Financial cycles in the euro area: a wavelet analysis*

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Abstract

We study the relationship of loan to non-financial corporations, loans to households, house prices and equity prices between countries or within countries for nine euro area countries. Wavelet analysis allows to account for variations in these relationships both over time and across frequencies. We find evidence of strong co-movements between the growth rates in loans to non-financial corporations over the sample from 1980 to 2015 for all nine countries. For loans to private households the co-movement increases with the start of EMU. The cycle length is in general shorter than claimed by the BIS. Equity prices co-move at various frequencies. The degree of synchronization is in general higher for specific series across the EMU countries than across financial series within specific countries.

Keywords: financial cycles, real activity, business cycle, wavelet analysis

JEL classification: C30, E32, E51.

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1 Introduction

The financial crisis has led to a renewed interest in macro-financial linkages, with one important aspect being the financial cycle and its possible relationship with cycles in real activity. A recent literature which has been strongly advanced by researchers from the BIS and IMF has argued for the relevance of financial cycles, i.e. common cycles in various financial variables both within and across countries which operate on lower frequencies than business cycles. They have been suggested to represent the build-up of financial imbalances which might culminate in financial crises (Claessens, Kose, and Terrones, 2012; Drehmann, Borio, and Tsatsaronis, 2012; Borio, 2014). Empirical analyses suggest that the length and the amplitude of these financial cycles have increased over time.

A definition of the financial cycle often referred to is that by Borio (2014): "self-reinforcing interactions between perceptions of value and risk, attitudes towards risk and financing constraints, which translate into booms followed by busts". This kind of reasoning relates to the pro-cyclicality of the financial system. As the financial cycle is an unobserved variable this concept has to be operationalized. Therefore, a large literature concentrates on measurement issues.

Identification of financial cycles has been mainly achieved through the identification of turning points in time series of financial variables or through the use of statistical filtering techniques in order to extract time series components at specific frequencies. The latter approach suffers from selecting the frequency range at which to extract financial cycles either based upon ex-ante assumptions about the relevant frequency range or based on inspection of the spectrum of the financial series which has been estimated without accounting for possible time variation (Aikman, Haldane, and Nelson, 2015). The Basel committee applies the one-sided HP-filter with a pre-specific smoothing parameter ($\lambda = 400000$) based on the credit-to-GDP ratio to measure excessive credit. An alternative approach is applied in Strohsal, Proano, and Wolters (2015) who estimate univariate ARMA processes for financial variables and compute their corresponding frequency domain representations, again, without accounting for possible variation in the relationship.

Wavelet analysis as a tool for time series analysis in the frequency domain can be applied to estimate dominant frequencies of fluctuations in specific time series as well as the strength in co-movement among time series. It allows for changes across the frequency spectrum as well as over time. Furthermore, by computing wavelet cohesion it also be used to study the co-movement of multiple time series with respect to synchronization or similarity.

In this paper the relationship between financial variables and real activity is analyzed by wavelet analysis for nine euro area countries. The advantage of this approach is that there is no need to pre-specify a specific frequency band or turning points. The analysis is not restricted to either the time domain or the frequency domain, but using simultaneously both approaches. "Connecting time and frequency analyzes is especially relevant in the current state of the literature, when we have yet to understand the financial cycle and its properties" (Ardila and Sornette, 2016). Section 2 presents a brief overview of the literature. The applied tools of wavelet methodology are described in Section 3. Empirical results with respect to the duration of cycles, the potential co-movement of financial cycles and business cycles and the co-movement of financial series are presented in Section 4. The latter analysis is based on estimating cohesion. This concept was proposed by Croux, Forni, and Reichlin (2001) and applied by Rua and Lopes (2015) in the context of analyzing the synchronization of business cycles. Section 5 concludes.

2 Literature

The financial cycle can be defined in terms of its duration. In a turning point analysis the cycle length is measured as the number of periods between two adjacent peaks or troughs.[1] These are a priori defined by a minimum number of periods. This approach is applied by Claessens et al. (2012) and Drehmann et al. (2012). Claessens et al. (2012) analyze the interaction of financial cycles and business cycles using data for 21 advanced economies and 23 emerging market economies from 1960 to 2007. They find that financial variables (credit, property prices and equity prices) have a greater period and a larger amplitude than real GDP (estimated average length). They find that credit and house price cycles are highly synchronized within countries and that recessions that are caused by financial disruptions are longer and deeper. Haavio (2012) combines turning point analysis and the calculation of concordance indices for financial variables and real GDP for 17 OECD countries and finds similar results.

Drehmann et al. (2012) also apply a frequency-based filter (range: 8 to 16 years). Aikman et al. (2015) apply the Christiano-Fitzgerald bandpass filter to analyze the link between the credit cycle and the business cycle. The medium-term frequency is selected by estimating the spectral densities. They find that the estimated credit cycles have similar characteristics as those derived from the turning point analysis.

Koopman and Lucas (2005) and Ruenstler and Vlekke (2016) estimate multivariate unobserved component models for credit, house prices and real GDP. This approach allows for testing for similarity of cycle lengths. Ruenstler and Vlekke (2016) find that financial cycles and real GDP are closely related, even at frequencies lower than typical business cycles frequencies. For US, IT and FR the estimated cycle length is 12 to 15 years. For UK and ES they are larger and longer, whereas they are very small and short for Germany.

Strohsal et al. (2015) estimate ARMA models to calculate the corresponding spectral densities. This approach allows for the detection of very long cycles even in the case of a limited sample period. To assess time variation the sample has to be split a priori, as the Fourier transform is based on the stationarity of a time series implying the non-existence of structural breaks. The time series considered are credit, credit-to-GDP, house prices, equity prices and real GDP. For US data they find just a small increase in the period of real GDP and equity prices, but a large increase for credit and house prices. For the most recent period the duration of the financial cycles in US and UK is around 15 years. For Germany there is no evidence for a distinct financial cycle.

Verona (2016) applies wavelet methodology to estimate the duration of cycles in credit, house prices, equity prices and GDP for the US. He argues that the financial cycle is much longer than the business cycles, although there is spectral power for GDP at similar frequencies. His conclusion is only valid for credit and house prices, but not for equity prices characterized by higher frequencies. Coherency between financial and real cycles is not analyzed. In contrast to Strohsal et al. (2015) his results only indicate minor changes

[1] Ardila and Sornette (2016) propose a wavelet-based estimation of turning points taking uncertainty into account. This approach is not applied in this paper as it is based on MODWT.

in frequencies over time. Mandler and Scharnagl (2015) show that there is high wavelet coherency of bank-lending and real GDP for Italy and Spain and to a lower degree for France even at periods longer than those typically attributed to business cycles. These cycles are rather stable over time.

Apart from measuring cycles in individual financial variables, there are some papers on combining multiple variables into a single measure, i.e. testing whether there are separate cycles in the individual variables (credit cycle, house price cycle, etc.) or whether there is something like an underlying "common" financial cycle reflecting the co-movement of the "financial sector". Drehmann et al. (2012) and Hiebert, Schueler, and Peltonen (2015) estimate cycles for individual variables and average those. Hiebert, Klaus, Peltonen, Schueler, and Welz (2014) estimate individual cycles as well but average those by applying principal component analysis.

3 Wavelet Analysis

Wavelet analysis is an extended form of spectral analysis allowing for time variation.[2] Spectral analysis decomposes a time series into a set of cycles with specific periods and estimates the contribution of these cycles to the variance of the series. The co-movement of multiple time series can be analysed at different frequencies. As the underlying trigonometric functions have infinite support, it is implicitly assumed that the time series are stationary. It is not possible using the estimated spectrum to differentiate between series that are sums of several cycles and series that are characterized by structural changes having different sub-sample-specific dominant cycles which is quite common for macroeconomic time series.

Wavelet analysis is based on finite waves, changes in the importance of specific cyclical frequencies can be located in time (Cazelles et al., 2008). Another advantage (also compared to rolling window Fourier analysis) is its use of efficient windowing. The window width (sub-sample selection) is scale dependent as the wavelet is stretched or compressed (Aguiar-Conraria, Azevedo, and Soares, 2008).

The continuous wavelet transformation (CWT) is obtained by projecting the time series $x(t)$ onto wavelet functions ψ.

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

where s represents the scale ("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. High frequency fluctuations imply low values of the scaling factor, while low frequency fluctuations imply high values for s. The translation parameter τ controls the location of the wavelet, i.e. changes in τ shift the wavelet in time. The function ψ has to fulfil some requirements in order to have the properties of wavelets.[3]

In the empirical part, the Morlet wavelet is chosen, which is widely used in economic

[2] This section draws heavily on Aguiar-Conraria and Soares (2014).

[3] For details see, for example Percival and Walden (2002).

applications.

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

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 joint time-frequency resolution and a direct relation between scale and frequency (e.g. Aguiar-Conraria and Soares, 2014, p. 352).

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

$$WPS_x(\tau, s) = |W_x(\tau, s)|^2. \tag{3}$$

The bigger the wavelet power spectrum $WPS_x(\tau_i, s_i)$, the higher the correlation of the time series around τ_i and the wavelet scale s_i. It will be plotted in a 2-dimensional graph (heat map).

The co-movement of two time series can be estimated by dynamic correlation.

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

where $\Re$ denotes the real part of the cross-wavelet transform W_{x_i,x_j}. The latter is defined as

$$W_{x_i,x_j} = W_{x_i} W^*_{x_j}, \tag{5}$$

where * denotes the complex conjugate. The cross-wavelet transform represents the local covariance between x_i and x_j at each time and frequency. Based on dynamic correlation Rua and Lopes (2015) propose a measure of cohesion.

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

It is a weighted average of all pairwise dynamic correlations (fixed GDP weights).

The significance of areas is tested by parametric bootstrap. Based on estimated autoregressive processes, a number of simulated replications for each series are generated. The empirical distribution is based on calculated dynamic correlations for these replications.

To gain deeper insight into divergence between countries, the distances between wavelet power spectra can be analyzed. Following Aguiar-Conraria, Martins, and Soares (2013) wavelet distance matrices are calculated. It can then be tested, whether the estimated similarity is significant.

$$dist\left(W_{x_i}, W_{x_j}\right) = \frac{\sum_{k=1}^{K} \sigma_k^2 \left(d\left(l_{x_i}^k, l_{x_j}^k\right) + d\left(u_{x_i}^k, u_{x_j}^k\right)\right)}{\sum_{k=1}^{K} \sigma_k^2}. \tag{7}$$

The distance matrix $dist\left(W_{x_i}, W_{x_j}\right)$ is based on the most important patterns of the wavelet transform (Rouyer, Fromentin, Stensath, and Cazelles, 2008). These are estimated via singular value decomposition (maximum covariance analysis).

$$W_{x_i} \approx \sum_{k=1}^{K} u_{x_i}^k l_{x_i}^k$$

The structure of the distance matrix is then displayed as a cluster tree (dendrogram).

Wavelet bandpass filtering is applied to estimate cycles corresponding to specific frequency ranges. This is done by inversion of the wavelet transform of the pre-specified interval.

4 Empirical Results

We use quarterly data for the period from 1980 until the end of 2015 for a series of financial variables: loans to non-financial corporations (LNFC), loans to private households (LHH), equity prices (EQP) and house prices (HPR). The financial variables are deflated with the GDP deflator. The data was obtained from the ECB's statistical warehouse and from the BIS (residential property prices). The time series used are annual growth rates. This differs from other methods applied in the measurement of financial cycles (turning point analysis, unobserved component models, etc.). The latter use series in levels. However, the trends in the levels of the series would lead to spurious coherency and dynamic correlation when using spectral analysis. The sample includes data for nine euro area countries: Austria (AT), Belgium (BE), Germany (DE), Spain (ES), Finland (FI), France (FR), Italy (IT), Netherlands (NL) and Portugal (PT). Other member countries are not included as the approach needs relatively long time series. The lowest frequency to be analyzed is restricted by the sample length. In some cases, specific variables are not available over the full sample even for these nine countries: house prices for AT and PT and equity prices for PT. These series are then excluded from specific estimations.

The relative importance of frequencies can be analyzed by estimating the wavelet power spectra of the series.[4] In Figure 1 the duration of cycles is plotted for the four major euro area countries. The x-axis is the time dimension, the y-axis the frequency dimension. The power is represented by colour, where dark red indicates high power and dark blue indicates low power. The left and right red line in each plot represent the so-called cone of influence. The area outside is affected by end-of-sample problems, i.e.

[4]The estimations were performed using the AST-toolbox for MATLAB by Aguiar-Conraria and Soares. https://sites.google.com/site/aguiarconraria/joanasoares-wavelets/. In some cases modifications were implemented by the authors.

there are not enough data available for calculating the power at specific scales and points in time. Corresponding results should not be interpreted as the results might be affected by zero padding. Loans to non-financial corporations (LNFC) are characterized by cycles of 10 and 16 years in ES, FR and IT (top panel). These dominant cycles are displayed in the graph as white lines. The durations are relatively stable over time, although there seems to be a trend towards longer cycles in ES. For Germany there are no long cycles of 16 years, whereas a shorter cycle of around 6 years is observed. Very short cycles can also be observed in IT.

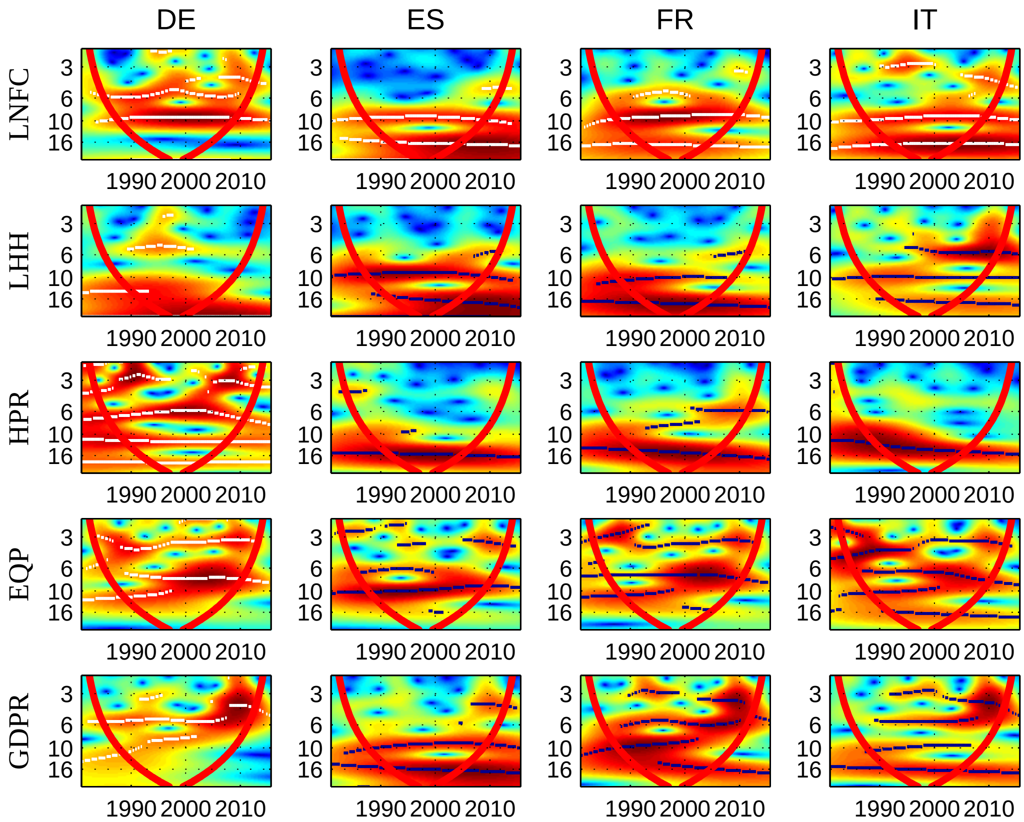

Figure 1: Wavelet power spectra

Similar periodicities (10 and 16 years) are estimated for loans to private households (LHH, second panel), with longer cycles showing a tendency to become even longer over time. Again, the results for DE are different as the low frequency cycle becomes less important after the early 1990s, while the dominant frequency shifts to shorter cycles. The power of house prices (third panel) is for most countries mainly in the lower frequencies around 14 to 16 years in ES, FR and IT and show a tendency to longer cycles as did loans to households. For DE the results indicate an important cycle at a somewhat lower frequency but also a cycle with fluctuations of about ten years which weakens and disappears after the late 1990s. The results for the other countries (shown in the appendix) are similar to those for the large countries shown here with the power spectra for some countries and variables more similar to ES, FR and IT or more similar to DE (e.g. NL and AT).

The wavelet power spectra for equity prices (fourth panel) are in stark contrast to those for the other financial series with various dominant frequencies within each country covering most of the frequency spectrum. Except for IT which also exhibits important cycles with duration of 16 years, the cycles tend to shorter fluctuations compared to loans and house prices.

The bottom panel shows the spectra for real GDP. The comparison to those for the other series might give a first impression of potential co-movements of financial variables and real activity. With the exception of DE, periodicities in loans and real GDP seem to be similar at 10 and 16 years while for DE only the shorter cycle of six years seems to be reflected in loans and real GDP. The results also suggest co-movement in real output growth and house prices in ES, FR and IT at low frequencies. In contrast there seems to be less similarity in fluctuations in equity prices and real output.

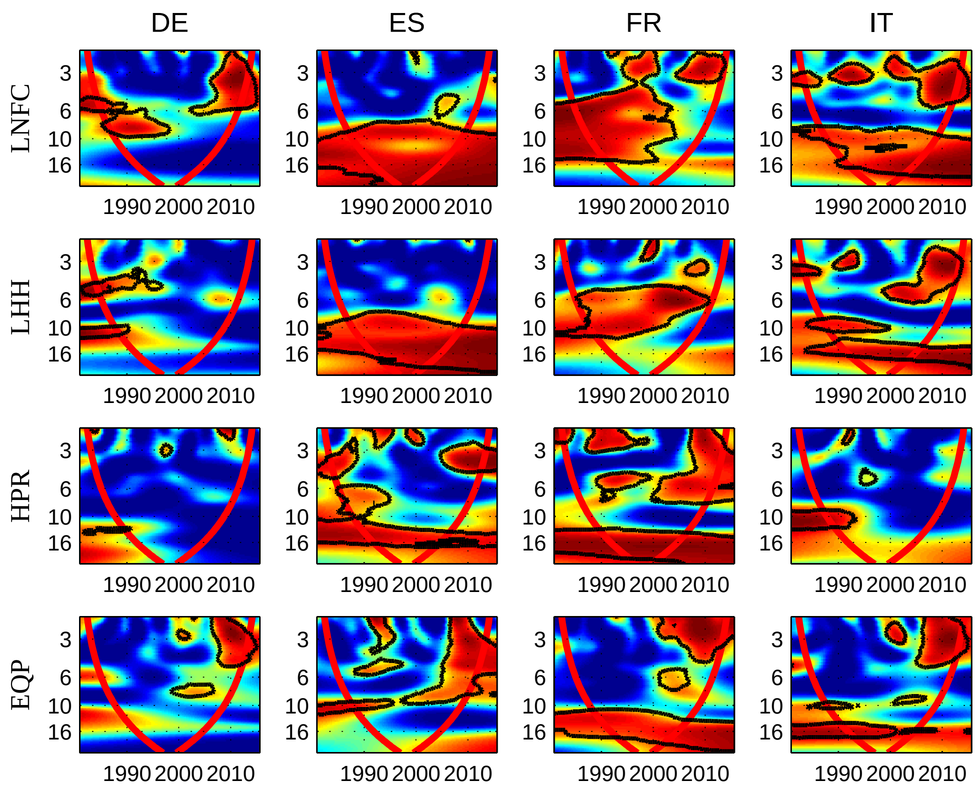

Figure 2: Cohereny of LNFC, LHH, HPR and EQP with real GDP for EA4

Figure 2 shows the coherency between loans, house prices, equity prices and real GDP which provides information on the co-movement between the financial variables and real activity. The panels show the level of coherency which falls between zero (dark blue) and one (dark red) with the black lines indicating significance at the 5% level.[5] The curved red lines indicate the cone of influence. Loans to non-financial corporations and real GDP (top panel) show high coherency for cycles with a duration of between six and ten years in ES and IT throughout the sample period. In FR, initially, coherency is large

[5]Results for all nine countries are in the appendix.

and significant across a broad frequency band, but weakens after the mid-2000s. Similar to the results for the wavelet power spectrum high coherency in DE is not estimated at longer durations but significant coherency is obtained at cycles with periodicities of six to ten years and is not stable over time. The results for lending to households (second row) are broadly similar with a narrower range of frequencies with significant coherencies. Again for ES and IT significant and stable coherency is estimated at low frequencies. For FR we estimate significant coherency for cycles with duration of between six and years but with a tendency to the shorter end of this frequency spectrum over the 2000s. For DE, however, we find no evidence of stable co-movements between loans to households and real activity at any frequency. Coherency between house prices and real GDP (third row) is close to one and stable in ES and FR at periodicities around 16 years. For DE there is no evidence of significant co-movements between real GDP and real house prices at any frequency and for IT only in the late 1980s and early 1990s. Finally, for real equity prices significant coherency is estimated in FR and IT for cycles with durations of ten to 16 years and around 16 years, respectively. For ES coherency is only temporarily significant at higher frequencies and for DE coherency is generally relatively low.

Overall, these results indicate for many countries significant relationships between medium or long-run cycles in financial variables and real activity. However, there are also important cross-country differences, such as the weak correlations between these cycles in DE.

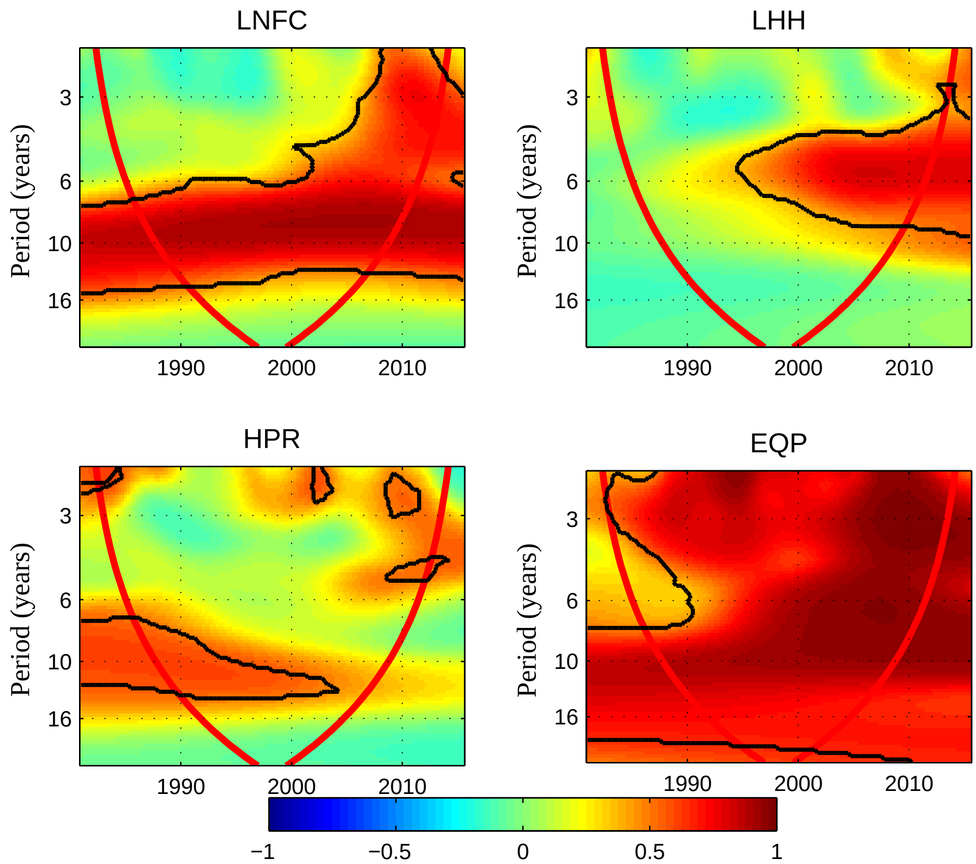

Figure 3: Cohesion across all countries

Figure 3 shows the estimated cohesion for these four financial variables, i.e. the strength of the cross-country dynamic correlation. For each variable the cohesion measure is computed as GDP weighted average of the dynamic correlations between all country pairs. Here, all nine countries (seven in the case of real house prices and eight in the case of equity prices) are considered. 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. For loans to non-financial corporations (top row, left) cohesion is close to one in the frequency range between six and ten years over the full sample suggesting a stable common cycle among euro area countries in this frequency range. At higher frequencies we also estimate increasing cohesion after the introduction of EMU. For loans to households (top row, right) cohesion is much lower until the late 1990s when it becomes significant over a widening frequency band. The dominant cycles in loans to households with durations of six and ten years thus do not display strong correlations across countries. In contrast, the co-movements are at higher frequencies. Real house prices (bottom row, left) display moderate and not significant cohesion for cycles with duration of six years and more in the late 1990s but then weakens over time. The estimates indicate a significant co-movement of house prices at low frequencies up to 2000 as highlighted in Figure 1. In contrast, cross-country cohesion of equity prices (bottom row, right) is large and significant for almost the full sample period and across all frequencies. Overall, these results suggest common cycles in the lending to non-financial corporations, households (for part of the sample) and real equity prices while there is little evidence of a common house price cycle at the end of the sample.

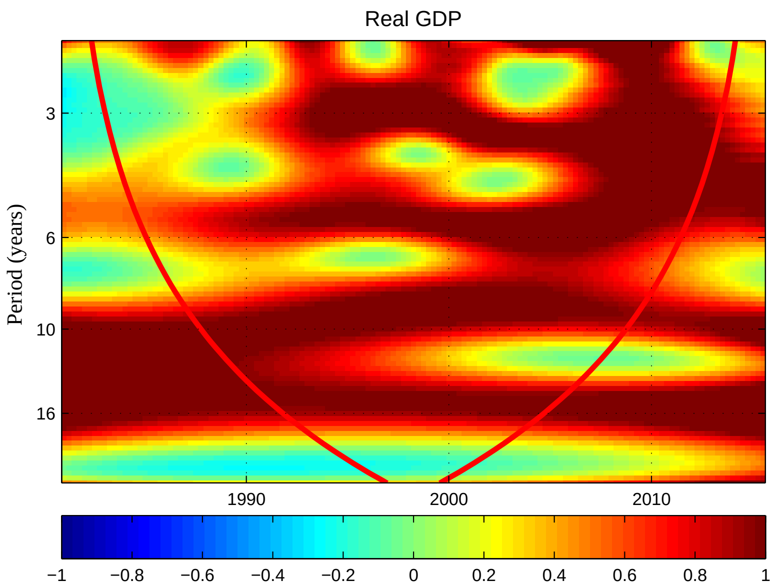

Figure 4: Cohesion of real GDP across all countries

For comparison Figure 4 shows the estimated cohesion for real GDP, i.e. synchronisation of real activity. We find persistently high cohesion for cycles with duration of about 10 and 16 years which were shown to be dominant frequencies in the wavelet power spectrum for many countries. Cohesion also attains high values at higher frequencies and the degree of synchronisation of output growth at these higher frequencies has become more pronounced after the 1990s. Thus, the estimated cohesion for the financial variables – with the exception of equity prices – indicates a more narrow frequency range of co-movements in bank lending and house prices than of co-movements in real activity.

The high cohesion of loans to non-financial corporations is reflected by relatively low distances between the wavelet spectra of different countries. Figure 5 shows this measure for frequencies between 6 and 16 years by means of a dendrogram (left panel). The smaller the value, the higher the similarity of the corresponding cycles. Cycles for BE and NL as well as those for ES and IT are quite closely linked. Those of FI and AT are further apart from the rest of the group as is also visible for the filtered series generated by inversion of the wavelet transform (right panel).

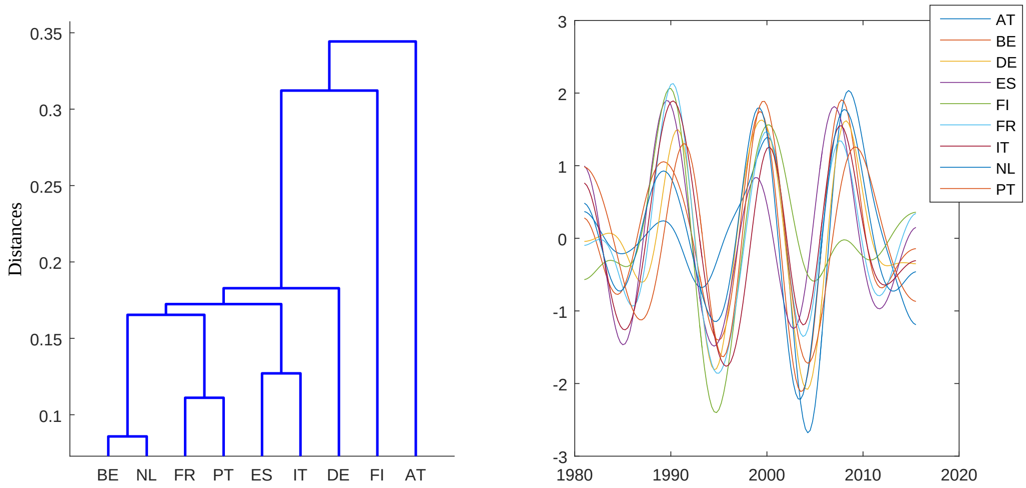

Figure 5: Distances and filtered series: LNFC, 6 to 16 years

Synchronization of loans to private households changes over time (Figure 6). Up to mid90s the time series evolve quite differently. From then onwards the co-movement becomes stronger. This is also reflected in the cohesion (upper right panel of Figure 3). Due to low synchronization in the 80s and early 90s the values of the estimated distances are considerably larger than those of loans to non-financial corporations as these are averages over the full sample. Starting in 2000 the co-movement of the filtered series in the frequency range from 4 to 10 years is much higher than before (right panel).

Reflecting the differences in cohesion for house prices and equity prices Figure 7 and Figure 8 show cross-country differences in distances and filtered series. Apart from some disturbances in the first half of the 90s the cycles in equity prices are highly synchronized.

Cohesion within a specific country is calculated as an un-weighted average of the dynamic correlations of all possible combinations (Figure 9). The correlation of cycles of all financial variables within DE is in general quite low. This picture is similar to those of FR and IT. For ES there is some correlation in the 2000s.

Adding further financial variables (long-term interest rate, spread between the long-term bond yield and the short-term rate and growth rate of M3) potentially reflecting a

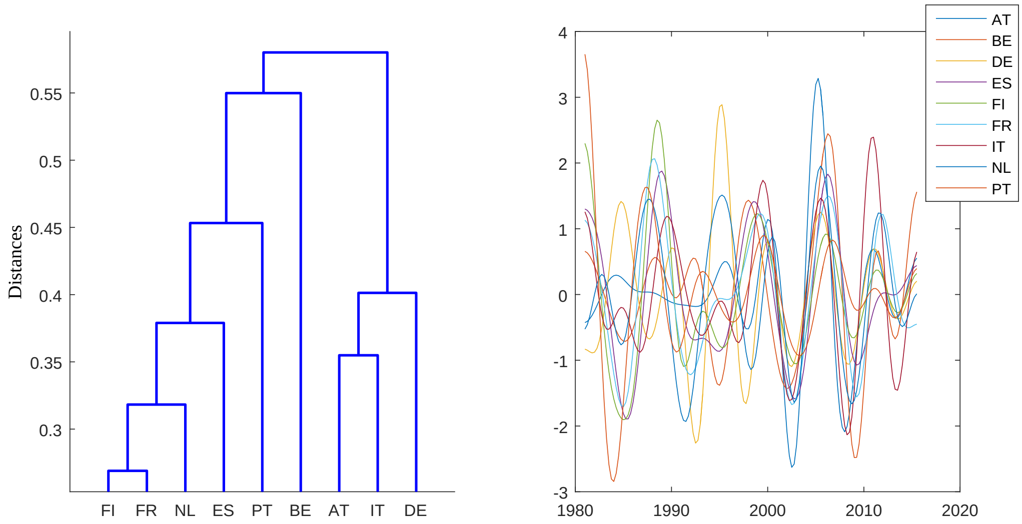

Figure 6: Distances and filtered series: LHH, 4 to 10 years

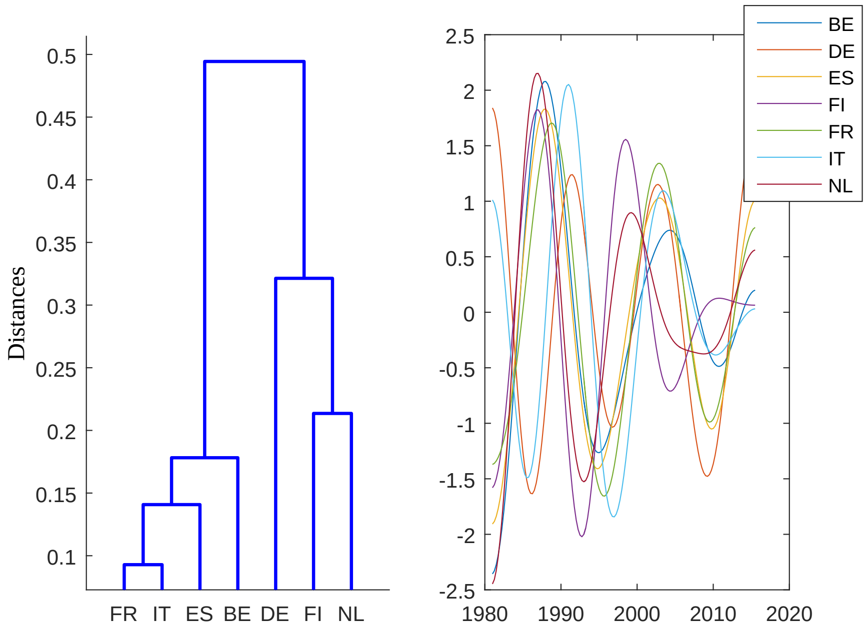

Figure 7: Distances and filtered series: HPR, 10 to 16 years

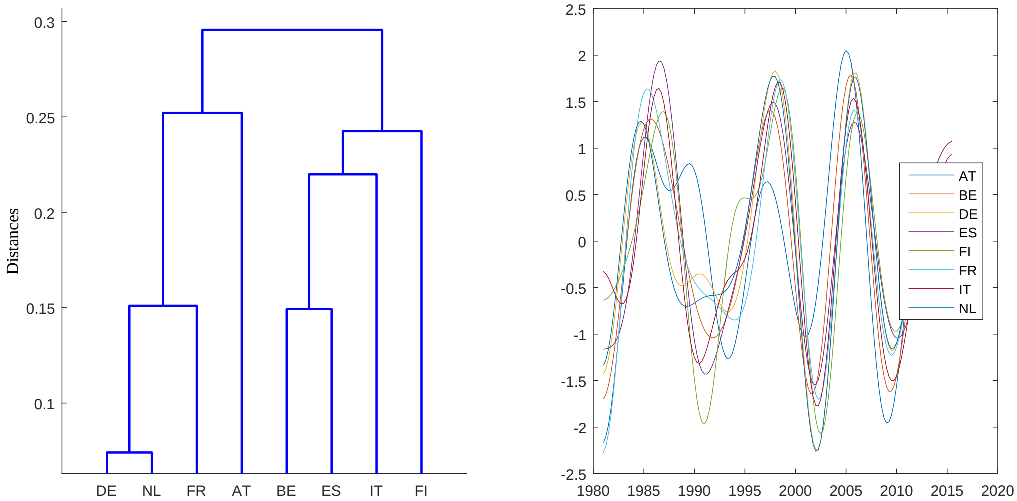

Figure 8: Distances and filtered series: EQP, 6 to 16 years

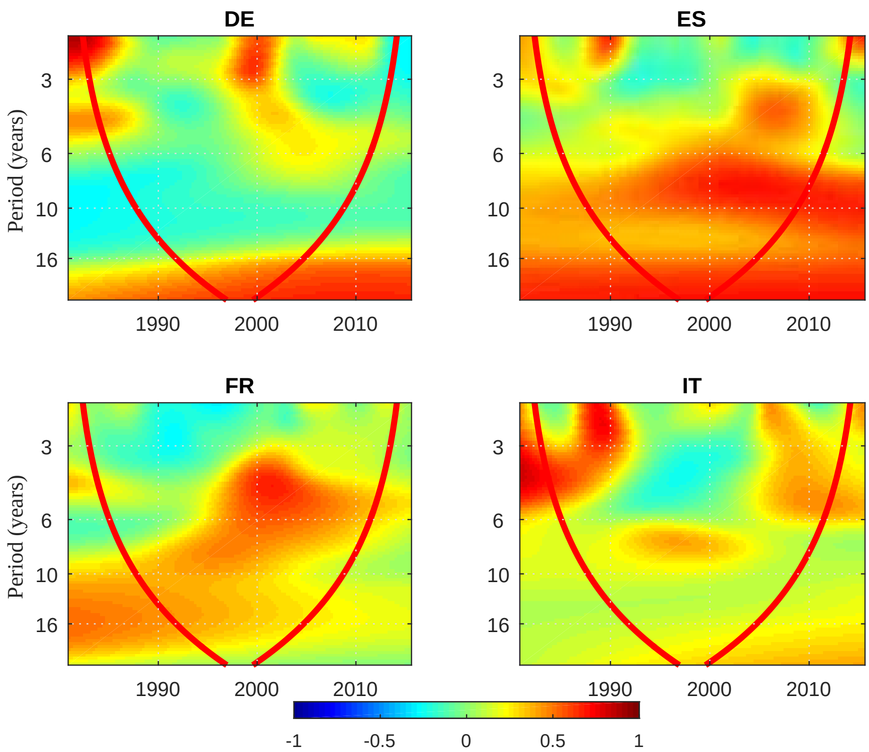

Figure 9: Cohesion of financial variables within each country

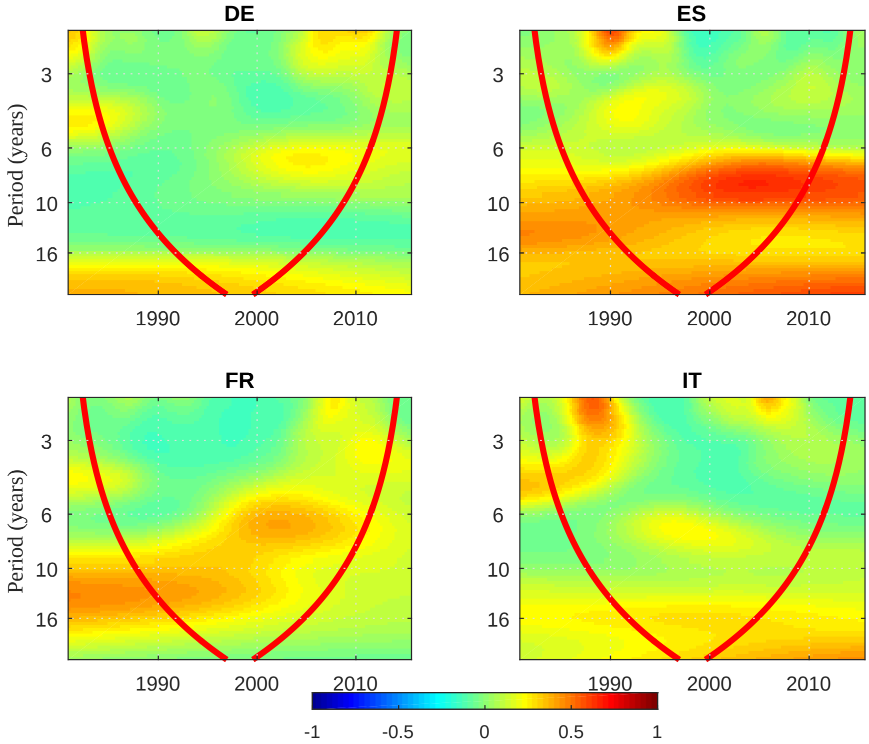

Figure 10: Cohesion of (seven) financial variables within each country

more broader definition of the financial cycle does not improve this result with respect to commonality (Figure 10).

5 Conclusions

We find evidence of strong co-movements between the annual growth rates in bank loans to non-financial corporations across all nine euro area countries in our sample. For bank lending to private households the degree of cross-country synchronization is relatively low in the first part of the sample and increases significantly after EMU. In contrast, we find no evidence of common cycles in house prices. In fact, the degree of cross-country synchronization has declined in the second half of our sample period. Our results indicate that the dominant cycles in the financial variables are shorter than claimed by the BIS. The evidence indicates the presence of common credit cycles in euro area countries.

Furthermore, we present evidence for strong co-movements in medium- to long-term cycles in financial variables, in particular bank lending to firms and households, and real activity in most countries suggesting a link between financial cycles, particular credit cycles and real economic fluctuations, which suggests that medium-term business cycle phenomena and financial cycles should not be considered as unrelated.

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Appendix

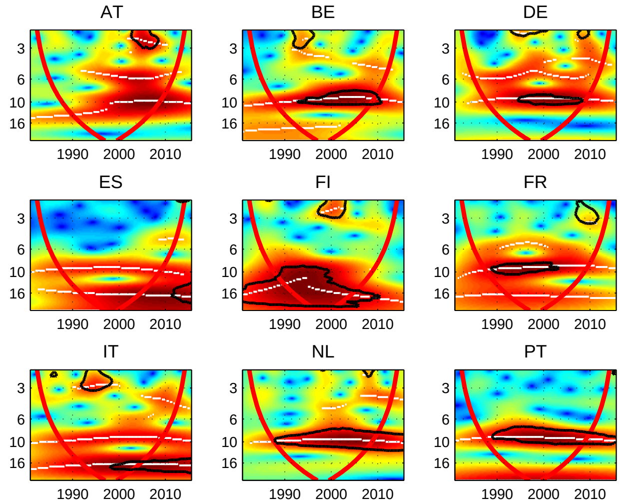

Figure 11: Wavelet power spectra: Loans to non-financial corporations

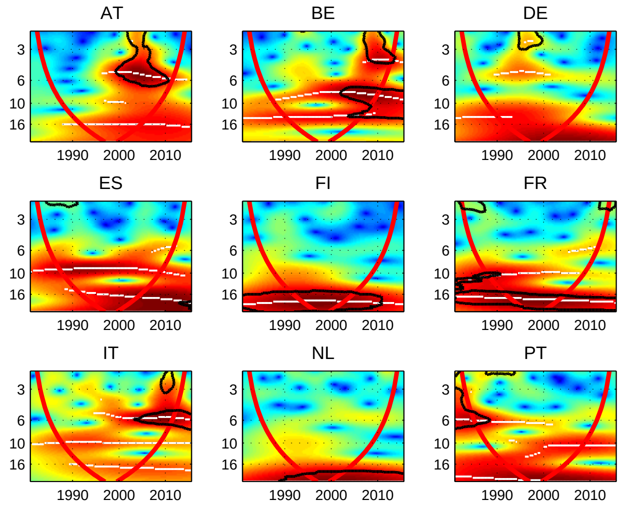

Figure 12: Wavelet power spectra: Loans to private households

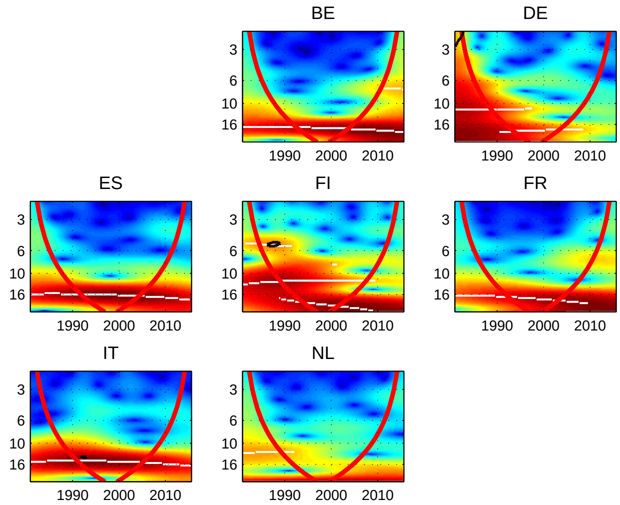

Figure 13: Wavelet power spectra: House prices

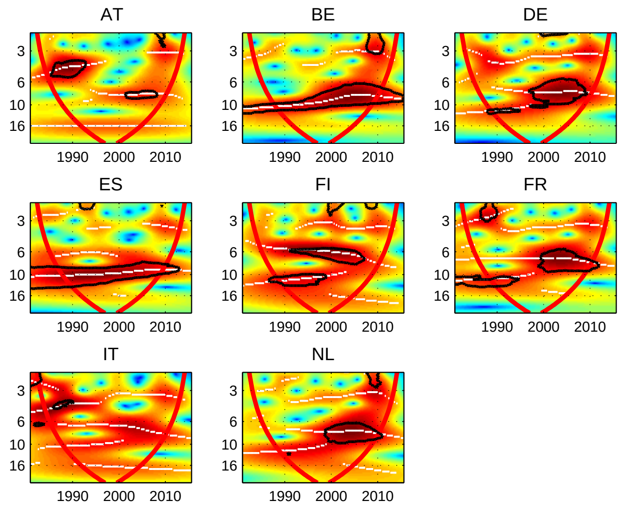

Figure 14: Wavelet power spectra: Equity prices

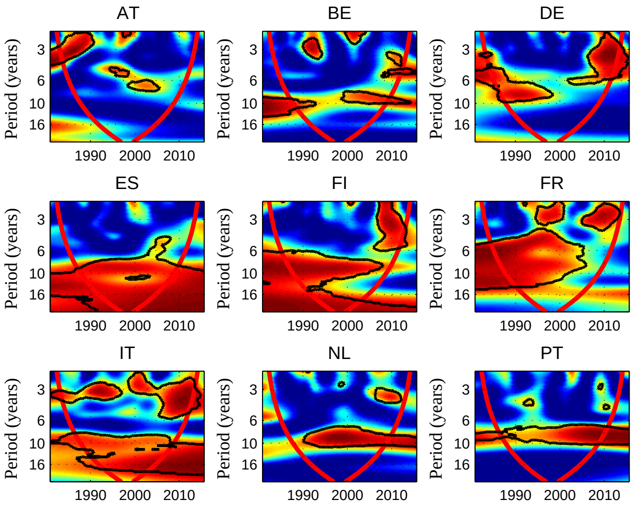

Figure 15: Coherency of loans to non-financial corporations and real GDP

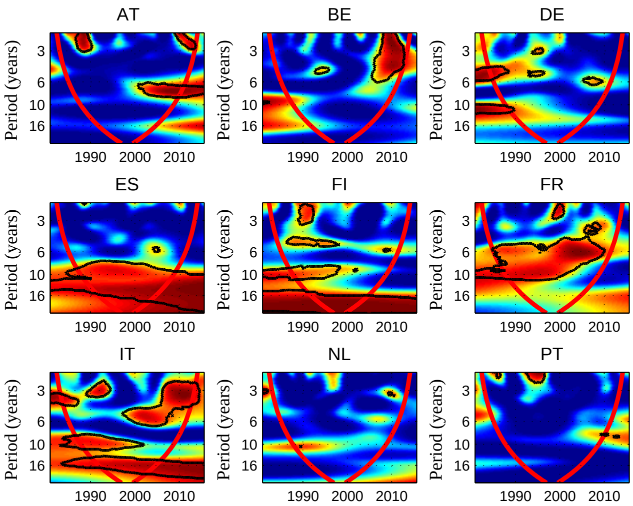

Figure 16: Coherency of loans to households and real GDP

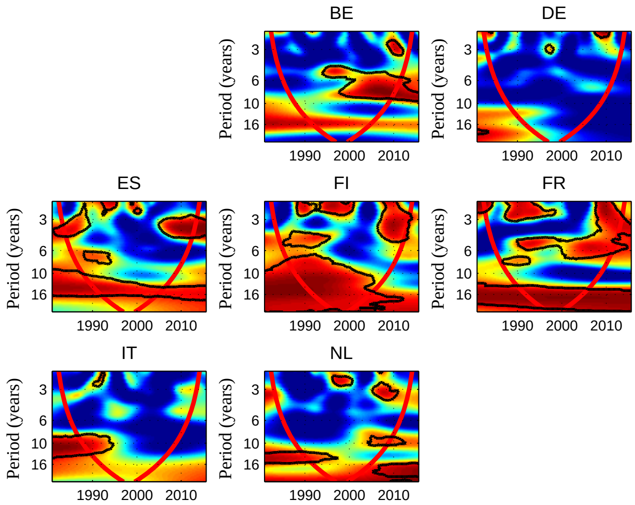

Figure 17: Coherency of house prices and real GDP

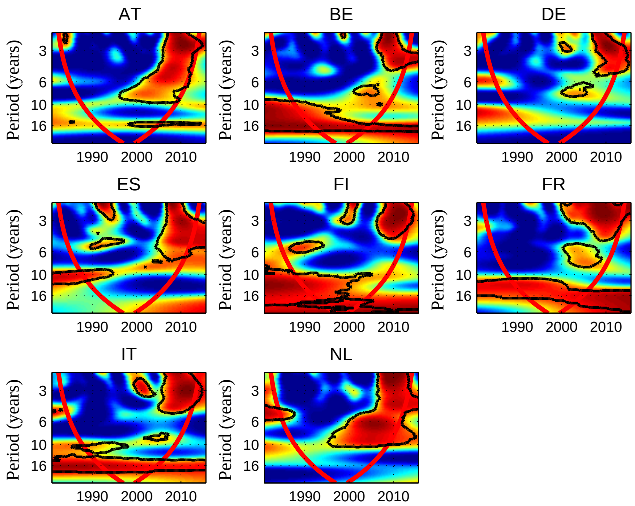

Figure 18: Coherency of equity prices and real GDP