they are more pronounced for some variables than for others. In the first step we use wavelet-based cohesion to identify common cross-country cycles for each variable. While there are already some applications of wavelet cohesion to the analysis of financial cycles we augment this approach in a second step with a novel analysis based on an extension of the spectral envelope to wavelet analysis. This analysis is similar to a principal component analysis (PCA) but is time varying and operates in the frequency domain. It allows us not only to corroborate the finding from using cohesion from an alternative perspective but also provides information if, and to what extent, individual countries contribute to or are part of the common cycle. Using the results from this analysis we construct financial cycle proxies for the different variables across countries.

We find that the co-movement of credit and house prices across euro area countries is moderate and lower than for real gross domestic product (GDP). In contrast, the co-movement of equity prices and interest rates is very high. Using the spectral envelope approach we show that Germany and the Netherlands participate less strongly in the common house price cycle than the other countries and that their medium-term cycle in loans to households is, in fact, negatively correlated with that among the other countries.

In a related paper (Scharnagl and Mandler, 2019) we use wavelet analysis to study the within-country dimension of financial cycles for the four largest euro area countries and investigate co-movements among financial variables as well as between credit and house prices and real activity within each country. By contrast, in this paper, we focus on the cross-country dimension and analyse co-movements in credit, house prices and

other financial variables across six euro area countries. Furthermore, the previous paper uses wavelet coherency and cohesion as principal tools. In this paper, we enhance our analytical toolset by the spectral envelope in order to estimate common cycles across countries and the individual countries' contributions to this common cycle.

II Relation to the literature

Previous analyses of cross-country synchronization in financial cycles and its changes over time have mostly focussed on credit and house prices. Aikman, Haldane and Nelson (2015); Meller and Metiu (2017) find for 14 industrialized countries using the Schularick and Taylor (2012) data set that cross-country correlation or phase synchronization of cycles in bank lending has increased after 1973. Meller and Metiu also find that in the post-Bretton-Woods period countries with more synchronized business cycles have tended to experience more synchronized credit cycles. Strohsal, Proaño and Wolters (2019) analyse interaction of the common component in credit and house prices between the United States and the United Kingdom, and show them to 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. We add to these analyses by including additional variables, such as interest rates and equity prices, and by applying an alternative empirical approach based on wavelet analysis.²

Schüler *et al.* (2020) investigate the relative importance of cross-country synchronization of variables related to the financial cycle compared to cross-country co-movements in real output. They present evidence for financial cycles being less strongly synchronized across countries than business cycles. They also find Germany to be an outlier across countries with little relation to a global or European financial cycle indicator (Schüler, Hiebert and Peltonen, 2015). Aikman *et al.* (2015) find that, despite its increase over time, absolute cross-country correlation of credit cycles to be still relatively low. Claessens, Kose and Terrones (2011) analyse cycles in credit, house prices and equity prices in 21 OECD countries using turning-point analysis. They show cross-country synchronization to be highest for credit and lowest for house price cycles.

Breitung and Eickmeier (2016) estimate that global factors on average explain about 40% of movements in financial variables in a data set for 24 countries. In their results common components are 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. Similarly, Miranda-Agrippino and Rey (2015) estimate that a single global factor accounts for more than 60% of the common variation of 303 asset price series from Europe, Japan and the United States.

Most of the analyses of cross-country synchronization of financial cycles have relied on band-pass filters to extract medium-term cycles from financial variables, as for example Aikman *et al.* (2015); Drehmann *et al.* (2012); Meller and Metiu (2017).

²This broader set of variables is also analysed in Rünstler *et al.* (2018) with respect to the within-country synchronization of the variables.

However, wavelet analysis does not require prefiltering of the data and allows analysing changes in co-movements between time series both across different frequencies and across time.

Wavelet analysis has been applied to study the cross-country dimension of financial cycles, for example in Kurowski and Rogowicz (2018) who analyse cross-country co-movements in the credit-to-GDP ratio of a large set of countries using wavelet coherency, cohesion and wavelet-based distance measures.³ However, the credit-to-GDP ratio does not allow us to disentangle whether common cycles are due to co-movement in real GDP, credit or in their ratio. Flor and Klarl (2017) study house price cycles in US metropolitan statistical areas using a cluster analysis based on the wavelet transform and then use wavelet coherency to study the bivariate relationship between clusters or between clusters and the US aggregate.

Coherency is a time–frequency-dependent analysis of local correlation between two time series while we are interested in the correlation between multiple (more than two) time series. Using coherency we would either have to investigate the correlation among all possible country pairs or between a single country and an aggregate of the other countries, for example as in Aguiar-Conraria and Soares (2011) for business cycle synchronization. Both approaches, however, do not allow drawing direct conclusions about the common cycle as they do not provide for a means of aggregation. Distance measures and cluster analysis, such as in Aguiar-Conraria and Soares (2011); Flor and Klarl (2017); Kurowski and Rogowicz (2018) provide information on the similarity of cycles across countries, in other words how ‘close’ their cycles are to each other but they represent averages over the sample period and, thus, do not provide information on time variation.

In contrast to coherency, cohesion and the spectral envelope allow us to focus on common cycles in a group of countries and to assess the extent to which individual countries participate in the common cycles in a time-varying way. In our analysis, we also consider a much wider set of variables than earlier work.

III Methodology and data

Wavelet analysis

Wavelet analysis is a 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

³Papers applying wavelet analysis to study the financial cycle within individual countries are, for example Ardila and Sornette (2016), Pontines (2017), Scharnagl and Mandler (2019), Verona (2016) and Voutilainen (2017).

structural change, that is, a single cycle with a frequency that shifts across subsamples.⁴

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 2 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, as will be shown later, most of the additional insights from the wavelet analysis apply to frequencies below business cycle frequencies. Furthermore, 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 ψ (Aguiar-Conraria and Soares, 2014).⁵

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

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. * denotes the conjugate transpose.

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

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

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 ($\omega \approx 1/s$).⁶

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:

⁴For an introduction to (continuous) wavelet analysis, see Aguiar-Conraria and Soares (2014) and Rua (2012).

⁵For estimation we used the AST-toolbox for MATLAB by Aguiar-Conraria and Soares (<https://www.sites.google.com/site/aguiarconraria/joanasoares-wavelets/>) which has been extended to estimate cohesion and spectral envelopes.

⁶In wavelet analysis there is a trade-off between time resolution and frequency resolution. The Morlet wavelet satisfies the lower bound of Fourier (Heisenberg) uncertainty being the product of the temporal variance and the frequency variance as it is characterized by Gaussian-modulated complex exponentials. ‘... this wavelet achieves an excellent compromise between time and frequency accuracy’ (Aguiar-Conraria and Soares, 2014, p.352).

$$WPS_x(\tau, s) = |W_x(\tau, s)|^2. \quad (3)$$

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 and 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:

$$\rho_{x_i x_j} = \frac{\Re(W_{x_i x_j}(\tau, s))}{\sqrt{|W_{x_i}(\tau, s)|^2} \sqrt{|W_{x_j}(\tau, s)|^2}}, \quad (4)$$

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.

The cross-wavelet transform $W_{x_i x_j}$ is defined as:

$$W_{x_i x_j}(\tau, s) = W_{x_i}(\tau, s) W_{x_j}^*(\tau, s), \quad (5)$$

where W_{x_i} and W_{x_j} are the wavelet transforms of x_i and x_j respectively. Setting $i = j$ results in the wavelet power spectrum WPS_x .

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.

$$coh(\tau, s) = \frac{\sum_{i \neq j} w_i w_j \rho_{x_i x_j}(\tau, s)}{\sum_{i \neq j} w_i w_j}. \quad (6)$$

In this application we use equal weights, which allows us to compare the cohesion results to results from the spectral envelope (see below). 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.

Wavelet-based spectral envelope

The spectral envelope approach applies PCA to the frequency domain. It can be used to evaluate across frequencies whether multiple time series have common components (McDougall, Stoffer, and Tyler, 1997). Stoffer, Tyler, and McDougall (1993) first introduced the concept for categorical time series. Stoffer (1999) derived a threshold for statistical significance of the spectral envelope.

In our analysis, we use the spectral envelope to investigate whether and how strongly the individual countries are related to the cross-country common financial cycles. The spectral envelope thus augments and adds an additional perspective to the cohesion analysis. Cohesion is a tool to identify common cycles and the frequencies at

which they operate over time. The spectral envelope allows us to map these results back to the individual countries and to assess whether and to what extent each country contributes to the common financial cycle.

The spectral envelope is defined as the maximum of the standardized spectral density that can be attained across all possible (multivariate) scalings of a vector of time series. It provides a way to identify scalings that emphasize periodic features common to a set of time series. The scalings are generally restricted to be linear (Stoffer *et al.*, 1993). Given the scaling, a common cycle can be computed as the linear combination that corresponds to the spectral envelope of the time series.

Spectral envelopes have been applied to analyse business cycle synchronization across European economies as well as the United States and Japan by Esser (2014), and for a set of advanced (EU, US) and emerging countries (BRICS, Indonesia) by Nachane and Dubey (2019). In the next paragraphs we provide a description of our modifications of the spectral envelope approach to wavelet analysis.

The frequency domain equivalent of PCA (Shumway and Stoffer, 2017, chapter 7) for a specific frequency ω is given as:

$$\max_{c(\omega) \neq 0} \frac{c(\omega)^* f_x(\omega) c(\omega)}{c(\omega)^* c(\omega)}, \quad (7)$$

where $f_x(\omega)$ denotes the $n \times n$ dimensional spectral density of a vector of n time series $x_t = (x_{1t}, \dots, x_{nt})$, $c(\omega)$ is an n -dimensional vector and $c(\omega)^*$ its complex conjugate. Its estimation relies on the standard tools of frequency domain analysis, in particular the Fourier transform. The frequency domain analysis is based on the spectral density where the PCA in the time domain uses the covariance matrix. As in traditional PCA $c(\omega)$ is of unit length.

The solution is given by the pairs of eigenvalues λ_i and eigenvectors c_i of the spectral density denoted as $\{(\lambda_1(\omega), c_1(\omega)), \dots, (\lambda_n(\omega), c_n(\omega))\}$, where the eigenvalues λ_i are in descending order. The eigenvalues and eigenvectors are computed for all frequencies of interest.

The first principal component (PC) at frequency ω is

$$y_{t1}(\omega) = c_1(\omega)^* x_t, \quad (8)$$

where not all (real or complex-valued) elements of c_1 are zero. The elements of the eigenvector c_1 represent the contributions (weights or loadings) of the individual time series to the common cycle at frequency ω .

We identify the frequencies of common cycles using the spectral envelope. It is based on the optimality criterion

$$\lambda(\omega) = \max_{\beta \neq 0} \frac{\beta(\omega)' f_x^{re}(\omega) \beta(\omega)}{\beta(\omega)' V \beta(\omega)}, \quad (9)$$

where $\beta(\omega)$ is an n -dimensional vector. The time series x_t are demeaned and assumed to be stationary. $f_x^{re}(\omega)$ is the real part of the spectral density $f_x(\omega)$. As the time series in x_t are not standardized, the maximization accounts for differing variances

between time series by $V = \text{var}(x_t)$. From (9) $\lambda(\omega)$ results as the ‘largest eigenvalue of $f_x^{re}(\omega)$ in the metric of V ’ (Shumway and Stoffer, 2017, p. 461).

The spectral envelope in (9) is based on the spectral density $f_x(\omega)$ of multiple time series estimated on the full sample. However, spectral densities may change over time. In other words, the series might be non-stationary. To allow for time variation in the spectral density, we extend the spectral envelope approach to wavelet analysis. We estimate the time-varying multivariate spectral densities via the cross wavelet transform.⁷ As the time series are standardized using their full-sample moments before applying the cross wavelet transform (see section Wavelet analysis), accounting for variances as in (9) is in principle not necessary. However, due to the potential non-stationarity of the time series their variances are varying over time, although being equal to one over the full sample. We take that into account by estimating the wavelet-based spectral envelopes using the real part of wavelet coherencies (WCO).

Complex wavelet coherency (WCO) φ_{x_i, x_j} between two time series x_i and x_j measures local correlation and is defined as:

$$\varphi_{x_i, x_j} = \frac{W_{x_i, x_j}(\tau, s)}{\sqrt{|W_{x_i}(\tau, s)|^2} \sqrt{|W_{x_j}(\tau, s)|^2}}. \quad (10)$$

The wavelet-based spectral envelope is similar to (9) but with WCO replacing the spectral density and the covariance matrix:

$$\lambda(\tau, s) = \max_{\beta \neq 0} \frac{\beta(\tau, s)' \varphi_x^{re}(\tau, s) \beta(\tau, s)}{\beta(\tau, s)' \beta(\tau, s)}. \quad (11)$$

We can test for time–frequency combinations of the spectral envelope significantly different from zero using the bootstrap and select a frequency band around the frequency for which the spectral envelope is maximized for further investigation.

For a given frequency, the corresponding PCA resembles the calculation of cohesion (6). However, in the presence of both positive and negative dynamic correlations between multiple time series, cohesion might turn out to be close to zero, indicating that there is no co-movement between the time series at the frequency in question. In contrast, wavelet-based spectral envelopes present a clearer picture as the divergent signs of the elements of the loading vector allow to distinguish subsets of time series with positive and negative correlations. Furthermore, the loadings show us whether all countries contribute similarly to the common financial cycle (similar loadings) or some countries do not participate in the common cycle (loadings around zero).

⁷Multiscale principal component analysis (MSPCA) applies PCA on the coefficients of the multiscale decomposition of a time series generated by discrete wavelet transformation (DWT or MODWT). DWT decomposes a time series into a set of orthonormal basic functions at a discrete set of (dyadic) scales (Nason, 2010). In the MSPCA at each scale the appropriate number of principal components is selected for the corresponding matrices containing the detail or scaling coefficients (Bakshi, 1998). The retained components are used to reconstruct the time series incorporating the most important features and eliminating noisy features of the time series. Rua (2017) applies this approach to enhance the forecast performance of factor models by improving the estimation of the underlying factor models.

Compared to the usually applied approach of performing PCA on prefiltered series the spectral envelope approach has two advantages: (i) it does not rely on the ex-ante specification of the relevant frequency range. Instead, the frequency range is selected endogenously as indicated by the peak of the spectral envelope. (ii) Furthermore, both the frequencies of the common cycle and the country loadings can be time varying.

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 are 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: Belgium (BE), France (FR), Germany (DE), Italy (IT), the Netherlands (NL) and Spain (ES). All time series end in 2019Q4 and hence predate the Covid-19 pandemic. We transform all time series except for the interest rates into annual growth rates.⁸

IV Empirical analysis

Cohesion

Figure 1 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 (white) and plus one (dark grey). Light grey indicates cohesion around zero, which implies no contemporaneous correlation on average across countries. The white lines mark the border of the cone of influence. Results outside the time–frequency combinations marked by the white lines should not be interpreted.⁹

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 10

⁸As a robustness test we repeated the analysis using quarter-on-quarter growth rates with similar results. These are available from the authors upon request.

⁹If 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 white 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.

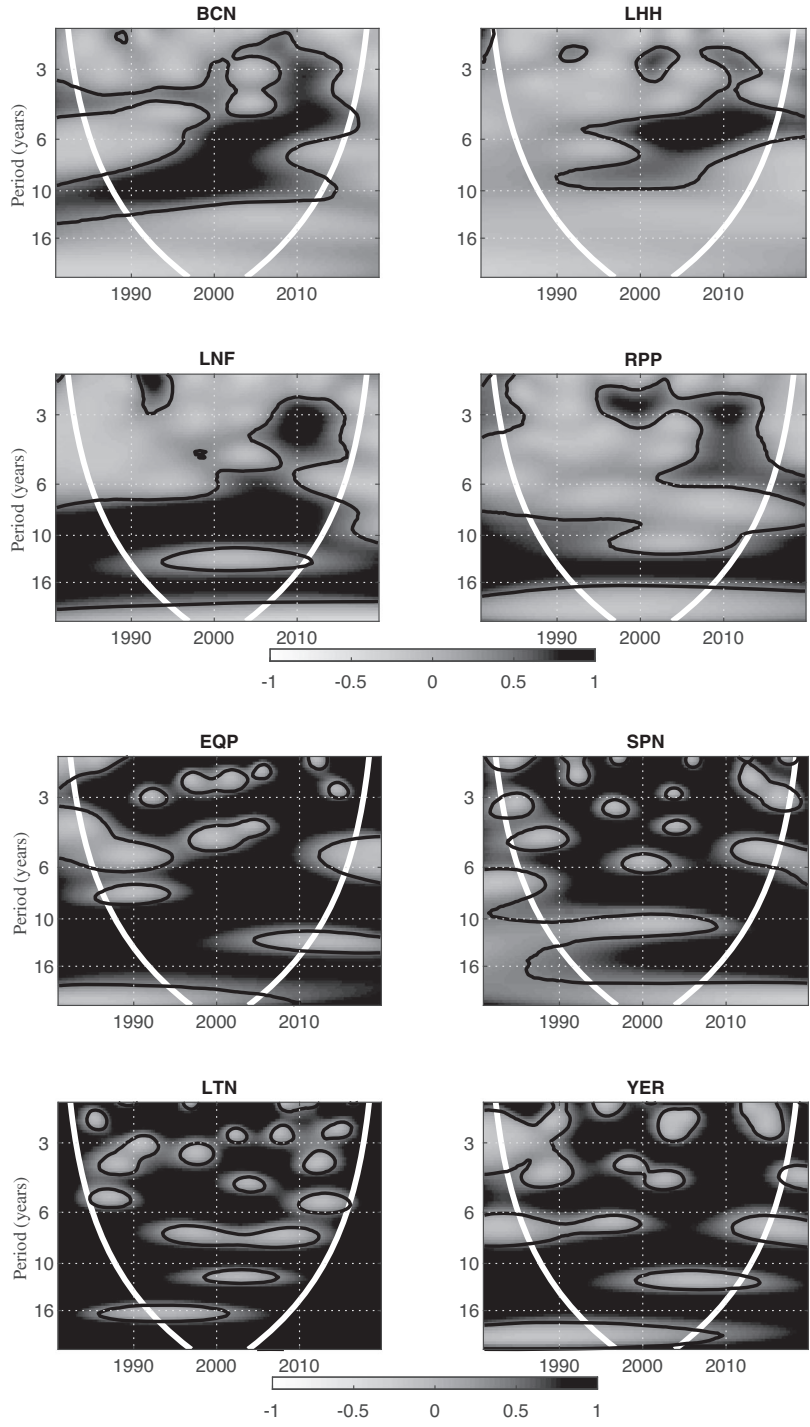


Figure 1. A contour plot of cohesion at different frequencies

Notes: The x-axis represents time, while the periodicity of the cycles is given in years along the y-axis. Cohesion is represented by shades of grey. Dark grey indicates cohesion close to +1, while white indicates cohesion close to -1. Black lines indicate regions with statistically significant positive cohesion at the 5%-level. The left and right white lines in each plot represent the cone of influence. The area outside the white lines should not be interpreted.

years over the full subsample for which the results can be interpreted, namely between about 1990 and the mid-2000s. The frequency range for which we find strong co-movements widens over time and includes cycles between 6 and 10 years in the 2000s.

Loans to households (LHH, upper right panel) display a very weak cohesion close to zero up to around 1990. Then significant common cycles emerge with durations of between 4 and 6 and between 8 and 10 years. In comparison, cohesion for loans to non-financial corporations (LNF, second row, left panel) is close to one for cycles of length between about 7 and 10 years over the full sample suggesting a stable common cycle among these six 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 10 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 at around 16 years. The time–frequency combinations with significant cohesion for LNF correspond to similar ones we estimate for real GDP (YER, bottom right panel) for which cohesion is significant for cycles with length around 10 years and around 16 years, too. The credit variables (BCN, LHH and LNF) show significant cohesion for cycles with duration of 6 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.

The transition to the European Monetary Union (EMU) in 1999 is around the mid-point of our sample period. Comparing the results between the first and the second half of the sample and excluding the significant cohesion at shorter cycle lengths than 6 years, which are most likely to be driven by the financial crisis, our results show an increase in cross-country co-movements for loans to households (LHH) and the overall lending aggregate (BCN) but not for loans to firms (LNF).

For real house prices (RPP) the estimates indicate significant cross-country co-movements for cycles with periods of about 12 to 16 years. In the EMU period there is an increase in cross-country co-movement for cycles with a length of 6 years and less, which, however, weakens again after 2010. The frequency range for which cohesion is significant throughout the sample period displays no overlap with that for which we find significant cohesion for lending to households (LHH) of which mortgage lending is the quantitatively most important component. This difference in the frequency ranges at which co-movements across countries emerge for these loans and house prices does not suggest that common credit-driven house price cycles have been important in the data.

For the next three variables we estimate significant cohesion over a broad frequency range. Co-movements in equity prices (EQP, third row, left column) are significant for various short- and medium-term frequencies for most of the sample period 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, bottom left panel) while for the term spread (SPN) cohesion starts out somewhat lower but increases over time and is significant over most of the frequency spectrum after the introduction of the common monetary policy. Since the long-term rate component of the term spread already shows significant cohesion for most time–frequency combinations, the overall increase in cohesion for the term spread is probably due to the stronger synchronization of short-term interest rates. This clearly reflects the effect of the common monetary policy within EMU. Overall, significant cross-country co-movements of the three financial market variables occur over a similarly broad frequency range as for real GDP.

Spectral envelope

Figure 2 contains the results of the analysis using wavelet-based spectral envelope. Similar to a PCA the spectral envelope approach searches over the space of a class of transformations, in this application linear transformations, that account for the maximum variation in the data. The contour plots in Figure 2 highlight the time–frequency combinations for which linear combinations of the country-specific time series explain most of the overall variations of a given variable across countries.

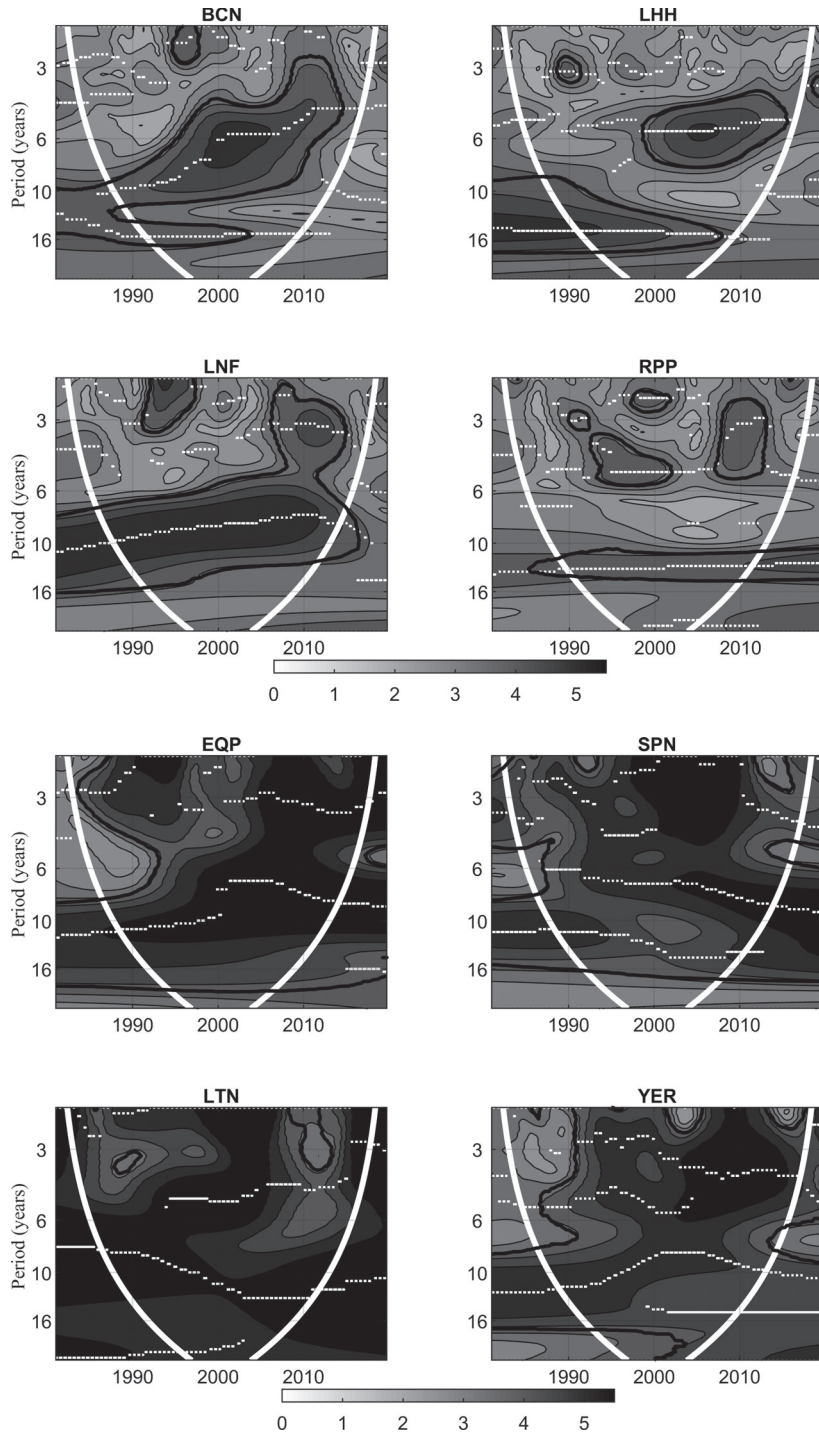
The spectral envelope should be large for those time–frequency combinations for which cohesion is large. However, the spectral envelope can highlight additional time–frequency combinations if the cycles of some countries are negatively correlated with those in the other ones. If this is the case the positive correlation between some country pairs will be compensated for in the cohesion by the negative correlation between other country pairs and the cohesion estimates will become insignificant. The spectral envelope, in contrast, does not average out positive and negative correlations.

The time–frequency combinations highlighted by the spectral envelopes turn out to correspond to those highlighted by cohesion for most of the variables. However, two interesting differences emerge for LHH and BCN. For both variables the spectral envelope suggests co-movement of cycles with duration of about 16 years either throughout the part of the sample period (LHH) for which we can interpret results, or at least at the beginning of the sample period (BCN).

We further investigate whether these differences between the results of the analyses based on cohesion and on the spectral envelope are indeed caused by cycles in a subset of countries being negatively correlated with those in the rest of the countries. For this,

Figure 2. A contour plot of the spectral envelope at different frequencies

Notes: The x-axis represents time, while the periodicity of the cycles is given in years along the y-axis. The spectral envelope is colour coded and increasing from white (zero) to black. Thick black borders indicate regions with statistically significant spectral envelope at the 5%-level. The left and right white lines in each plot represent the cone of influence. The area outside the white lines should not be interpreted.



we pick at each point in time the peak of the spectral envelope (across frequencies) and compute the country loadings on its first PC as described in section 3.2.

For this selection, we restrict the allowed cycle lengths to the range between 5 and 20 years. We set the lower bound because shorter cycles with length at the shorter range of business cycles clearly do not represent what the literature identifies as ‘financial cycles’. We choose the upper bound because, for longer cycles, the time period for which we can interpret the results (the area between the white curves) would become so short that no meaningful discussion of time variation would be possible anymore. While the lower bound is binding for some time periods for the financial market variables (EQP, LTN and SPN), the upper bound never binds.

Except for one case the first PC of the spectral envelope generally explains more than 70% of the overall variation in the time series at the peak of the spectral envelope (see Table A.1 in the online appendix). In fact, for all variables except for BCN, LHH and RPP it explains at least 89%. For each variable, the top panel in Figure 3 shows the periodicity of the maximum of the spectral envelope at each point in time, the bottom panel shows the country loadings on the first principal component (PC1). The dashed parts of the lines in the top panel mark results inside the cone of influence and those points in time too close to the start or end of the sample period to be interpreted. The loadings for these points in time should also not be interpreted.

For BCN the graph shows the gradual shortening of the dominant frequency range visible both in Figures 1 and 2. All countries load positive on the first PC at this cycle length, thus, it indeed represents a common cycle but DE loads somewhat weaker on this common component in the early part of the sample. On average, the first PC explains more than 75% of the variance at the peak of the spectral envelope (online appendix Table A.1).¹⁰

The maximum of the spectral envelope of LHH shifts in the 2000s from cycles with a length of about 15 years to those with length of about 5 years. This represents the jump from the black delineated region at the bottom in Figure 2 for LHH to the significant region that emerges in the middle of the frequency range after 2000. For the medium-term cycles in the 15-year region, which are highlighted by the spectral envelope but not by cohesion the loadings on the first PC contrast two country groups with opposite signs, DE and NL, vs. BE, ES, FR and IT. This explains the lack of cohesion for this frequency: As cohesion is an average of pairwise correlation, the negative correlation between the first two countries and the rest compensates for the positive correlation within each country grouping. This pushes cohesion towards zero. Instead of one common cycle we have evidence for two, opposed, common cycles, one for DE and NL and another one for the other four countries. As described above, shortly after 2000 the peak of the spectral envelope shifts to the business cycle range.

¹⁰The loadings on the second PC vary strongly over time with a persistently positive loading only on DE and a negative loading on NL for most of the time while the loading on IT changes from positive to negative from the first to the second part of the sample (online appendix Figure A.9).

On this shorter cycle all countries load with positive sign, thus, there are no opposing cycles. This cycle probably reflects both the credit booms that started around 2004/05 as well as the financial crisis.¹¹

For LNF the maximum of the spectral envelope is at a fairly stable duration of around 10 years and all countries load similarly on the first PC. Together with the results from the cohesion analysis this indicates a stable common cycle in this frequency range. The loadings are actually similar to those for real GDP (last panel) which is consistent with co-movements in LNF mainly reflecting co-movements in real GDP across countries and the relationship between loans and real activity.

The maximum of the spectral envelope of RPP is at cycles with duration of about 12 to 13 years. The loadings of DE are consistently smaller than those of BE, FR, IT and ES with only NL showing smaller loadings for the middle part of the sample. DE and NL also tend to have smaller loadings compared to the other countries on the PC1 for the second largest peak of the spectral envelope (see the online appendix).¹²

For the three financial markets variables (EQP, LTN and SPN) the restriction on the selection of the peak of the spectral envelope to cycles of at least a length of 5 years is often binding in contrast to loans and house prices. For subperiods the peak of the spectral envelope shifts to very short cycles with length of for example only half a year or 1 year. As explained, we exclude these short frequencies as they clearly do not represent ‘financial cycles’ and focus on the maximum of the spectral envelope after this exclusion. For all three variables the loadings on the first PC are very similar across countries.¹³ This also applies to real GDP. The exception is the loading of IT on the first PC of SPN: in the first part of the sample for which the maximum of spectral envelope occurs at a cycle length around 10 years the country loading of IT has the opposite sign to that of the other countries. The change might be related to the beginning of the convergence process implied by the run-up to EMU after the signing of the Maastricht Treaty in 1992.

Overall, the results 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 credit variables and house prices, cross-country co-movements are confined to much narrower frequency ranges. DE stands out from the other countries with its medium-term cycle in lending to households being (together with NL) negatively correlated with the other countries’ cycles. DE (and NL) also contribute less to the common cycle in house prices and, in case of DE in the early part of the sample, lending to the non-financial private sector. These results for DE are similar to those in Schüler *et al.* (2015, 2020).

We find some evidence of stronger common cycles in total bank credit and bank lending to private households after the transition to EMU as well as for the term

¹¹For LHH the second PC at the peak of the spectral envelope also is of some importance (the first PC explains on average 80% of the time-series variation at the peak of the spectral envelope). Its loadings shown in the online appendix are more dispersed as is generally the case for the second PC for all variables and offer no clear interpretation.

¹²The first PC accounts on average for 70% of the variance at the peak of the spectral envelope.

¹³The loadings on the first PC for the second highest peak of the spectral envelope are also very similar across countries.

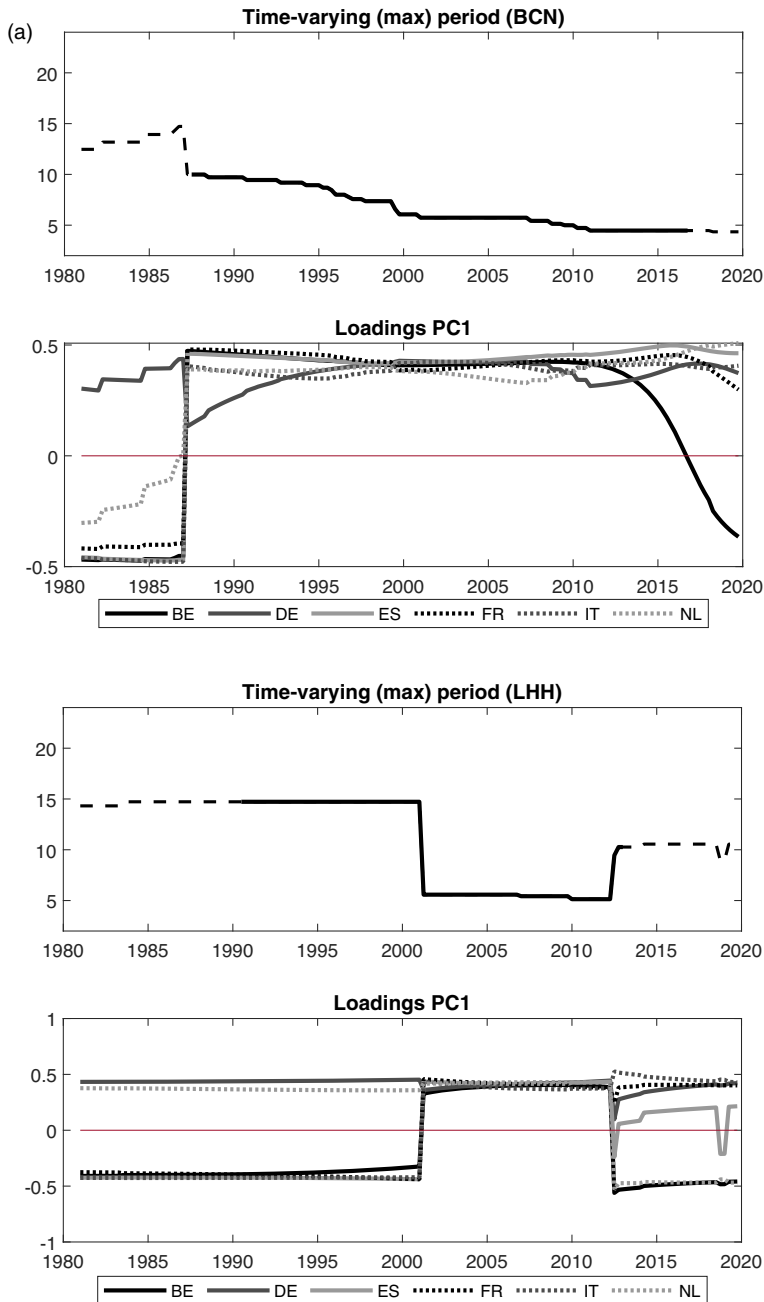


Figure 3a. Cycle length of peak of spectral envelope and loadings on first principal component (BCN and LHH)

Notes: The top panel in each subfigure shows the cycle length of the peak of the spectral envelope. The dashed parts of the line indicate the time periods too close to the beginning and end of the sample period for the results to be interpreted (cone of influence). The bottom panel in each subfigure shows the loadings of each individual country on the first principal component at the frequency picked by the maximum of the spectral envelope.

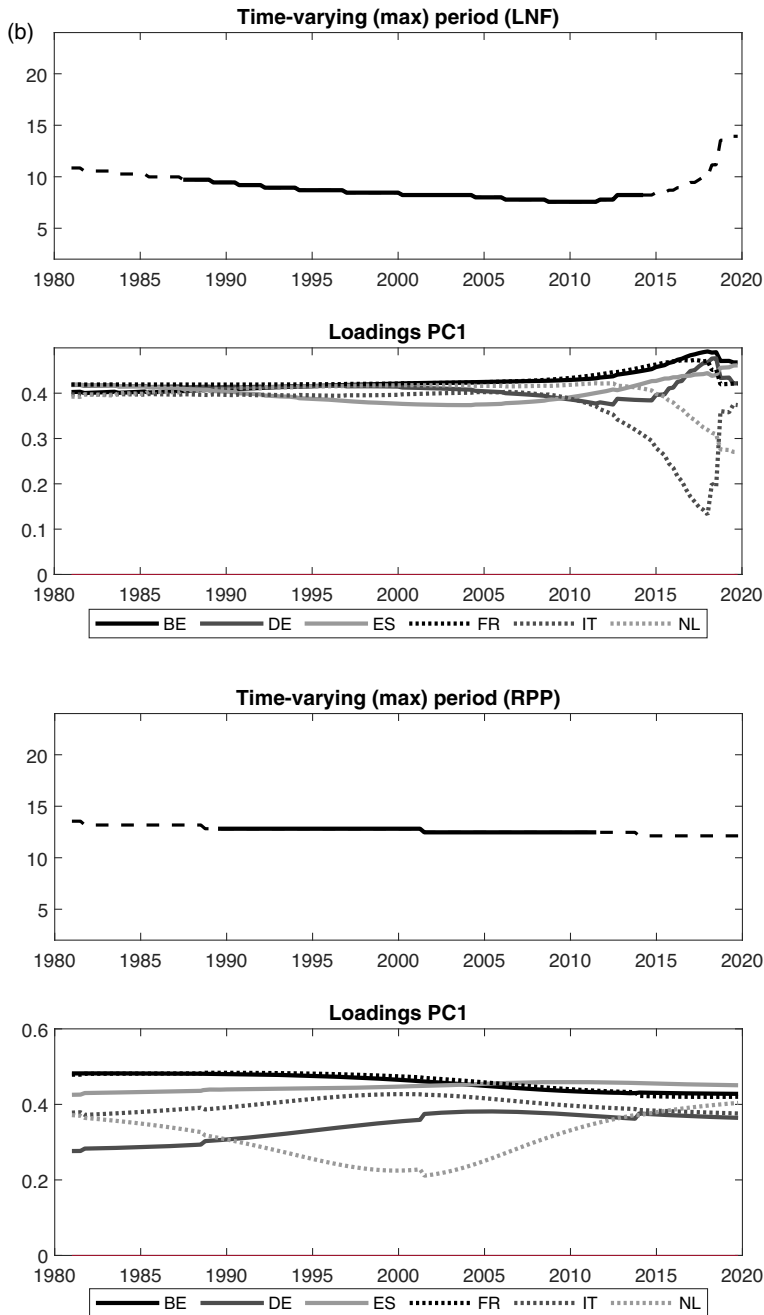


Figure 3b. Cycle length of peak of spectral envelope and loadings on first principal component (LNF and RPP)

Notes: The top panel in each subfigure shows the cycle length of the peak of the spectral envelope. The dashed parts of the line indicate the time periods too close to the beginning and end of the sample period for the results to be interpreted (cone of influence). The bottom panel in each subfigure shows the loadings of each individual country on the first principal component at the frequency picked by the maximum of the spectral envelope.

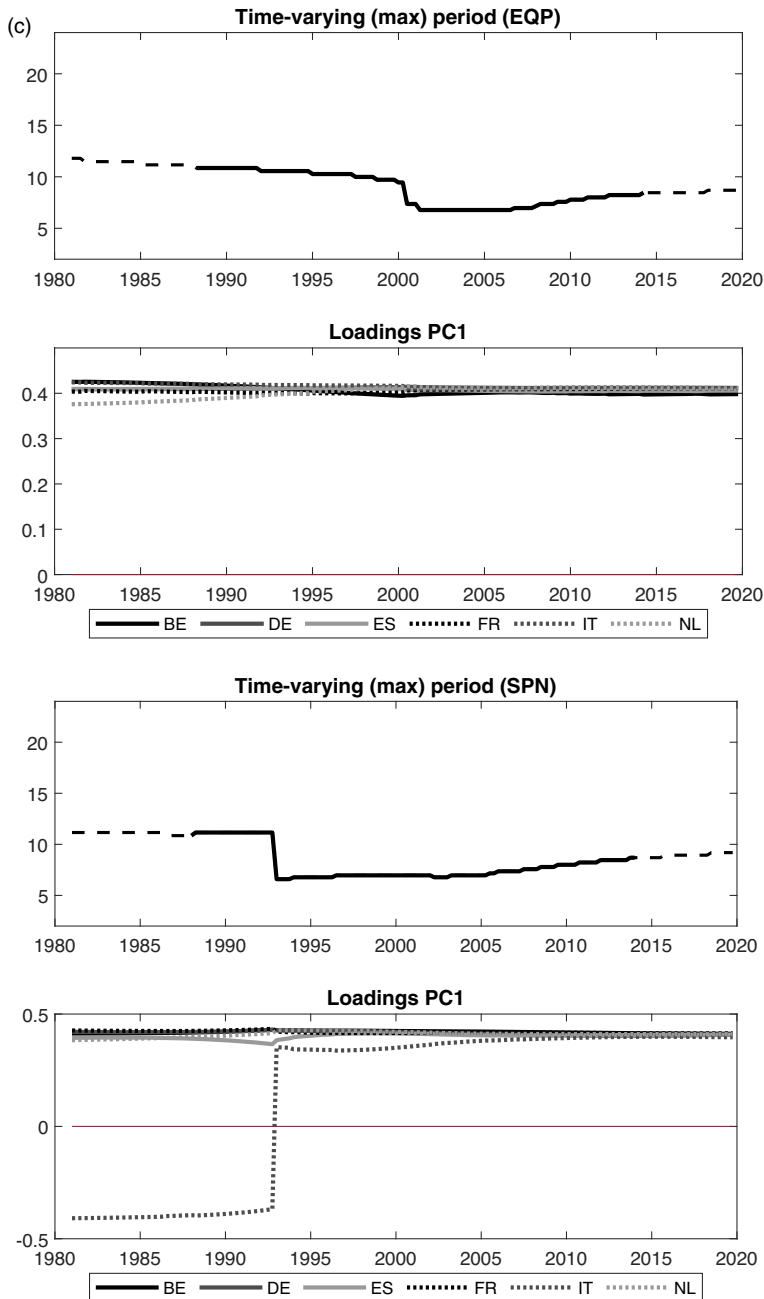


Figure 3c. Cycle length of peak of spectral envelope and loadings on first principal component (EQP and SPN)

Notes: The top panel in each subfigure shows the cycle length of the peak of the spectral envelope. The dashed parts of the line indicate the time periods too close to the beginning and end of the sample period for the results to be interpreted (cone of influence). The bottom panel in each subfigure shows the loadings of each individual country on the first principal component at the frequency picked by the maximum of the spectral envelope.

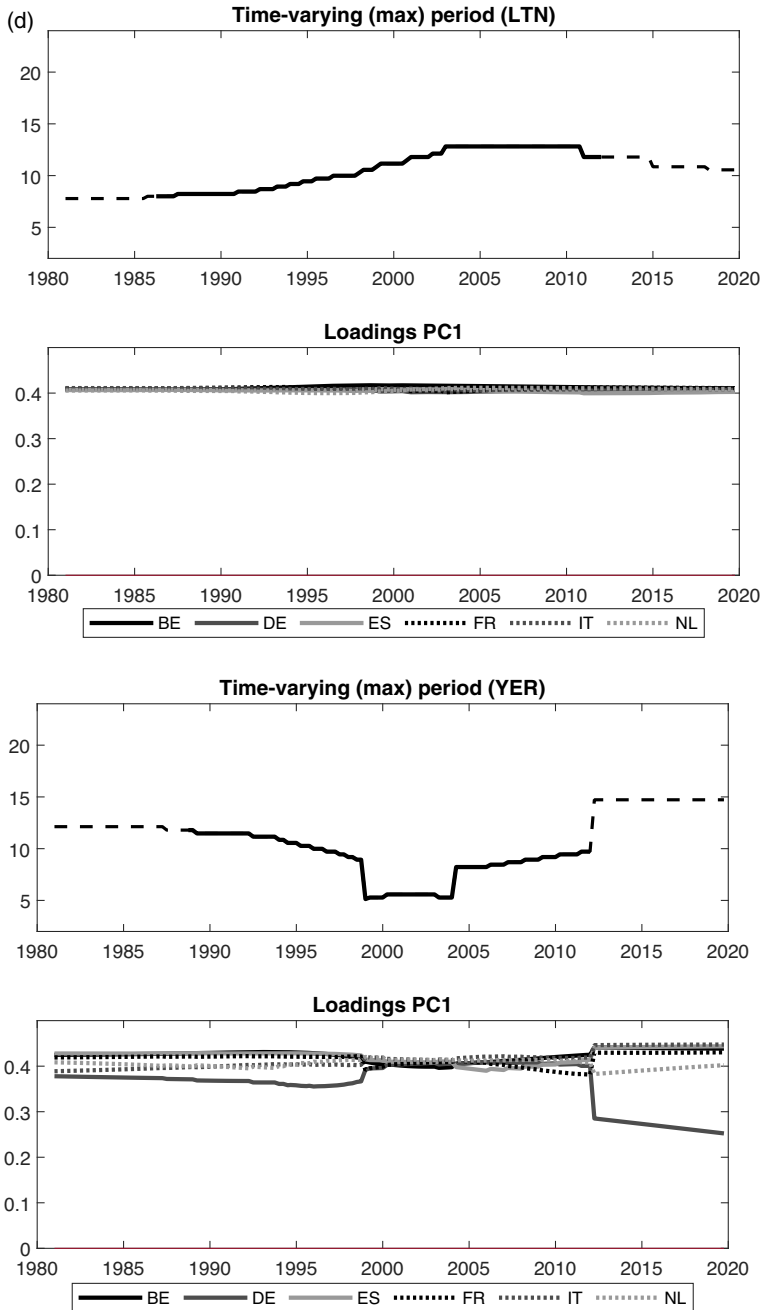


Figure 3d. Cycle length of peak of spectral envelope and loadings on first principal component (LTN and YER)

Notes: The top panel in each subfigure shows the cycle length of the peak of the spectral envelope. The dashed parts of the line indicate the time periods too close to the beginning and end of the sample period for the results to be interpreted (cone of influence). The bottom panel in each subfigure shows the loadings of each individual country on the first principal component at the frequency picked by the maximum of the spectral envelope.

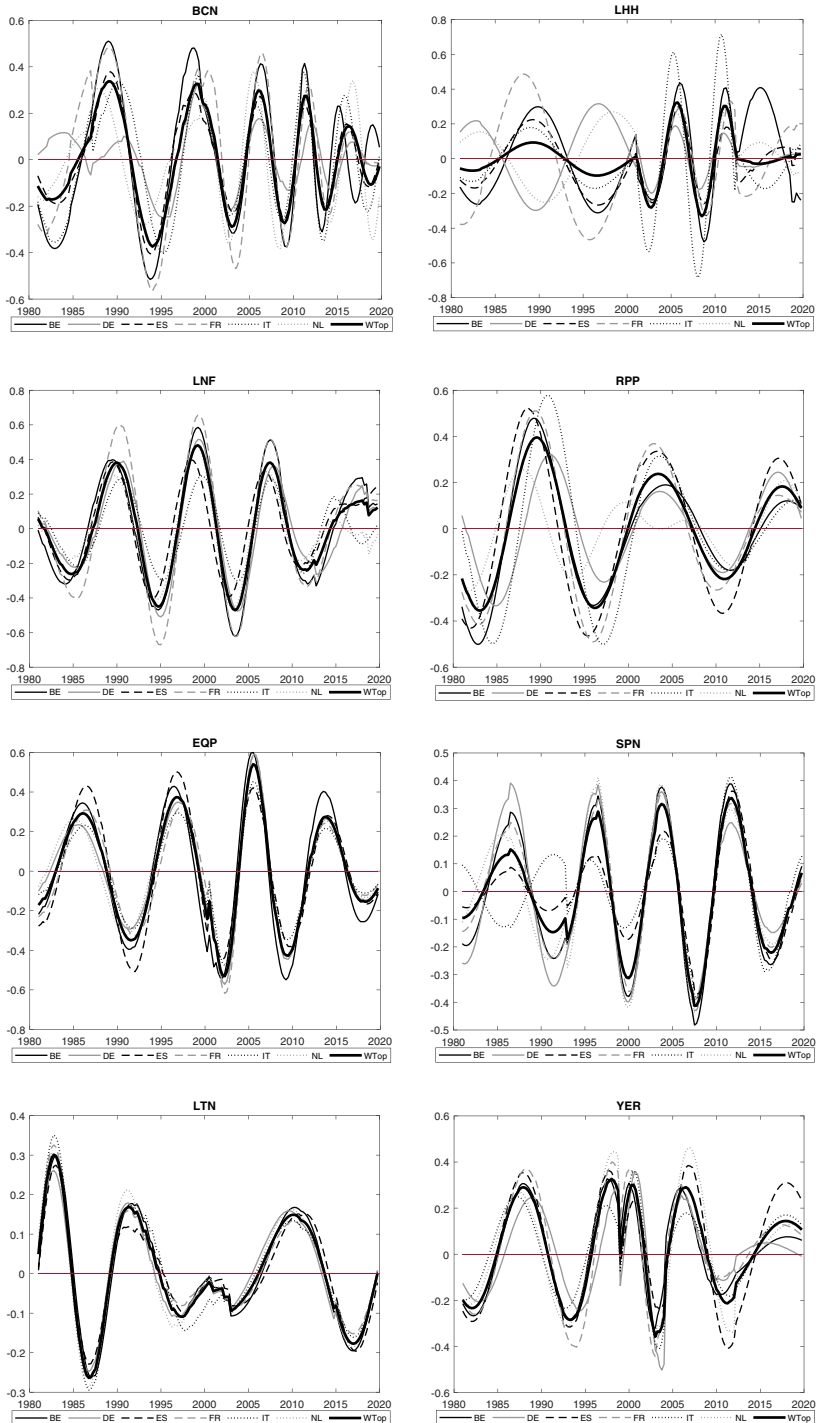


Figure 4. Common cycle and country-specific components

Notes: WTop denotes the common cycle.

spread. For the spread this is not surprising as EMU implies identical short-term interest rates in all countries.

Kunovac *et al.* (2018) apply the Christiano and Fitzgerald (2003) band-pass filter to the time series (in levels) and perform a PCA on the components with cycles between 2 and 20 years duration.¹⁴ Although their analysis does not account for time variation, it can be seen as a robustness check to our results. As with our spectral envelope analysis their estimated loadings on the first PC indicate much stronger commonalities in cycles in EQP, SPN and LTN than in the credit variables and house prices. It also shows the signs in the loadings on DE and NL opposite from the other countries for LHH.

Financial cycle indicators

Using the results from the spectral envelope we construct cross-country financial cycle indicators for the variables which are shown in Figure 4. Each panel shows the measure of the common cycle together with its components, measured in percentage points. These are constructed as follows: (i) for each point in time, we select the frequency with the global maximum of the spectral envelope (shown in Figure 3). (ii) Within a band centred at this frequency and a width of \pm five scales¹⁵ for each point in time we invert the wavelet transform of each country-specific time series, which gives us the country-specific cycles that contribute to the common cycle.¹⁶ (iii) Finally, we compute the common cycle as the linear combination of the country-specific cycles using the time-varying loadings shown in Figure 3.

This differs from a common cycle extracted as the PC of country-specific (filtered) time series in two important ways: (1) The frequency range is time varying and automatically selected according to the peak of the spectral envelope. (2) The loadings (weights) are also time varying.

In each panel, the thick black line represents the common cycle. For those variables, such as EQP and LTN, for which the country loadings are very close to each other, this common cycle is almost an average of the individual country series. As already suggested by the cohesion and spectral envelope analysis Figure 4 shows a high synchronization across countries and of the individual countries with the common cycle for LNF, EQP and LTN.

The gradual shift of the peak of the spectral envelope for BCN (top left panel) over time towards shorter cycles is clearly visible as is the jump to a higher peak frequency for LHH (top right panel) in the early 2000s. The special role of DE and NL for LHH and RPP is clearly shown: for LHH the cycles for NL and, particularly, for DE are negatively correlated with those for the other countries in the first half of the sample.

¹⁴The frequency range for the filter is based on Rünstler *et al.* (2018).

¹⁵Because of the relationship between scale and frequency $\omega \approx 1/s$, the frequency band $\Delta\omega$ corresponding to a range of \pm five scales depends on the initial frequency or scale $-\Delta\omega \approx \frac{1}{s+\Delta s} - \omega$. For LNF, for example, the band corresponds to about roughly \pm 2 years, for BCN to about \pm 0.6 years.

¹⁶Note that the wavelet transform is based on the standardized time series (using the full sample variance) and the standardization is not reversed after inverting the wavelet transform.

For RPP (third row, left column) the cycles in DE and NL reflect a phase shift relative to the other countries until the mid-to-late 1990s.¹⁷

V Discussion and conclusions

Our results show that those variables which represent financial asset prices or returns (long-term interest rates, the term spread and real equity prices), are characterized by a high degree of cross-country co-movement that is at least as strong as that of cycles in real GDP. In contrast, real property prices and credit variables overall show comparatively weaker cross-country co-movements. In particular, real property prices but also real bank loans to private households, of which loans for house purchases are by far the most important component, display relatively weak cross-country co-movements. For these variables DE and NL stand out with their property price cycles being less strongly related to the common cycle compared to the other countries and their medium-term cycle in lending to households moving against that of the rest. This is not picked up by cohesion analysis where the opposing cycles among the two groups of countries cancel each other out. From a policy perspective, this result could be interpreted as lending support for keeping the macroprudential policy mandates at the individual country level and against centralization in this policy field.

Among the credit variables, we estimate relatively strong common cycles across countries for real bank loans to non-financial corporations. As shown in Scharnagl and Mandler (2019) for the four large euro area countries, bank loans to non-financial firms exhibit common cycles with real activity, for example 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.¹⁸

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 (e.g. European Central Bank, 2017). Concerning possible changes following the start of EMU, our results indicate stronger co-movements in cycles in total bank credit, bank lending to private households and the term spread after the transition to EMU.

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¹⁷Real GDP cycles start deviating across countries in terms of amplitude from around 2010, which probably reflects the heterogeneous impact of the financial crisis and its aftermath.

¹⁸See also Rünstler *et al.* (2018) and Rünstler and Vlekke (2018) for evidence on co-movements between real activity and credit.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Figure A.1. Wavelet power spectra (BCN).

Figure A.2. Wavelet power spectra (LHH).

Figure A.3. Wavelet power spectra (LNF).

Figure A.4. Wavelet power spectra (RPP).

Figure A.5. Wavelet power spectra (EQP).

Figure A.6. Wavelet power spectra (SPN).

Figure A.7. Wavelet power spectra (LTN).

Figure A.8. Wavelet power spectra (YER).

Figure A.9. Loadings on the first and second principal component at the peak of the spectral envelope (BCN).

Figure A.10. Loadings on the first and second principal component at the peak of the spectral envelope (LHH).

Figure A.11. Loadings on the first and second principal component at the peak of the spectral envelope (RPP).

Table A.1. Share of variance at peak of spectral envelope explained by first principal component.