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Financial cycles across G7 economies: A view from wavelet analysis

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Non-technical summary

Research Question

We analyse the cross-country dimension of cycles in credit aggregates, house prices, equity prices and interest rates across the G7 economies. Medium-to-longer term cycles in these variables are generally considered to represent financial cycles. We investigate whether there exist common financial cycles among these countries. To this end, we assess the extent of common cycles in each variable across countries, whether these common cycles have become more important over time and how important cross-country common cycles are for explaining developments in individual countries.

Contribution

Using tools from wavelet analysis, we analyse for each variable whether there are common cycles across countries, at which frequencies these cycles operate and whether these frequencies or the strength of the co-movements have changed over time. Using a new metric, for each variable we estimate the share in its variance at the country level which is explained by cross-country common cycles.

Results

We find evidence for important common cycles in equity prices and interest rates across countries. These cycles are at least as synchronized as cycles in real GDP. In contrast, cycles in credit and house prices are less synchronized across countries than those in real GDP. For the latter variables country-specific developments turn out to be more important than for equity prices and long-term interest rates.

Nichttechnische Zusammenfassung

Fragestellung

Wir untersuchen länderübergreifende Zyklen in Krediten, Immobilienpreisen, Aktienkursen und Zinssätzen der G7-Länder. Die Literatur interpretiert mittel- bis langfristige Zyklen in diesen Variablen als Finanzzyklen. Wir analysieren, ob diese gemeinsamen Zyklen in den Daten vorliegen, wie stark ausgeprägt sie sind und ob sich ihre Bedeutung im Zeitverlauf verändert hat. Wir gehen außerdem der Frage nach, welche Bedeutung gemeinsame länderübergreifende Zyklen für die Schwankungen der Variablen in den einzelnen Ländern haben.

Beitrag

Mit Hilfe von Ansätzen aus der Wavelet-Analyse können wir untersuchen, für welche Zykluslängen gemeinsame, länderübergreifende Zyklen vorliegen und wie sich ihre Bedeutung und ihre Dauer im Zeitverlauf verändert haben. Wir entwickeln ein Maß zur Schätzung jenes Anteils an der Varianz der einzelnen Variablen auf Länderebene, welcher mit gemeinsamen länderübergreifenden Zyklen im Zusammenhang steht.

Ergebnisse

Aktienkurse und Zinsen enthalten bedeutsame länderübergreifende Zyklen. Die Zyklen dieser Variablen sind mindestens genauso stark synchronisiert wie Zyklen des realen BIP. Im Unterschied dazu sind Kredit- und Immobilienpreiszyklen über die Länder hinweg weniger stark synchronisiert als Zyklen des realen BIP. Für Kredit- und Immobilienpreiszyklen sind länderspezifische Entwicklungen von größerer Bedeutung als für Aktienkurse und langfristige Zinssätze.

Financial cycles across G7 economies: A view from wavelet analysis[1]

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Abstract

We analyse the cross-country dimension of financial cycles by studying cyclical co-movements in credit, house prices, equity prices and interest rates across the G7 economies. We use wavelet-based statistics to assess at which frequencies cyclical fluctuations and their cross-country co-movements are important and how these change over time. We show cycles in interest rates and equity prices to be at least as synchronised as cycles in real GDP while cycles in credit and house prices are less synchronised. As a result, cross-country common cycles in equity prices and long-term interest rates account for a larger share of the volatility of these variables at the country level than common cycles in credit aggregates and house prices. A cluster analysis shows a high degree of similarity in the spectral characteristics of cycles in interest rates and equity prices across all countries but less similarities for cycles in credit and house price. For credit and house price cycles country-specific developments turn out to be more important than the common cross-country cycles.

Keywords: financial cycles, wavelet analysis, cluster analysis, cross-country synchronisation

JEL-Classification: C32, C38, E44, E51

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1 Introduction

The concept of financial cycles has often been described as a representation of the build-up of financial imbalances and boom and bust cycles in financial and credit markets (eg. Borio, 2014). Peaks of the financial cycle are often close to financial crises (Borio, 2014), in fact, studies have pointed to the predictive information in financial cycle indicators for financial crises (eg. Alessi and Detken, 2009; Borio, 2014; Borio and Drehmann, 2009; Drehmann and Juselius, 2014; Schüler, Hiebert and Peltonen, 2017; Voutilainen, 2017). Macroprudential policy uses indicators, such as deviations in the credit-to-GDP ratio from a benchmark (eg. Drehmann and Tsatsaronis, 2014), which are related to financial cycle proxies, to assess the build-up of systemic risk and vulnerabilities in the financial system and the need for policy interventions.[2] In fact, the effectiveness of these tools themselves might be dependent on the state of the financial cycle (Cerutti, Claessens and Laeven, 2017). Financial cycles might also have implications for the conduct of monetary policy, as, for example, Juselius, Borio, Disyatat and Drehmann (2017) have argued that asymmetric responses of monetary policy to the financial cycle have led to an artificial depression in real interest rates.

The empirical challenge in measuring financial cycles is that they are unobserved and various empirical approaches for their measurement have been applied. An important feature is that financial cycles inherently are a multivariate phenomenon, ie. they represent related or common cycles in financial variables across countries and/or across multiple financial time series.[3] This paper analyses the cross-country dimension of financial cycles, ie. we study co-movements in cycles across the G7 countries. We analyse if there are common financial cycles across countries and on which frequencies these operate. We further investigate how much of the variation in the financial series at the country level can be attributed to these cross-country common cycles and study whether the characteristics of these cross-country common cycles and their importance have changed over time.

Our analysis uses wavelet-based methods. In contrast to other widely used approaches, such as turning-point analysis (eg. Claessens, Kose and Terrones, 2011; Drehmann, Borio and Tsatsaronis, 2012; Hubrich et al., 2013; Stremmel, 2015) or band-pass filters (eg. Aikman, Haldane and Nelson, 2015; Drehmann et al., 2012; Meller and Metiu,

[2] For a comprehensive survey on early warning indicators for financial crises, see Tölö, Laakkonen and Kalatie (2018).

[3] This definition borrows from the definition of business cycles which are also defined as multivariate phenomena (eg. Burns and Mitchell, 1946).

2017) we do not require the ex-ante specification of a frequency range on which financial cycles are assumed to operate or of a minimum cycle length - parameters which are usually assumed to be constant over time. Instead our statistics, such as wavelet power spectrum, cohesion and coherency, allow us to assess at which frequencies cyclical fluctuations and their co-movements are important and how they have been changing over time. This is particularly important as the distinction between financial cycles and cycles in real activity drawn in the literature is often the result of assuming different frequency ranges for these two phenomena (eg. Rünstler et al., 2018). Some analyses, eg. Strohsal, Proaño and Wolters (2015a) or Schüler, Hiebert and Peltonen (2015, 2017) use spectral analysis to pin down the frequency ranges for their financial cycle estimates but these approaches do not allow for shifts in this range. As in most studies on financial cycles we use various credit aggregates and residential property prices. We also include equity prices, long-term interest rates and the term spread.[4]

In our analysis we proceed in multiple stages. We first inspect the wavelet power spectra in order to assess for each variable and country at which frequencies important cycles are present. We then use a measure of cross-country cohesion to investigate for each variable at which frequencies common cycles operate across countries. In the next step, we assess how important these common cycles are for each country. For this, we compute for each variable and country the share in the overall variance that is covered by the frequency ranges on which the common cycles operate. Tracking the changes in these shares over time allows us to assess whether common cycles have become more important for explaining variation at the country level.

Since the cohesion measure is an indicator of average cross-country co-movement might hide common cycles among subgroups of countries, we perform a cluster analysis on the closeness of the wavelet power spectra to assess, which countries experience cycles that are close to each other. Since this step in the analysis does not allow for time-variation per se we compare results from the full sample period to those from a subsample covering only the final half of the sample period.

Our results show that the importance of cross-country common cycles is variable dependent and that countries participate in these common cycles to different degrees: cross-country common cycles in long-term interest rates and equity prices cover frequency ranges at least as wide as for real GDP while common cycles for credit aggregates and house prices operate on narrower frequency ranges. Furthermore, cross-

[4] Most of these variables correspond to those analysed in Rünstler et al. (2018) for European Union and in Kunovac, Mandler and Scharnagl (2018) for Euro Area countries.

country common cycles account for larger variance shares for equity prices and long-term interest rates at the country level than for credit aggregates and house prices. Thus, fluctuations in equity prices and long-term rates in each country are more strongly related to international common movements than those in credit and house prices.

Turning to the relation between individual countries' cycles, based on a cluster analysis, we find evidence for a high degree of similarity in the spectral characteristics of cycles in interest rates and equity prices across all countries. In contrast, the analysis shows less similarity between the spectral characteristics of cycles in credit and house prices. For these variables Japan tends to experience mostly idiosyncratic cycles while the U.K. and in the second half of the sample period France and Italy, as well, are clustered with other countries more often.

2 Literature

Cycles in credit and house prices generally have been found to operate on longer frequencies than commonly associated with business cycles (eg. Borio, 2014; Drehmann et al., 2012; Hiebert, Jaccard and Schüler, 2018; Rünstler et al., 2018; and, for credit cycles, Aikman et al., 2015, Verona, 2016) and to display a larger amplitude than real cycles (eg. Drehmann et al., 2012; Galati, Hindrayanto, Koopman and Vlekke, 2016; Hiebert et al., 2018; Rünstler et al., 2018).

Concerning the cross-country dimension of financial cycles, Aikman et al. (2015) analyse medium-term cycles in real bank lending in 14 industrialized economies. While, on average, absolute cross-country correlations are relatively low, they increase after 1980. Meller and Metiu (2017) extract bank lending cycles from the Schularick and Taylor (2012) data set. These cycles are more strongly synchronized across countries in the post-1973 subsample compared to the 1923-73 period. They also estimate that in the post-Bretton-Woods sample economies with more synchronized credit cycles also had more synchronized business cycles. Across OECD countries Anguren-Martin (2011) finds a high synchronisation of credit regimes during the recent financial crisis. Claessens et al. (2011) study cross-country co-movements in credit, house price and equity price cycles across 21 OECD countries. They estimate higher cross-country synchronisation for credit cycles than for cycles in house prices. Rünstler et al. (2018) extract cycles from credit aggregates, house prices, equity prices and interest rates for a set of European Union countries. They show cycles in interest rates and equity prices to be more strongly synchronized than real GDP while cycles in credit and house prices are less synchronized. Similar results are presented in Kunovac, Mandler and Scharnagl (2018) for six Euro Area economies.

Strohsal, Proaño and Wolters (2015b) extract common components from credit and house prices in the U.K. and the U.S., respectively, and show that these country-specific financial factors have been more closely related in the post-1985 period than before. Rünstler and Vlekke (2016) estimate multivariate structural time-series models for credit, house prices and real GDP for Germany, Italy, France, Spain, the United Kingdom and the United States. Their financial cycle proxy for each country is the common cyclical component in the three time series which they show to be highly synchronised across countries. Schüler, Hiebert and Peltonen (2015) construct financial cycle measures as common cyclical components in credit, house prices, equity prices and bond yields. For this indicator they estimate high pairwise concordance between many European economies with Germany as an outlier which shows little correlation with the other countries. However, their country-specific financial cycle measures are less synchronised across countries than similarly constructed business cycle indicators. Using the same approach to derive financial cycle proxies for the G7 countries, Schüler, Hiebert and Peltonen (2017) estimate a global financial cycle indicator as their first principal component across countries. The correlation between the global and the country-specific financial cycle indicators exceeds that between national and global business cycle indicators except for DE and JP. Evidence for the importance of the global financial cycle is also presented in Breitung and Eickmeier (2016) based on about 350 time series for 24 countries. They estimate that about 40 percent of variation in financial variables can be explained by global factors. This share is even higher for “fast-moving” variables, such as stock prices and interest rates but lower for money, credit and house prices. According to Miranda-Agrippino and Rey (2015) more than 60 percent of the common variation of more than 300 international asset prices can be explained by a single global factor.

Wavelet analysis has been used to analyse financial cycles in only a few papers: Verona (2016) studies properties of cycles in credit, house prices, equity prices and real GDP in the United States but does not address co-movements in these series while Voutilainen (2017) computes financial cycle indicators for 13 EU countries out of credit, house prices and equity prices based on an early-warning exercise for financial crisis. Kunovac, Mandler and Scharnagl (2018) use wavelet cohesion together with other non-wavelet based analyses for an assessment of financial cycles in euro area countries based on a broad set of empirical approaches. They show that cross-country common cycles are more important for credit aggregates and house prices than for interest rates and equity prices.

3 Data

We use data for the G7 countries (Canada (CA), Germany (DE), France (FR), Italy (IT), Japan (JP), the United Kingdom (UK) and the United States (US)). We consider eight time series of quarterly data: real bank credit to the non-financial private sector (BCN), real credit to households (CHH), real credit to non-financial corporations (CNF), 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) as a benchmark variable to compare the cross-country dimension of cycles in the financial variables and in house prices to that of cycles in real activity. Information on the data sources is provided in the appendix. Note that credit to firms (CNF) and to households (CHH) do not sum up to bank credit to the non-financial private sector (BCN) because it covers credit from all economic sectors and not only from banks. Credit aggregates, house prices and equity prices are deflated using the GDP deflator. Our sample starts in the first quarter of 1971 and ends in the second quarter in 2018. All variables, except for interest rates are transformed into annual growth rates.

4 Empirical approach

Wavelet analysis can be characterized as a time-varying extension of Fourier analysis with a focus on frequency-specific windowing. The spectral density reflects the contribution of cycles of a given frequency to the overall variance of a time series and allows for the identification of important cycles. Whereas Fourier analysis is based on cycles with infinite support, wavelet analysis uses local base functions (finite support) and, thus, can account for changes in the frequency of important cycles over time and is not restricted to applications to stationary time series.[5]

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

The **continuous wavelet transformation** is obtained by projecting the time series $x(t)$ onto the wavelet functions ψ (Aguiar-Conraria and Soares, 2014)

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

with s representing the scale and τ the location in time. The transformation is computed for all combinations of scales and locations. Applying the **Morlet wavelet**, which can be characterized as a Gaussian modulated sine wave,

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

with $\omega_0=6$ produces an optimal time-frequency localization and a direct relation between scale and frequency ($\omega\approx 1/s$).

The **wavelet power spectrum** measures the relative contribution of cycles 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 greater the power spectrum, the more important are fluctuations at the corresponding frequency at the specific point in time. A significance test for the wavelet power spectrum can be performed by parametric bootstrap (Cazelles et al., 2008).[6]

The **cross-wavelet transform** allows for analysing the interaction between two time series x and y in the time-frequency domain

$$W_{xy}(\tau,s)=W_x(\tau,s)W_y^*(\tau,s), \tag{4}$$

where * denotes the complex conjugate. As the Morlet wavelet is complex, the cross wavelet transform is also complex valued.

Coherency can be interpreted as local correlation between two time series and is defined as

$$R_{xy}=\frac{|W_{xy}(\tau,s)|}{\sqrt{|W_x(\tau,s)|^2}\sqrt{|W_y(\tau,s)|^2}}\,. \tag{5}$$

[6] For each time series we generate artificial time series based on a model that includes only a constant and a white-noise disturbance term which implies a spectrum of zero for all but the shortest periodicities. The test relies on the simulated distribution of the power spectrum under the null hypothesis.

A measure of the co-movement of a set of time series is cohesion. **Cohesion** is defined as weighted average of all pairwise combinations of dynamic correlation which is defined as

$$\rho_{xy} = \frac{\Re\left(W_{xy}(\tau,s)\right)}{\sqrt{\left|W_x(\tau,s)\right|^2}\sqrt{\left|W_y(\tau,s)\right|^2}}, \tag{6}$$

where $\Re$ denotes the real part of the cross-wavelet transform W_{xy} (Rua, 2010). Cohesion, as proposed by Rua and Silva Lopes (2015) is given by

$$\mathrm{coh}(\tau,s) = \frac{\sum_{i\neq j} w_i w_j \rho_{xy}(\tau,s)}{\sum_{i\neq j} w_i w_j}. \tag{7}$$

w_i and w_j represent the weights of x and y, respectively. In our analysis they are based on real GDP. This version of dynamic correlation in (6) extends correlation coefficients in the time domain by revealing frequency dependent information and a Fourier analysis based measure proposed by Croux, Forni and Reichlin (2001) by allowing for variation over time.

We test for the statistical significance of coherency and cohesion by parametric bootstrap (Cazelles et al., 2008). For each time series we generate a number of artificial time series using estimated univariate ARMA models based on the null hypothesis of the series being unrelated among each other. The test relies on the simulated distribution of coherency and cohesion under the null hypothesis.

As in Fourier analysis, the original time series can be recovered by inversion, i.e. by integrating over all scales and locations in time (Rua, 2010; Aguiar-Conraria and Soares, 2011).

$$x(t) = \frac{1}{C_\psi}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \psi\, W_x(\tau,s)\frac{d\tau ds}{s^2}. \tag{8}$$

Equation (8) can be used for **filtering** of a series by integrating over a selected range of scales (frequencies).

Distances between cyclical components of different series are based on the spectra of the corresponding series within the frequency band of interest (Aguiar-Conraria and Soares, 2011). Rouyer, Fromentin, Stenseth and Cazelles (2008) argue that the spectra should not be compared directly as this may lead to poor results due to areas of low power. Hence, the comparison is based on common properties extracted by maximum covariance analysis (MCA). A singular value decomposition (SVD) is applied to the covariance matrix of the spectra

$$C_{xy} = W_x W_y^* = U \Sigma V^* . \tag{9}$$

$\Sigma = \mathrm{diag}(\sigma_i)$ is a diagonal matrix with elements in decreasing order. The columns u_k of U and v_k of V are the singular vectors for W_x and W_y respectively. The linear combinations l_x^k and l_y^k (leading patterns) defined as

$$l_x^k = u_k^* W_x \qquad \text{and} \qquad l_y^k = v_k^* W_y \tag{10}$$

maximize their mutual covariance (orthogonality constraints). They are obtained by projecting the spectra onto their respective k-th singular vector. To reduce the information contained in the wavelet spectra the dimension K is set to be much lower than the number of scales.

$$W_x \approx \sum_{k=1}^{K} u_k l_x^k \qquad W_y \approx \sum_{k=1}^{K} v_k l_y^k . \tag{11}$$

To measure the distance between two vectors, l_x^k and l_y^k or u_k and v_k, respectively, the angles between pairs of corresponding segments are computed and averaged. This produces a dissimilarity matrix.

$$\mathrm{dist}(W_x, W_y) = \frac{\sum_{k=1}^{K} \sigma_k^2 \left[d\left(l_x^k, l_y^k\right) + d\left(u_k, v_k\right) \right]}{\sum_{k=1}^{K} \sigma_k^2}, \tag{12}$$

where σ_k^2 are weights equal to the squared covariance. As the vector elements in u_k and v_k are complex valued the Hermitian angle is computed (similarly for l_x^k and l_y^k).

$$\cos(\theta_H) = \frac{\left| \langle u_k, v_k \rangle_{\mathbb{C}} \right|}{\|u_k\| \, \|v_k\|} . \tag{13}$$

A hierarchical cluster analysis is applied to the estimated distances of the spectra between all bivariate combinations. The proximity between clusters (groups) is computed by the unweighted average distance of the elements of the different groups. The resulting groupings are graphically displayed as a tree-like structure (dendrogram). The average distance between groups is represented by the height of the intermediate nodes. The significance of similarity is checked using the parametric bootstrap like for testing for cohesion.

5 Results

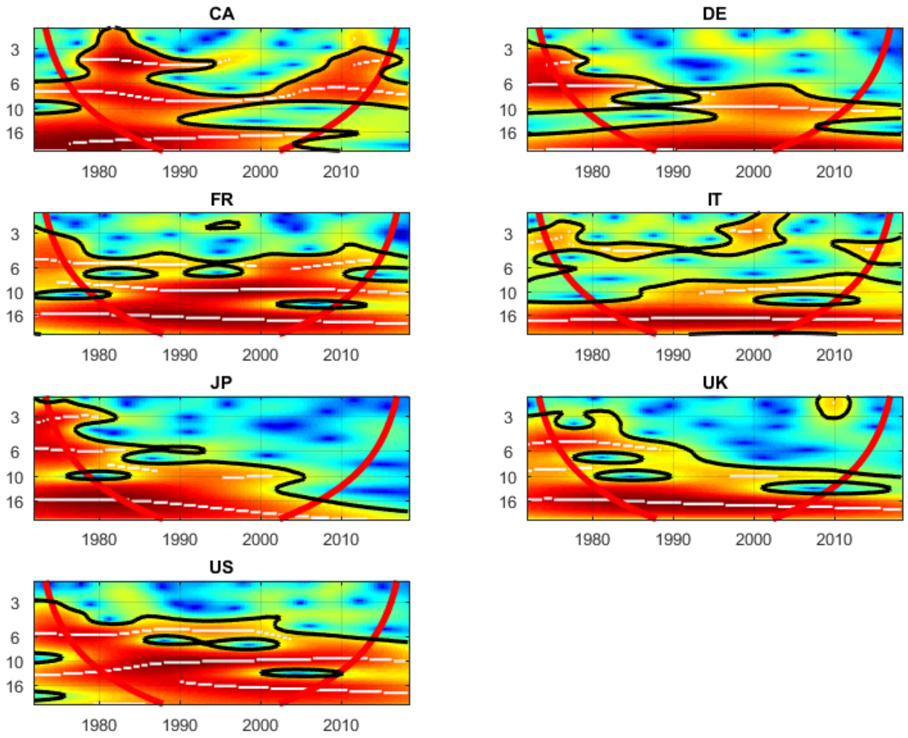
5.1 Wavelet power spectra and cohesion

In this section we analyse the wavelet power spectra (3) for each variable and compare them across countries. We then construct the cohesion measure (7) in order to assess the extent of cross-country co-movements and the frequency ranges on which common cycles exist. We discuss the results from these two analyses in combination because we need the power spectra for cross-checking the results from the cohesion analysis: if the cohesion analysis points to significant common cycles for specific time-frequency combinations we need to verify from the wavelet power spectra that these time-frequency combinations also reflect the presence of important cycles at the country level and, thus, are economically relevant.

Figure 1 presents the wavelet power spectra for the growth rate of bank credit to the non-financial private sector. The vertical axis indicates cycle length in years. Estimates of the power spectrum are colour coded from blue (low) to red (high) with the white lines following local maxima of the power spectrum. Red lines indicate the cone of influence. Only estimates in the region between these red lines should be interpreted as the estimates between the red lines and the start or, respectively, end of the estimation period are affected by edge problems.[7] The maximum length of cycles we consider is about 20 years. This is a restriction implied by the data set as, for longer cycles the time period for which we can interpret the results would shrink to an extent that no meaningful conclusions about time variation would be possible anymore. For cycles with a duration of 16 years, a cycle length that turns out to be important for many variables, the time period for which we can interpret the results starts in 1983Q1 and ends in 2007Q2, i.e. is almost 25 years.

[7] In the region between the left (right) red line and the start (end) of the sample there is only an insufficient number of past (future) observations available to apply the wavelet transform at a given point in time. In these cases the algorithm extends the sample backwards or forward by “reflecting” the first (last) observations. The area of estimates not affected by reflecting becomes smaller as cycles become longer since the flexible determination of the window length used for the wavelet transform implies broader windows and, thus, the use of more observations for extracting lower frequency components.

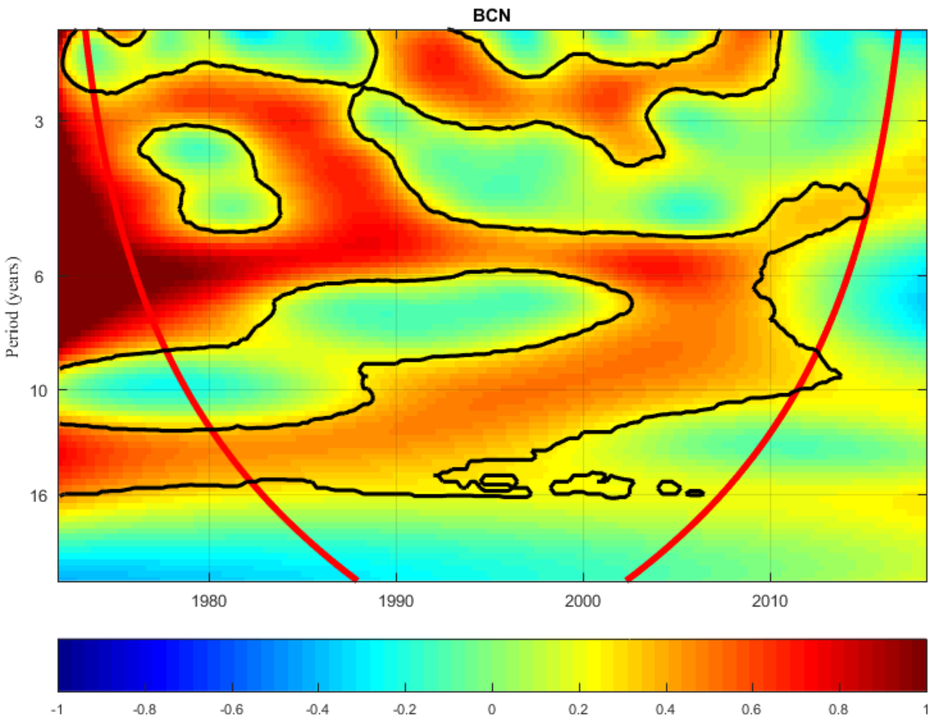
Figure 1: Wavelet power spectra for bank credit to the domestic non-financial private sector (BCN)



Horizontal axis denotes time, vertical axis cycle length. Black lines are drawn around time-frequency combinations with estimates of the power spectrum significantly different from zero at the 10% level. Red lines denote the cone of influence. White lines highlight local maxima of the power spectrum.

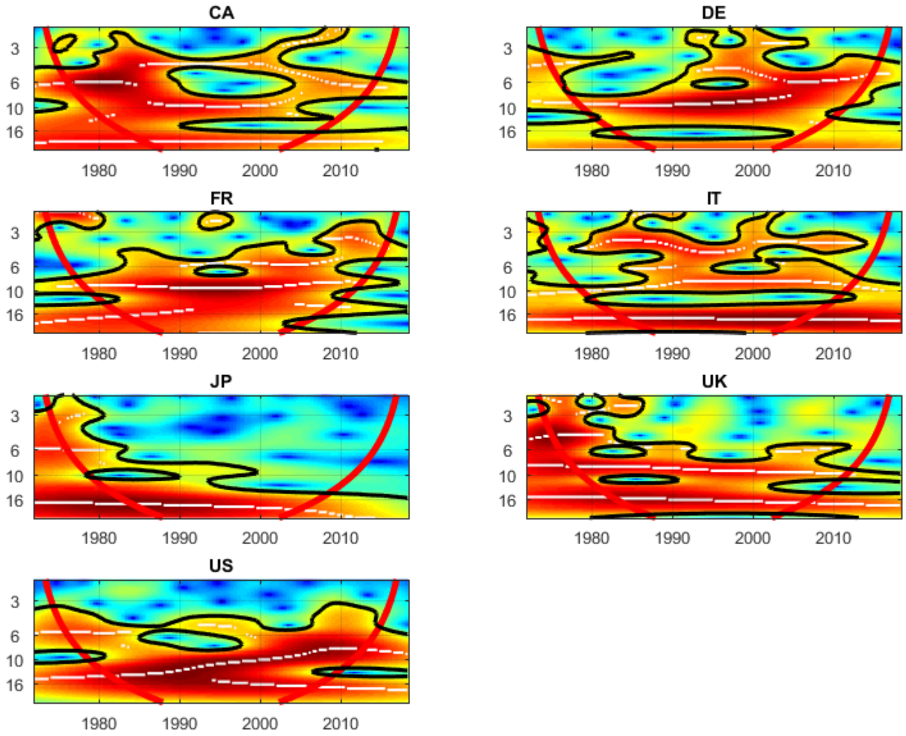
For bank credit (BCN) the wavelet power spectra suggest for most of the countries at least two important cycles, one with length of roughly about ten years and another one with length of 16 years and more. For FR and for US the estimates also indicate a third important cycle with length of around six years and for IT of around four years which, however, does not extend into the 2000s. The extent of cross-country co-movements in BCN growth can be assessed using the wavelet cohesion in Figure 2. Cohesion estimates can range from minus one (dark blue) to plus one (dark red). Green indicates cohesion close to zero. An estimate of plus one implies that all cross-country dynamic correlations are equal to one. The regions denoted by black borders are time-frequency combinations for which the hypothesis of zero cohesion can be rejected at the 10% level. The estimates suggest strong cross-country co-movements in bank credit for cycles with length of around six years and less before 1990 which covers significant cycle lengths in the power spectra for all countries. For cycles with duration of around six years cohesion remains significant until late in the sample period and this corresponds to significant cycles in the power spectra for CA, FR, US, and, to some extent also for DE. Cohesion is also significant for longer cycles, covering a range of cycle lengths between about 12 and 16 years, initially, which then slowly shifts towards higher frequencies over time. These time-frequency combinations include significant cycles in the power spectra for DE, FR, IT, UK and US and, in part, also for CA and JP. However, the 16-years cycles at the country level do not show up consistently in the cohesion estimates after the early 1990s. This suggests, that these cycles, from the mid-1990s onwards, are, to a large extent, country specific and do not reflect common cycles. The cohesion estimates do not point to a substantial increase in cross-country co-movement in credit over time.

Figure 2: Wavelet cohesion for bank credit to the domestic non-financial private sector (BCN)



Horizontal axis denotes time, vertical axis cycle length. Cohesion measure as real GDP-weighted average of all pairs of dynamic cross-country correlations. Black lines are drawn around time-frequency combinations of cohesion estimates significantly different from zero at the 10% level. Red lines denote the cone of influence.

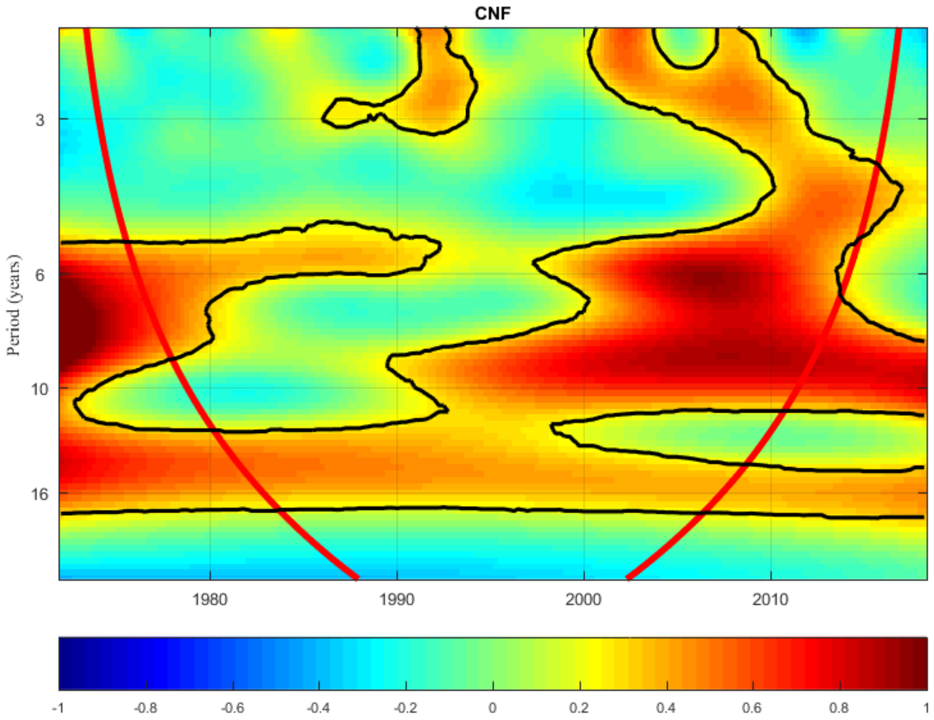
Figure 3: Wavelet power spectra for credit to non-financial corporations (CNF)



Horizontal axis denotes time, vertical axis cycle length. Black lines are drawn around time-frequency combinations with estimates of the power spectrum significantly different from zero at the 10% level. Red lines denote the cone of influence. White lines highlight local maxima of the power spectrum.

Figure 3 and Figure 4 show the power spectra and cohesion for credit to non-financial corporations (CNF). For this variable the power spectra indicate important cycles with length of about ten years in all countries except for JP. Additional cycles with duration of about sixteen years are highlighted in CA, IT, JP, UK and US and to some extent in FR, but not in DE. For some countries the spectra also point to temporarily important cyclical variation at higher frequencies. The cohesion estimates in Figure 4 highlight common cycles with a periodicity of more than ten years up to 16 years throughout the part of sample period for which we can interpret the results. This frequency range matches that of important cycles in all countries. Cohesion is also significant in the 1970s and 1980s for six-year cycles and in the latter part of the sample period for cycles with a length of between six and ten years which is consistent with the cycles at the country level except for JP.

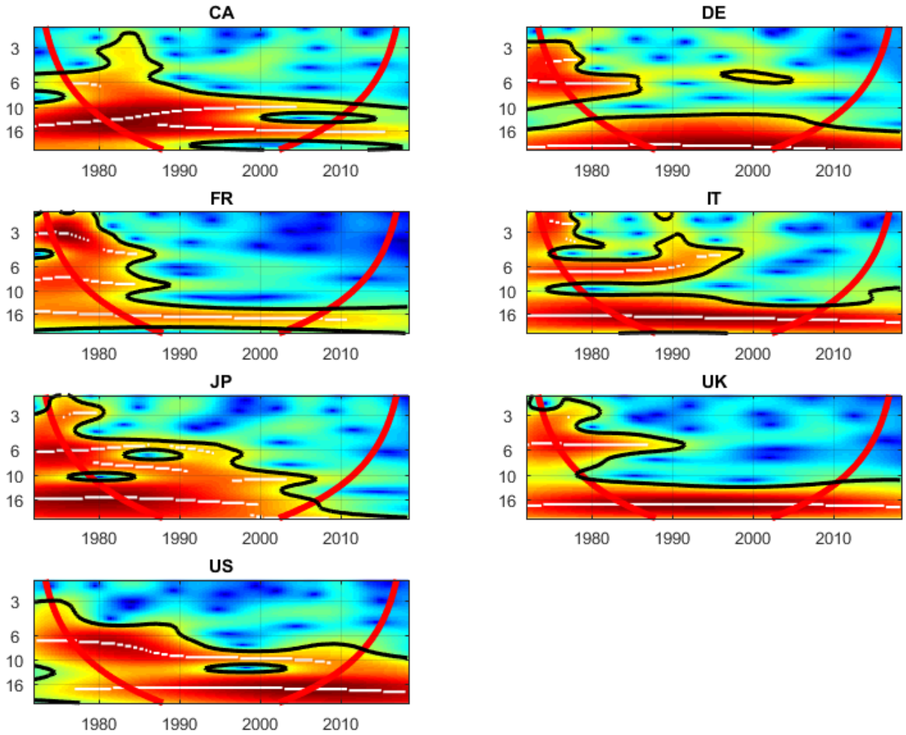
Figure 4: Wavelet cohesion for credit to non-financial corporations (CNF)



Horizontal axis denotes time, vertical axis cycle length. Cohesion measure as real GDP-weighted average of all pairs of dynamic cross-country correlations. Black lines are drawn around time-frequency combinations of cohesion estimates significantly different from zero at the 10% level. Red lines denote the cone of influence.

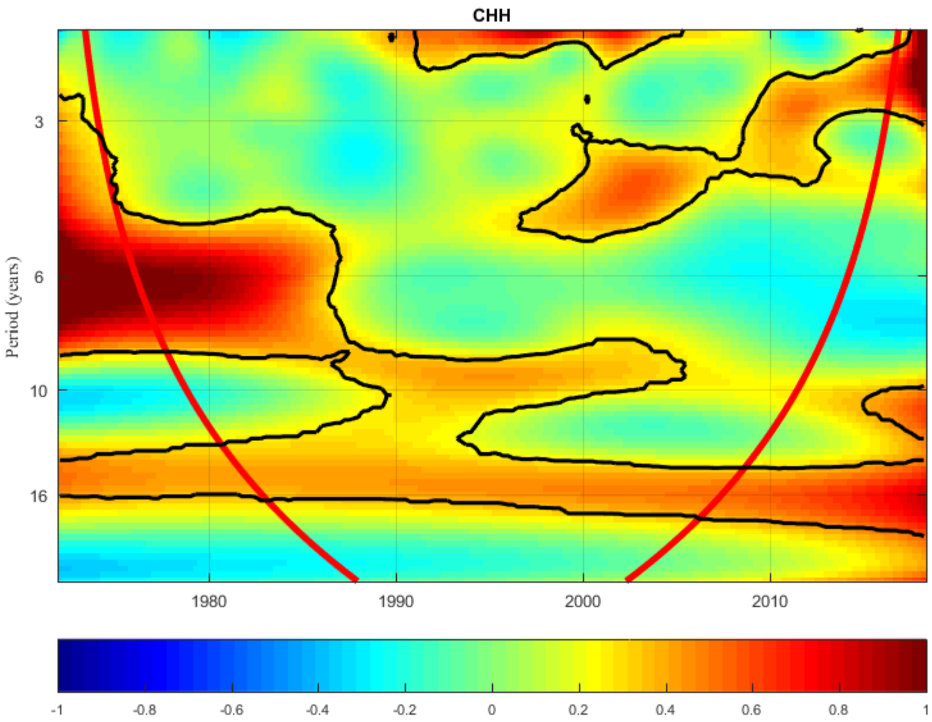
For credit to households (CHH) the wavelet power spectra in Figure 5 show for almost all countries dominant cycles with length of about 16 years. There are additional important cycles with duration of about six-to-ten years in US and CA. In the other countries the cycles at these frequencies disappear as time progresses, although the ten-year cycle persists in JP until the mid 2000s. According to the cohesion estimates these cycles reflect common cycles across countries: time-frequency combinations with significant cohesion estimates (Figure 6) include the cycles with duration of about sixteen years throughout as well as shorter cycles up into the 2000s.

Figure 5: Wavelet power spectra for credit to households (CHH)



Horizontal axis denotes time, vertical axis cycle length. Black lines are drawn around time-frequency combinations with estimates of the power spectrum significantly different from zero at the 10% level. Red lines denote the cone of influence. White lines highlight local maxima of the power spectrum.

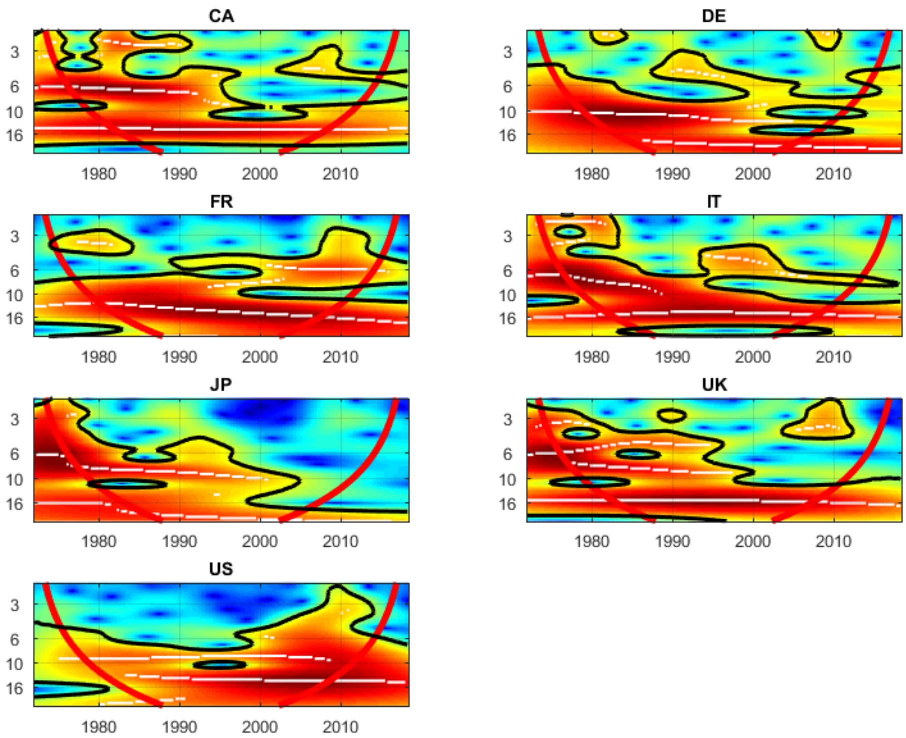
Figure 6: Wavelet cohesion for credit to households (CHH)



Horizontal axis denotes time, vertical axis cycle length. Cohesion measure as real GDP-weighted average of all pairs of dynamic cross-country correlations. Black lines are drawn around time-frequency combinations of cohesion estimates significantly different from zero at the 10% level. Red lines denote the cone of influence.

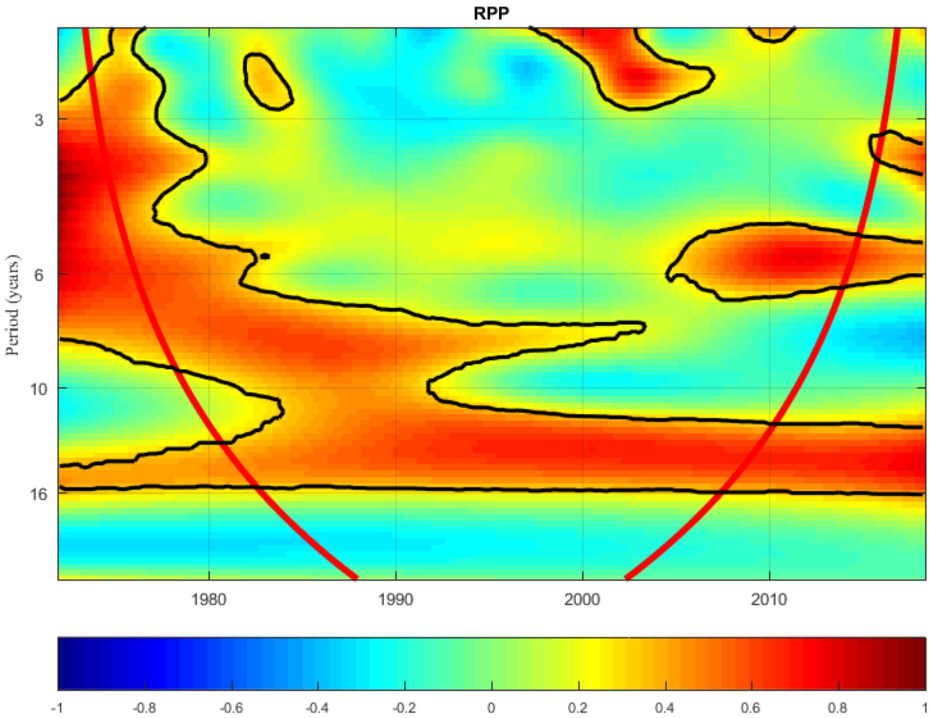
Real house prices (RPP) contain cycles in CA, FR, IT, UK and US with duration between ten and 16 years, in DE and in JP even longer (Figure 7). In DE, FR and US there are also relatively stable cycles with length of about ten years while cycles of these lengths are highlighted only for shorter periods in the other countries. In Figure 8 we estimate stable and significantly positive cohesion for cycles between about 12 and 16 years. These common cycles correspond to significant cycles in the wavelet power spectra at the country level. There is also strong evidence for common cycles with duration of six years and up to ten years until around 2000 and for cycles with a length of around six years towards the end of the sample period. These frequency ranges are also highlighted in most of the individual countries' power spectra. The areas of significant cohesion are broadly similar to those for CHH.

Figure 7: Wavelet power spectra for real house prices (RPP)



Horizontal axis denotes time, vertical axis cycle length. Black lines are drawn around time-frequency combinations with estimates of the power spectrum significantly different from zero at the 10% level. Red lines denote the cone of influence. White lines highlight local maxima of the power spectrum.

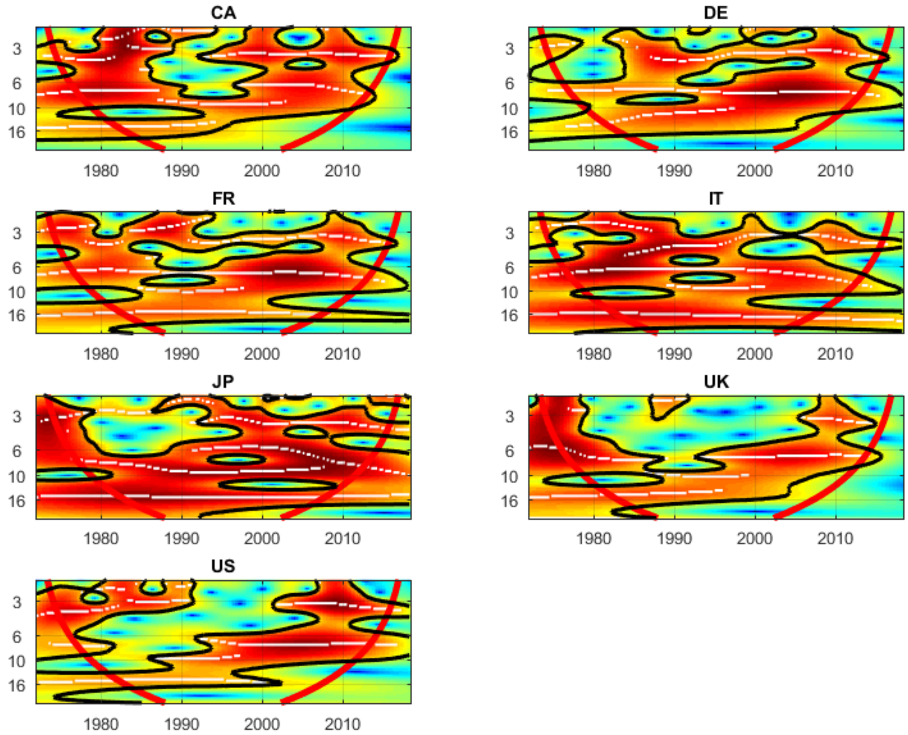
Figure 8: Wavelet cohesion for house prices (RPP)



Horizontal axis denotes time, vertical axis cycle length. Cohesion measure as real GDP-weighted average of all pairs of dynamic cross-country correlations. Black lines are drawn around time-frequency combinations of cohesion estimates significantly different from zero at the 10% level. Red lines denote the cone of influence.

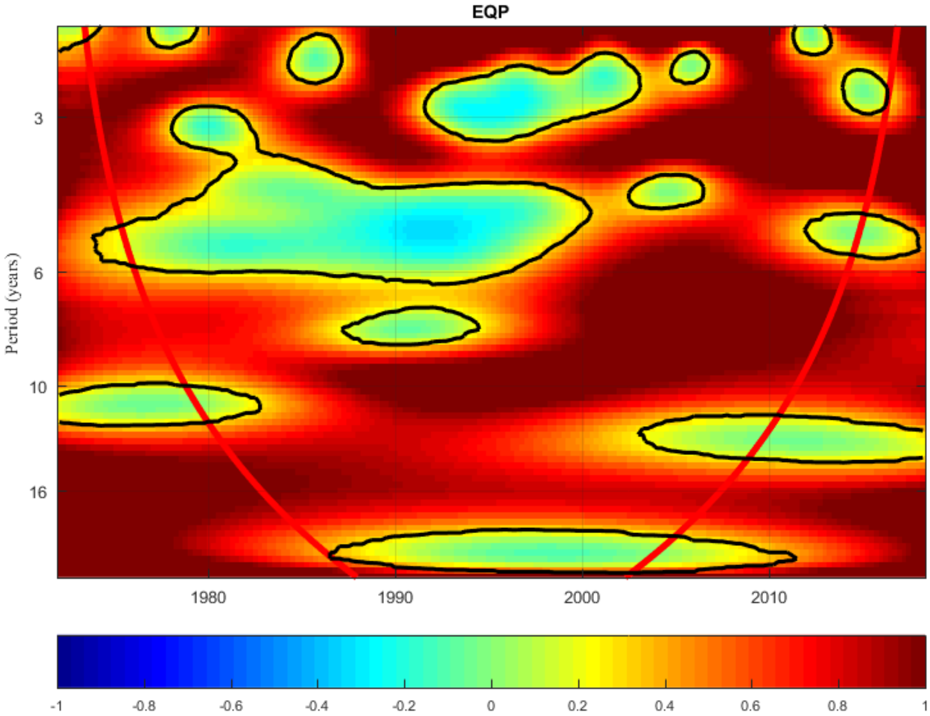
The power spectra for real equity prices (EQP, Figure 9) point at important cyclical movements at many frequencies, particularly in CA, DE, FR, IT and JP. In the UK cycles shorter than six years lack importance from around 1980 to the mid-2000s but their importance increases afterwards. In the U.S. there is a "gap" in the power spectrum similar to the U.K. but very short cycles retain their importance up to 1990. The time-frequency combinations with significant cohesion (Figure 10) cover most of the frequencies with significant estimates for the power spectrum of the individual countries. Overall, compared to credit cycles common cycles in equity prices affect a broader range of frequencies and the frequency range of these common cycles broadened over time.

Figure 9: Wavelet power spectra for real equity prices (EQP)



Horizontal axis denotes time, vertical axis cycle length. Black lines are drawn around time-frequency combinations with estimates of the power spectrum significantly different from zero at the 10% level. Red lines denote the cone of influence. White lines highlight local maxima of the power spectrum.

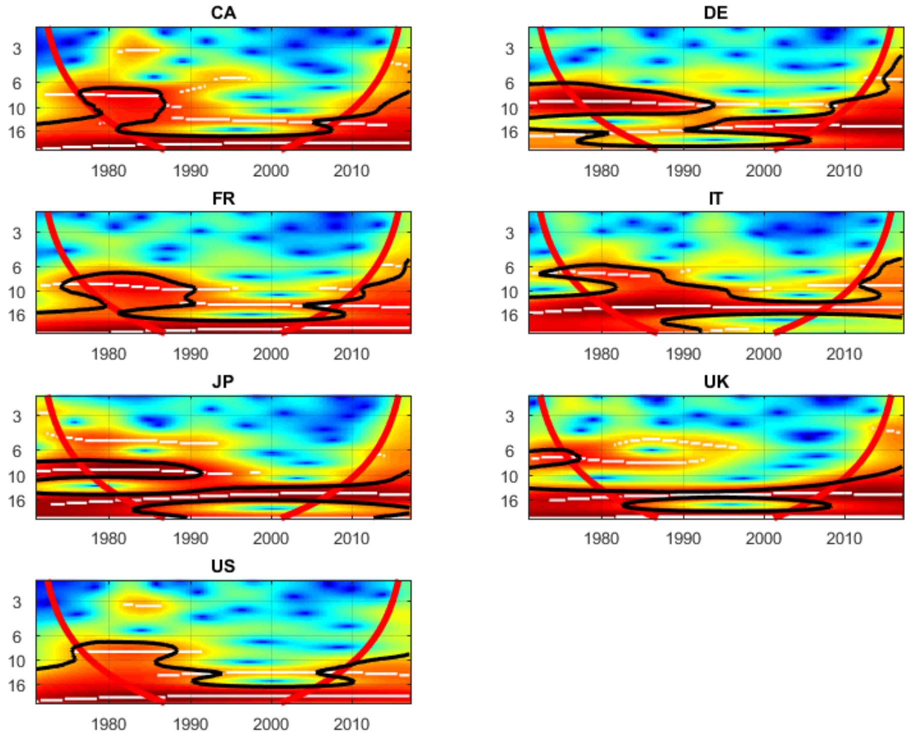
Figure 10: Wavelet cohesion for equity prices (EQP)



Horizontal axis denotes time, vertical axis cycle length. Cohesion measure as real GDP-weighted average of all pairs of dynamic cross-country correlations. Black lines are drawn around time-frequency combinations of cohesion estimates significantly different from zero at the 10% level. Red lines denote the cone of influence.

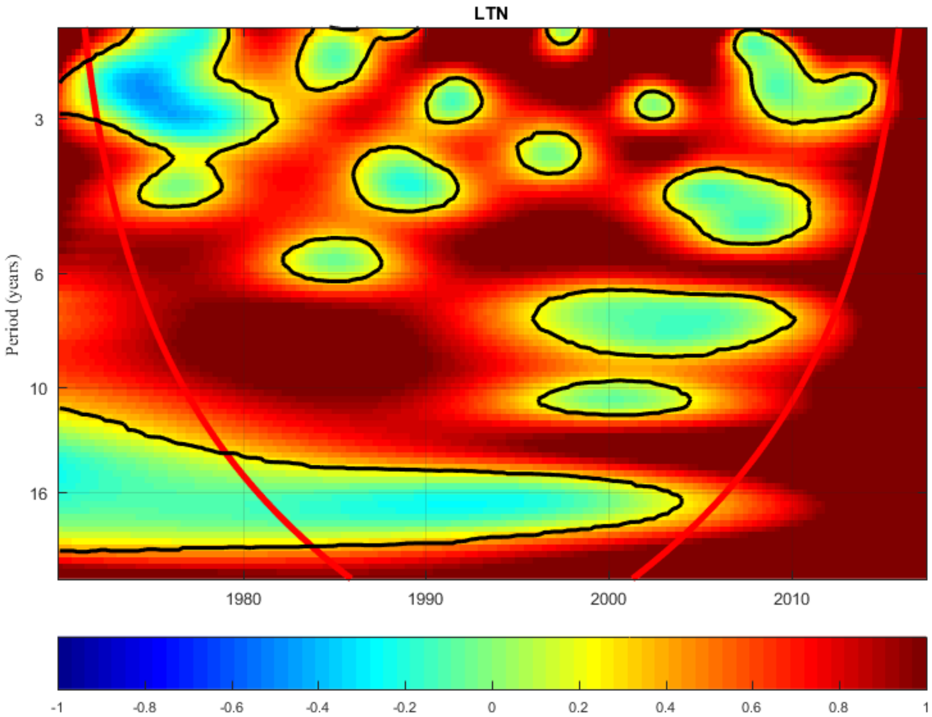
Long-term interest rates (LTN) contain cycles at the bottom of the frequency range in Figure 11 as well as for cycle lengths of between ten and sixteen years depending on the country in IT and UK. In DE the duration of this second dominant cycle shifts from around ten to around 16 years in the early 1990s. We obtain significantly positive cohesion both for cycles at the bottom of Figure 12 as well as for cycles with a length of ten years and somewhat longer. Thus, the time-frequency combinations with significant cohesion broadly correspond to the combinations with significant estimates for the power spectrum at the country level. The significant cohesion estimates at higher frequencies should not be interpreted as they do not correspond to important cycles in the power spectra.

Figure 11: Wavelet power spectra for long-term interest rates (LTN)



Horizontal axis denotes time, vertical axis cycle length. Black lines are drawn around time-frequency combinations with estimates of the power spectrum significantly different from zero at the 10% level. Red lines denote the cone of influence. White lines highlight local maxima of the power spectrum.

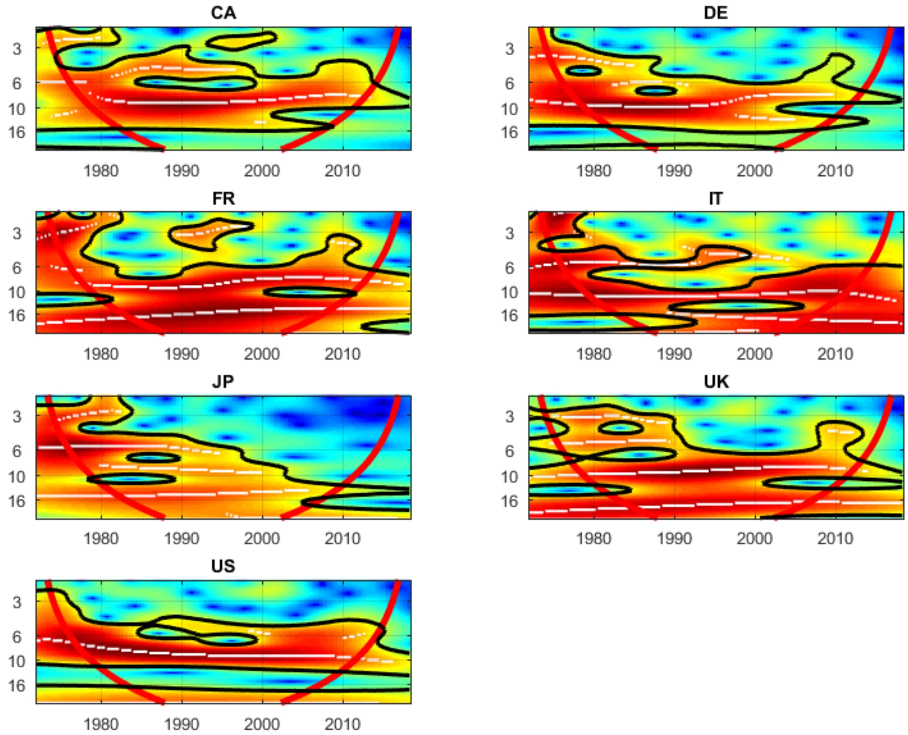
Figure 12: Wavelet cohesion for long-term interest rates (LTN)



Horizontal axis denotes time, vertical axis cycle length. Cohesion measure as real GDP-weighted average of all pairs of dynamic cross-country correlations. Black lines are drawn around time-frequency combinations of cohesion estimates significantly different from zero at the 10% level. Red lines denote the cone of influence.

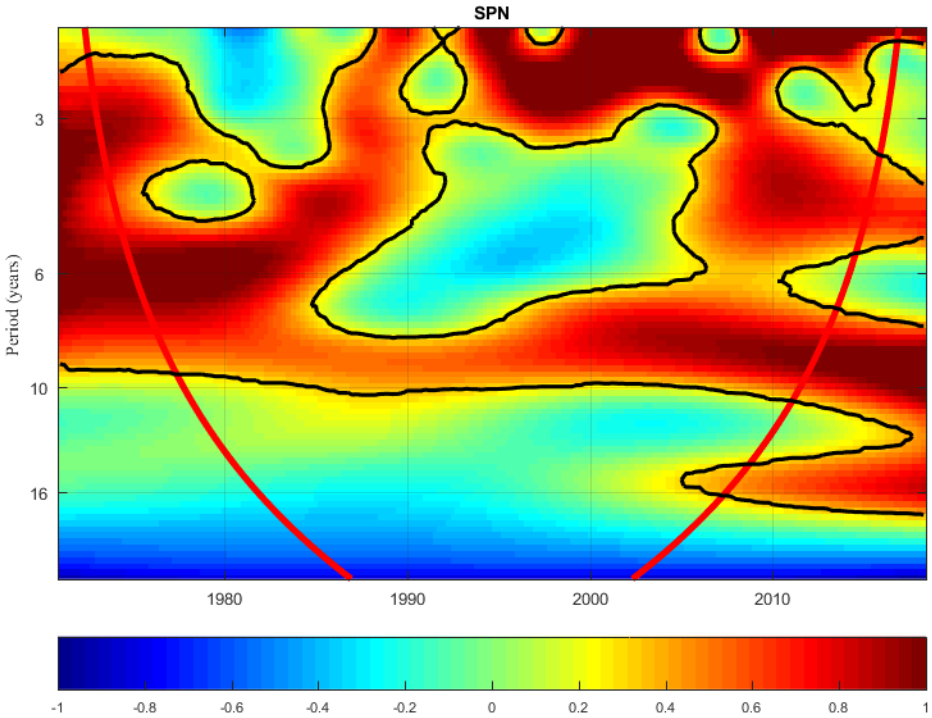
The term spread (SPN) in all countries contains important cycles at 10 years and for some countries at around 16 years as well (Figure 13). In most countries there are also shorter cycles with duration of about six years which, however, are not stable over time. The cycles with length of about ten years coincide with strongly positive cohesion (Figure 14). However, the even longer cycles are not included in the time-frequency combinations with significant cohesion and, thus, do not reflect common cycles across countries.

Figure 13: Wavelet power spectra for term spread (SPN)



Horizontal axis denotes time, vertical axis cycle length. Black lines are drawn around time-frequency combinations with estimates of the power spectrum significantly different from zero at the 10% level. Red lines denote the cone of influence. White lines highlight local maxima of the power spectrum.

Figure 14: Wavelet cohesion for term spread (SPN)

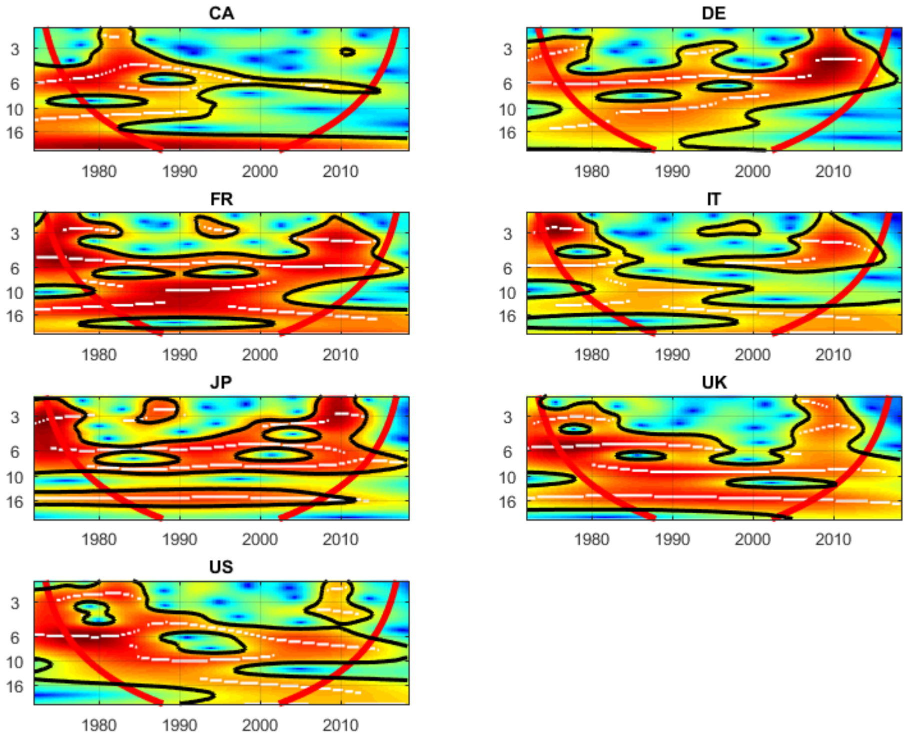


Horizontal axis denotes time, vertical axis cycle length. Cohesion measure as real GDP-weighted average of all pairs of dynamic cross-country correlations. Black lines are drawn around time-frequency combinations of cohesion estimates significantly different from zero at the 5% level. Red lines denote the cone of influence.

Drawing on the full set of cohesion estimates we find evidence for cross-country synchronised cycles for all variables. For each variable, except for BCN, there is at least one frequency range for which cohesion is significantly positive throughout the sample period. The frequency bands for which we find stable and significant cohesion differ across variables. For many variables this frequency range includes cycles with a length of between ten and sixteen years, a length often associated with the financial cycle (eg. Borio, 2014). The frequency range of common cycles is particularly broad for equity prices. Comparing the earlier to the later part of our sample period we do not find substantial evidence for an increase in the importance of common cycles across countries over time.

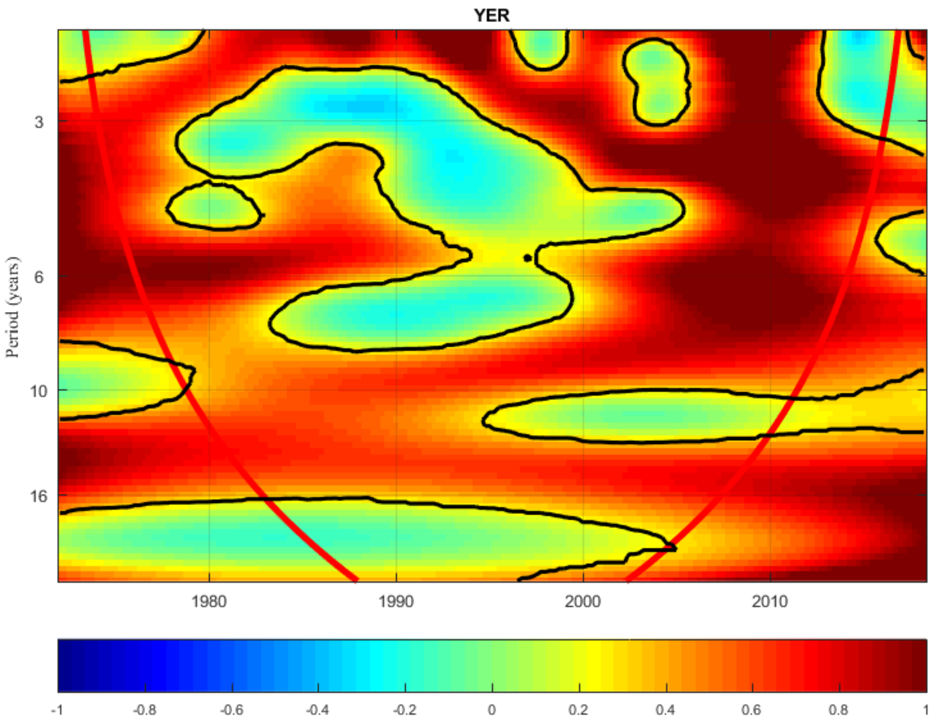
Figure 15 and Figure 16 present the power spectra and cohesion for real GDP growth. Real GDP growth contains important cycles with duration of around 16 years and in many countries also with duration around ten years (JP, UK and US throughout and CA, FR and IT for subperiods). In many countries there are also important cycles with length of about six years. The time-frequency combinations with statistically significant cohesion include both the cycles with length of around 16 and around ten years. In the late 2000s they also extend broadly over higher frequencies probably reflecting the common economic downturn in the financial crisis and the Great Recession.

Figure 15: Wavelet power spectra for real GDP (YER)



Horizontal axis denotes time, vertical axis cycle length. Black lines are drawn around time-frequency combinations with estimates of the power spectrum significantly different from zero at the 10% level. Red lines denote the cone of influence. White lines highlight local maxima of the power spectrum.

Figure 16: Wavelet cohesion for real GDP (YER)



Horizontal axis denotes time, vertical axis cycle length. Cohesion measure as real GDP-weighted average of all pairs of dynamic cross-country correlations. Black lines are drawn around time-frequency combinations of cohesion estimates significantly different from zero at the 5% level. Red lines denote the cone of influence.

5.2 Importance of common cycles for individual countries

In the previous section we presented evidence for important cross-country common cycles in all variables although with differences in the position and width of the relevant frequency ranges across countries. In this section we investigate how important these common cycles are for the individual countries.

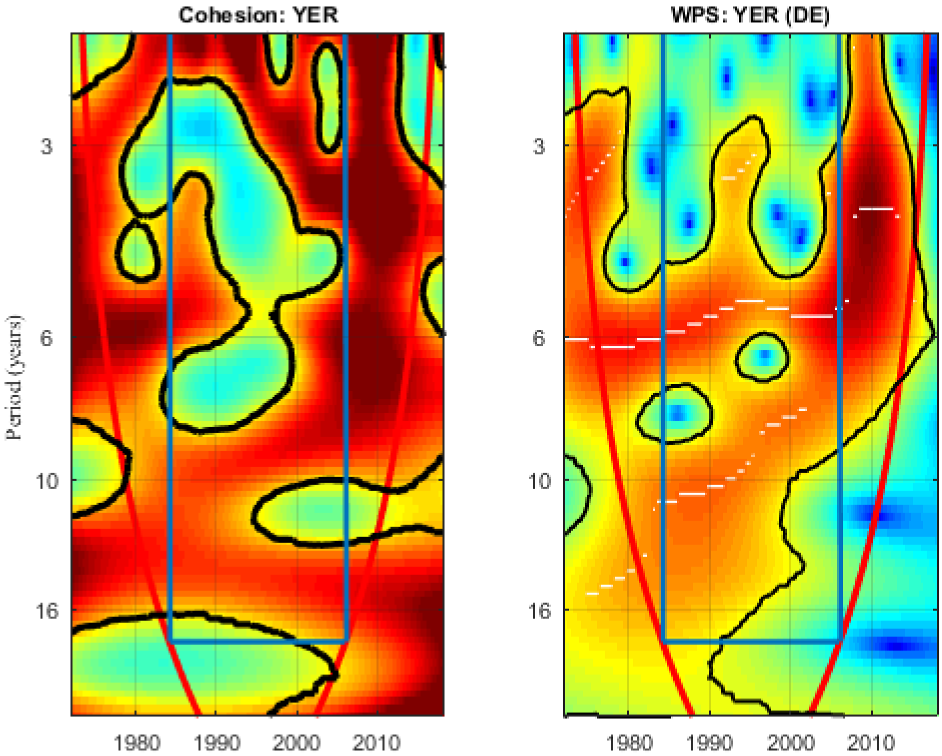
Our assessment is based on a time-varying measure of the variance share of each time series in each country that is explained by common cycles. This analysis works as follows: (1) we define the range of cycle lengths for the analysis. The time period for which we can perform the analysis is given by difference between the two lines denoting the cone of influence for the maximum cycle length chosen. The left panel of Figure 17 shows an example for a maximum cycle length of 18 year which results in a time period for the analysis indicated by the horizontal blue bar. (2) Within the rectangle given by minimum and maximum cycle length and the start- and end-points given by the cone of influence we pick all time-frequency combinations with significant cohesion.[8] (3) For each point in time and for each country we numerically integrate the wavelet power spectrum over the frequencies with significant cohesion and express the results as a share of the overall mass under the power spectrum between the minimum and maximum cycle length. (4) Finally, we graph the resulting time series of these shares for each variable and country.

Figure 17 shows an example for real GDP in DE. For each point in time we make a vertical slice through the WPS in the blue rectangle in the right panel. Our measure is the share in the area below the WPS of those frequencies for which we find significant cohesion in the left panel. In the actual application we do not include cycles shorter than two years because these mostly reflect short-run noise.

Put more simply, the analysis shows for each variable and country over time the share in the variance of the series (i.e. the share in the power spectrum) due to cycles with length of between two and 18 years that is explained by common cycles (cycles with significant cohesion).

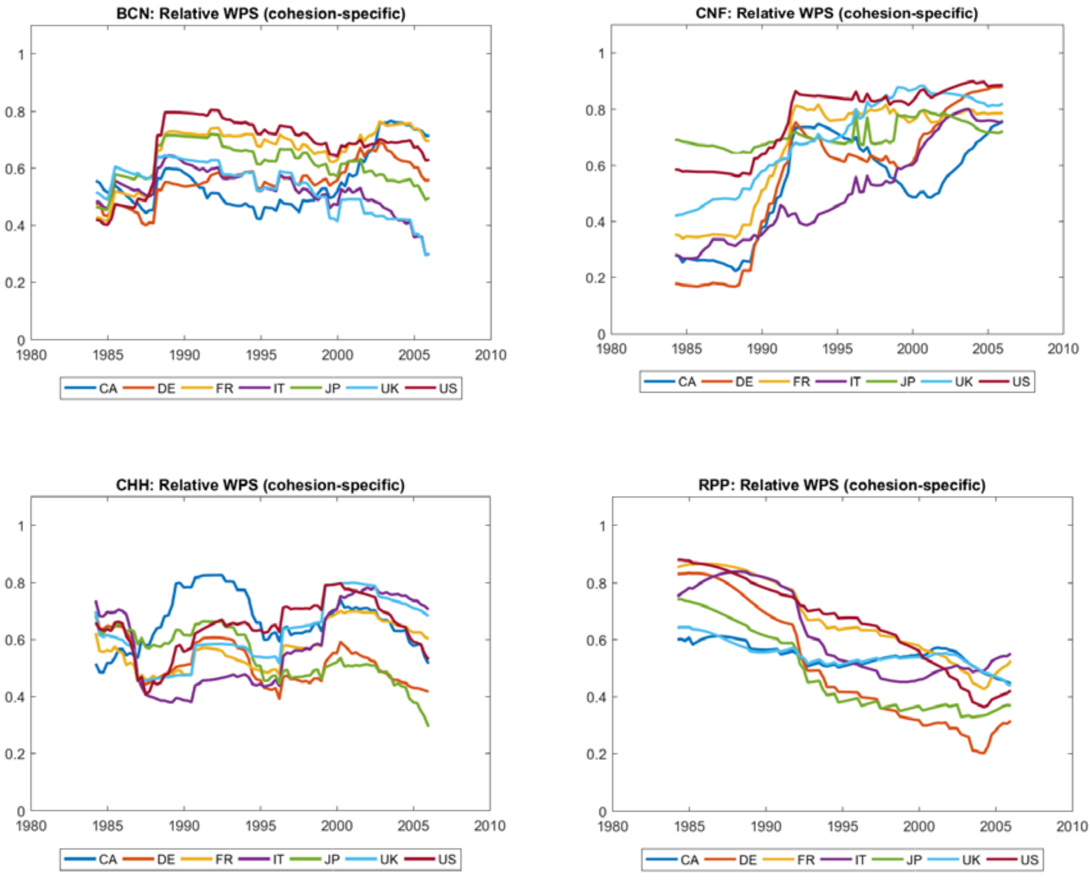
[8] Using the full range of possible cycle lengths and the full sample period, i.e. the complete range of time-frequency combinations shown in Figure 17 would dilute the results with estimates from inside the cone of influence which cannot be interpreted. The impact of estimates from within the cone of influence would first decline over time, as the left red line curves downward and the frequency range for which we have interpretable cohesion and power spectrum estimates increases, and then increase again as the cone of influence slopes up again. Using the full area between the curved red lines instead of the blue rectangle in Figure 17 would cause another problem: at the beginning and the end of the sample period the estimates of the coverage shares would be dominated by results for short cycles which can lead to erroneous conclusions. Consider the example that cohesion was significant for cycles of less than four years duration throughout but insignificant for longer durations and that the power spectrum is constant over time and flat across frequencies. In this case the share of the mass under the power spectrum covered by frequencies with significant cohesion would start at one and would begin to decline as cycles longer than four years are included in the computation. Towards the end of the sample, these longer cycles would again drop out of the computation and the share would go up again. Although the importance of the common short cycles is constant over time the statistic would suggest a decline in their importance followed by an increase.

Figure 17: Example for coverage analysis



Horizontal axis denotes time, vertical axis cycle length. Left panel: Cohesion measure as real GDP-weighted average of all pairs of dynamic cross-country correlations. Right panel: Wavelet power spectrum for DE. Black lines are drawn around time-frequency combinations of cohesion or power spectrum estimates significantly different from zero at the 10% level. Red lines denote the cone of influence.

Figure 18: Importance of common cycles for country-specific dynamics – credit and house prices



Share of mass under the wavelet power spectrum of frequencies with cohesion significant at the 10%-level. Minimum and maximum cycle range are two and 18 years.

Figure 18 presents these common cycle shares for the three credit variables and for real house prices. The shares are computed for cycle lengths between two and 18 years which, given the cone of influence, results in an estimation period from 1984 to 2006. For BCN the share of common cycles in each country's variability of the time series ranges between around 0.4 and 0.8. The share increases for all countries, although to a different extent in the late 1990s but then trends downwards. For FR, DE, and particularly for CA common cycles become more important, again, in the early 2000s. Comparing the beginning to the end of the estimation period the relative importance of common cycle has increased over time except for IT and UK.

For CNF the measure starts out lower than for BCN for many countries but increases substantially in the late 1980s and remains at a higher level afterwards. For IT and UK the increase is more gradual and for JP, which already started out with a high variance share, the share of common cycles at the overall variance ends up at a similar level as it started. For CA the statistic drops from the early 1990s up until around 2000 but rises again to a similar level as in the early 1990s.

For CHH the importance of common cycles towards the end of the estimation period turns out similar to that in the beginning with values fluctuating between around 0.4 and 0.8. In contrast the share of common cycles in RPP in each country's variance declines for most of the countries. The shares start out between 0.6 and 0.9 and decline to about 0.2 to 0.6. The decline is particularly pronounced for DE while it is more modest in CA and UK. This result suggests that over time country-specific developments in real house prices have become relatively more important compared to common cycles.

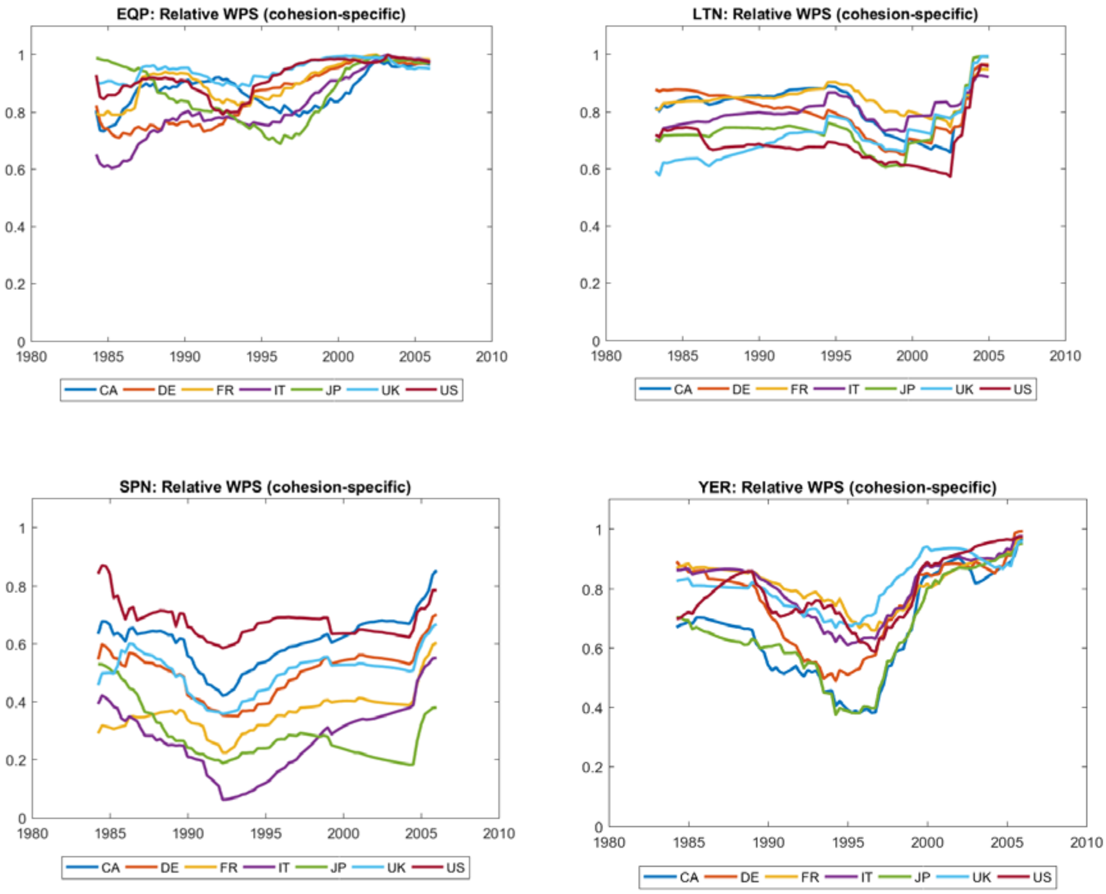
Figure 19 presents the results for real equity prices, long-term interest rates, the term spread, and, for comparison, real GDP. The importance of common equity price cycles for developments at the country level was already quite high in the beginning and has increased even more. The estimated shares of the overall variance of the equity price growth accounted for by common cycles start at values between around 0.6 and one and ends up close to one for all countries. The increase has been particularly pronounced for IT. For JP the share dropped from almost one in 1985 to less than 0.8 in the mid-1990s but rose again to values of close to one afterwards. Concerning LTN our measure has remained broadly stable from the start of the estimation period until the mid-2000s when cross-country common cycles for the dynamics at the country level became more important. In this time period the shares moved up from values between around 0.6 to 0.9 before to values between 0.9 and one. Given the lack of importance of shorter cycles in the wavelet power spectra for LTN (Figure 11) the high shares for this variable are driven by the importance of common cycles for the variation in LTN at lower frequencies.

For SPN the shares are overall lower and more dispersed across countries. At the start of the sample period they cover a range from around 0.3 to somewhat more than 0.8, then decline somewhat and end in a similar range they started in. The lesser importance of common cycles for the term spread compared to the results for the long-term interest rate is probably driven country-specific cycles being more important for short-term interest rates (monetary policy) than for longer-term rates. The uptick towards the end might be related to the financial crisis and the resulting expansionary monetary policy in the countries: although our estimation period ends before the crisis, both cohesion and the power spectra estimates from which the final estimates in Figure 19 are derived are in part based on data from the late 2000s or even later.[9] Similarly the uptick for LTN

[9] This is due to the two-sided nature of the estimation of the wavelet-power spectra and the dynamic correlation. The extent, to which data from the financial crisis and the great recession period affect

towards the end of the sample might also be related to the simultaneous use of unconventional monetary policy in many countries which reduced long-term interest rates.

Figure 19: Importance of common cycles for country-specific dynamics – equity prices, interest rates and real GDP



Share of mass under the wavelet power spectrum of frequencies with cohesion significant at the 10%-level. Minimum and maximum cycle range are two and 18 years.

The final panel in Figure 19 shows that common cycles in real GDP accounted for 70% to 90% of the variance of real GDP growth at the country level but that this share declined broadly over time to between 40 and 80% in the late 1990s before picking up again and reaching values above 80% towards the end of the sample.[10]

already estimates in the mid-2000s depends on the frequency under consideration, due to the frequency dependent scaling of the wavelet projection. For details, see Section 4.

[10] The relatively high importance of common cycles at the end of the estimation period might be due to the financial crisis and the Great Recession, see footnote 9.

Comparison of the results for real GDP to those for the other variables shows cross-country common cycles representing a larger variance share for EQP and LTN than for real GDP at the country level. In contrast, the shares for the credit aggregates both at the start of the estimation period and towards the end, and, in particular for house prices (RPP) are mostly lower than those for real GDP. Thus, our results suggest that the global financial cycle is more important for fluctuations in prices or returns on highly liquid assets (shares and bonds) than for fluctuations in credit and house prices.

5.3 Distance measures

In section 5.1 we showed results on the common cyclical movements across all the countries. In this section we focus on the comparison of cycles between individual countries. If common cycles are restricted to a subset of the G7 countries, they might not be picked up by cohesion as an average measure of co-movements. We construct distance measures (12) between the wavelet power spectra for each pair of countries and then use a hierarchical clustering algorithm based on the estimated distances between all bivariate combinations (see section 4). For all possible pairs of countries contained in a cluster we can reject the null hypothesis of unrelated cycles at the 10% level.[11] A drawback of this analysis is that it does not allow for time-variation. Instead it shows the “closeness” of different countries’ cycles on average. In order to check whether there are substantial changes in the results depending on the sample period we compare we compare results for the full sample period to results from the second half of the sample only.

The left panels of Figures C1-C7 in the Appendix show the results of the distance and cluster analysis using dendograms derived from the cross-country distances of the wavelet power spectra for each variable. For most variables we have split the frequency band into cycles with length of six to ten and ten to 16 years. This enables us to capture the important cycles visible in the wavelet power spectra and allows for possible differences in the cross-country relationship across frequencies. For equity prices we look at cycle durations over the full range between six and 16 years because of the high degree of cross-country association of this broad range of cycles shown in the cohesion estimates.

We summarize the results of the cluster analysis in Table 1 which shows for each pair of countries for how many variables these two countries are in the same cluster. The

[11] This analysis uses the AST Toolbox (Aguiar-Conraria and Soares, 2014), see footnote 5, and the distance function provided by Aguiar-Conraria and Soares (2011).

variables are classified into slow-moving variables (numbers in black; house prices and credit variables – bank credit to non-financial private sector, credit to non-financial corporations and credit to households) and fast-moving financial markets variables (numbers in blue and in italics; equity prices, long-term interest rates and term spread, black). The combination 4+3 in a cell implies that these two countries are in the same cluster for all variables, 0+0 shows that they are never found in the same cluster.

Table 1: Summary of results from cluster analysis (full sample)

	CA	DE	FR	IT	JP	UK	US
CA	-						
DE	1+*3*	-					
FR	1+*3*	1+*3*	-				
IT	1+*2*	1+*2*	0+*2*	-			
JP	0+*3*	0+*3*	0+*3*	0+*2*	-		
UK	2+*3*	1+*3*	1+*3*	2+*2*	3+*3*	-	
US	1+*3*	0+*3*	2+*3*	0+*2*	0+*3*	0+*3*	-

Numbers indicate for how many variables the country pair is estimated to be part of the same cluster for at least one of the cycle duration ranges (6-10, 10-16 years or 6-16 years for EQP). Colours of numbers indicate results for subsets of variables; black: credit and house prices (BCN, CHH, CNF, RPP), *blue:* financial markets variables (EQP, LTN, SPN); maximum possible numbers are 4+3; each country can be element of 24+18 pairs (6 for each variable).

For the fast-moving financial markets variables most of the country pairs are in the same cluster for all of the three variables. The exception is IT which is close to the long-term interest rate and equity price cycles to all of the other countries but is not clustered with the other countries for the term spread. Concerning the credit aggregates and the house prices the cluster analysis suggests less co-movement across countries than for the financial market variables. DE is assigned to any other country in a cluster at most once. The other countries are in the same cluster with any other country for two or more variables only once (the black “2s” or “3s” in the table). Only UK is placed in the same cluster with four other countries for two or three variables. Summing up the numbers for credit and house prices for each country, JP appears only three times in clusters with another country out of 24 possible clusters and these three instances are all with the UK Thus, cycles in credit and house prices in JP are least related to those in other countries. In contrast, out the country most often found in clusters with other countries for these variables is the UK in nine out of 24 possible cases. However, this is still modest compared to the three fast-moving variables where the sums are 12 for IT and 17 (out of 18) for all other countries. This evidence supports the result from the previous section, that equity prices and interest rates are more strongly synchronised internationally than credit and house prices.

Table 2: Summary of results from cluster analysis (1995Q1 to 2018Q2)

	CA	DE	FR	IT	JP	UK	US
CA	-						
DE	0+3	-					
FR	1+3	1+3	-				
IT	2+2	1+2	2+2	-			
JP	0+2	0+3	1+2	0+2	-		
UK	1+3	0+3	1+3	2+2	1+2	-	
US	1+3	0+3	1+3	0+2	0+2	1+3	-

Numbers indicate for how many variables the country pair is estimated to be part of the same cluster for at least one of the cycle duration ranges (6-10, 10-16 years, 6-16 years for EQP). Colours of numbers indicate results for subsets of variables; black: credit and house prices (BCN, CHH, CNF, RPP), *blue:* financial markets variables (EQP, LTN, SPN); maximum possible numbers are 4+3; each country can be element of 24+18 pairs (6 for each variable).

Table 2 shows results for the cluster analysis on the second half of the sample period (1995Q1 to 2018Q2, Figures C9-C15 in the appendix). As for the full sample, the countries are more strongly clustered for the three fast-moving financial variables compared to credit and house prices. There is also no strong evidence for an overall increase or decline in the cross-country commonalities of cycles as the number of clusters each country appears in does not change in a systematic way. The only exception is JP which for the financial market variables drops out from some of the clusters with other countries. For credit aggregates and house prices JP, as before, is found less often in clusters with other countries (two times) while for this sample FR and IT are found most often (seven times).

Meller and Metiu (2017) perform a cluster analysis on cycles in bank loans to households and non-financial corporations extracted from the Schularick and Taylor (2012) data set using a band-pass filter and a cycle length of between eight and 20 years. Since their results do not consider lending to firms and households separately, the closest variable in our data set to their credit variable is BCN for which we find two clusters, one containing JP and UK, the other containing FR and US for both six-to-ten and ten-to-sixteen year cycles. Their cluster analysis assigns these four countries to the same cluster and, among the G7 countries, also includes IT. They do not include DE in any cluster which is also consistent with our results for BCN.

Table 3: Summary of results from cluster analysis for real GDP (YER)

	CA	DE	FR	IT	JP	UK	US
CA	-						
DE		-					
FR		○●	-				
IT		●	●	-			
JP		○●	○●	●	-		
UK		●	●	●	●	-	
US		●	●	●	●	○●	-
○ (●) indicates that both countries are in the same cluster for cycles in real GDP of length between six to ten years (ten to 16 years).							

For comparison Table 3 summarizes the results from the cluster analysis for real GDP (Figure C8). Except for CA all countries are in the same cluster for GDP cycles between ten and 16 years and two subsets of countries (DE, FR, JP and UK and US) also are clustered for cycles with a length of between six and ten years. The comparison to Table 1 shows that countries are clustered more strongly with respect to real GDP cycles than for cycles in credit and house prices.

6 Summary and conclusions

In this paper we use a broad set of empirical tools based on wavelet analysis to study the cross-country dimension of financial cycles in the G7 countries. Using wavelet analysis allows us to avoid imposing ex-ante restrictions on the frequency range on which we investigate possible financial cycles and provides results on possible shifts in the relevant frequencies or in the strength of cross-country co-movements over time.

We show that G7 countries experience important cycles in credit, house prices, long-term interest rates and in the term spread which have duration of about ten and 16 years – longer than standard business cycle frequencies. In principle, the importance of cycles at similar frequencies across countries can be consistent with the existence of common cycles. Our wavelet-based cohesion measures shows evidence for marked and stable cross-country co-movements for the credit to households and credit to non-financial corporations as well as for house prices for cycles with length between ten and 16 years. Long-term interest rates and equity prices display strong cross-country synchronisation with cohesion close to one over a broad range of frequencies. Using cross-country cohesion of real GDP as a benchmark, long-term interest rates and equity prices are similarly or more synchronized than real GDP while credit and house prices display less cross-country synchronisation. Rünstler et al. (2018) and Kunovac et al. (2018) present similar results for European Union or Euro Area countries. In contrast to the results in

Kunovac et al. (2018) for Euro Area countries we find no evidence for an increase in the cross-country synchronisation in credit and house prices over time for the G7 countries.

Further analyses show that, in the individual countries, fluctuations at frequencies for which we find evidence for significant cross-country co-movements account for a larger share in the variance of changes in equity prices and in long-term interest rates than in that of credit and house price growth. This suggests that fluctuations in equity prices and long-term interest rates are more closely linked to cross-country common cycles than movements in credit and house prices. This result is consistent with Breitung and Eickmeier (2016) who show global factors as being particularly important for "fast moving" variables, such as stock prices and interest rates. Thus, the global financial cycle turns out to be more important for fluctuations in prices or returns on highly liquid assets. In fact, we show that the importance of the common-cycle frequencies for explaining the variance of house prices has declined over time. Thus, country-specific developments have become increasingly important for the growth in house prices.

Cohesion is a summary statistic of cross-country correlation and may fail to indicate the presence of cross-country co-movements if these pertain only to a subset of countries. Using cluster analysis based on distance measures of the wavelet power spectra allows us to focus on possible subgroupings of countries that experience common cycles. Focusing on the frequency ranges for which the power spectra indicated important fluctuations we find more pronounced clustering for interest rates and equity prices than for credit aggregates and house prices, results which are similar to those using cohesion.

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Appendix A: Data sources

Real GDP (YER):

Data sources: ECB Statistical Data Warehouse (SDW), ESA 2010 main national accounts (SDW: MNA), ESA 95 national accounts (SDW: ES), OECD Main Economic Indicators (OEC:MEI) and OECD Economic Outlook (OECD: ECO).

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

Wavelet power spectra, coherency and dendograms use annual growth rates of the time series only. However, for the construction of the cohesion measure we use GDP weights for aggregating the pairwise correlations. This requires comparable GDP figures expressed in the same unit. For this we use real GDP expressed at constant PPP from the OECD Economic Outlook.

Bank credit to the non-financial private sector (BCN) is taken from the BIS data base "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). For IT we extend the series backwards from 1974Q4 using the growth rates of the sum of credit to households and credit to non-financial corporations (see below). Series are deflated using the GDP deflator.

Credit to households (CHH) and credit to non-financial corporations (CNF) are taken from the BIS data base "Long series of total credit to the non-financial sectors". (CHH: Households and NPISHs - All sectors - Market value - Domestic currency - Adjusted for breaks; CNF: Non-financial corporations - All sectors - Market value - Domestic currency - Adjusted for breaks). These series cover credit provided by all sectors, not only by banks: "They capture the outstanding amount of credit at the end of the reference quarter. Credit is provided by domestic banks, all other sectors of the economy and non-residents. In terms of financial instruments, credit covers the core debt, defined as *loans, debt securities and currency & deposits*." (see: https://www.bis.org/statistics/totcredit.htm). For the 1970Q1 to 1977Q3 we use annual data from the Jordà-Schularick-Taylor Macrohistory Database (Jordà, Schularick and Taylor, 2017) and interpolate to a quarterly frequency using the Chow-Lin procedure based on quarterly data on loans to the non-financial private sector from the Banque de France. For the UK we extend the series on credit to non-financial corporation backwards from 1974Q4 using the Bank of England's time series on "quarterly 3 month growth rate of monetary financial institutions' sterling net lending to private non-financial corporations (in percent) seasonally adjusted".

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 available from 1960Q1 onwards and are deflated with the GDP deflator.

Residential property prices

Residential property prices are taken from the BIS ("Long-term series of residential property prices"). All series are available at least from 1970Q1 onwards and deflated with the GDP deflator.

Long-term interest rates

For DE, FR, and JP we use data from the IMF's International Financial Statistics which are available at least from 1970Q1 onwards. For IT we extend the series backwards before 1978 using data from the OECD Economic Outlook. For CA, UK and US we use data from the OECD's main economic indicator database downloaded from the SDW.

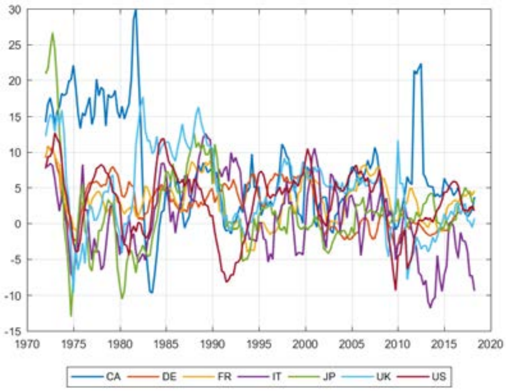
Short-term interest rates

We use interbank rates or three-month interest rates from the OECD's main economic indicator database downloaded from the SDW. For IT we extend the series backwards before 1978Q4 using a money market rate from the IMF's international financial statistics. For UK we extend the series backwards using data on yields for three-month treasury securities from the St.Louis Fed's FRED database

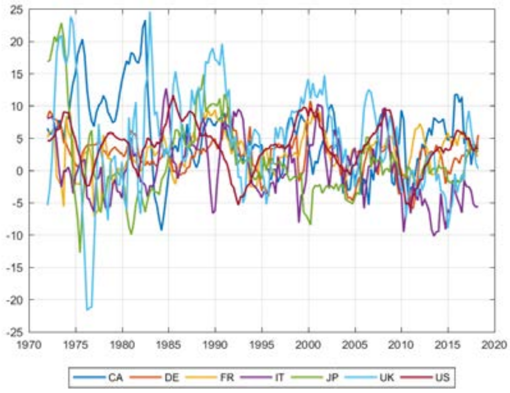
The **nominal term spread** (SPN) is computed as difference between long-term and short-term interest rates.

Appendix B: Plots of time series

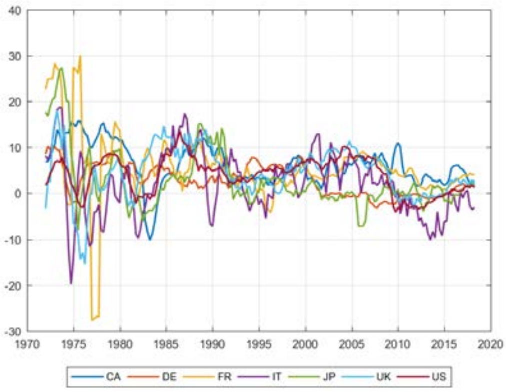
BCN



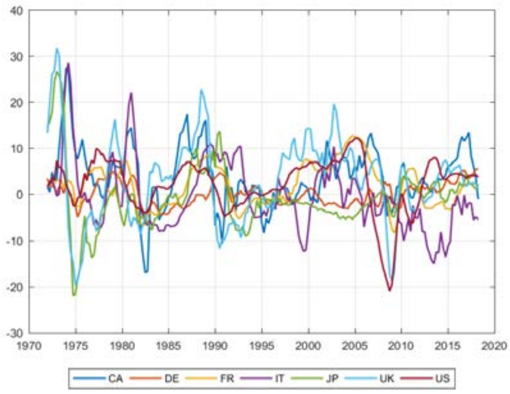
CNF



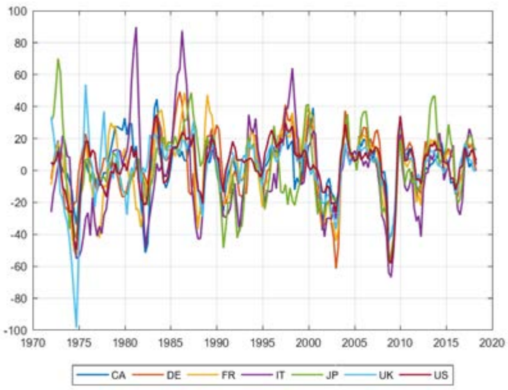
CHH



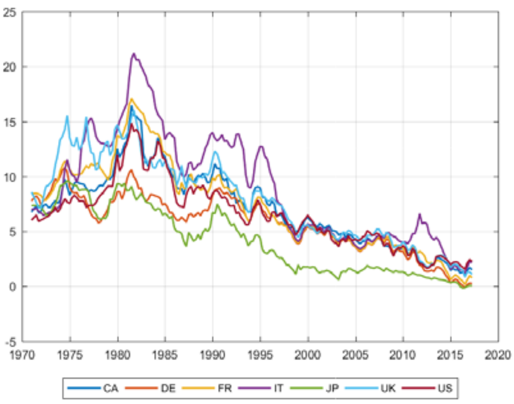
RPP



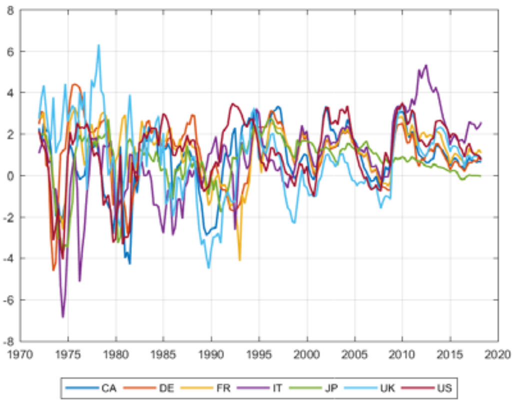
EQP



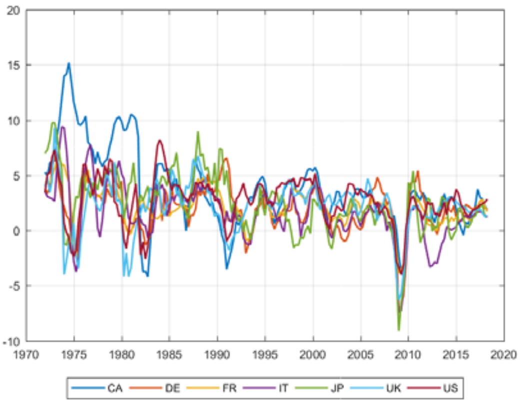
LTN



SPN


8
6
4
2
0
-2
-4
-6
-8
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020
CA DE FR IT JP UK US

YER

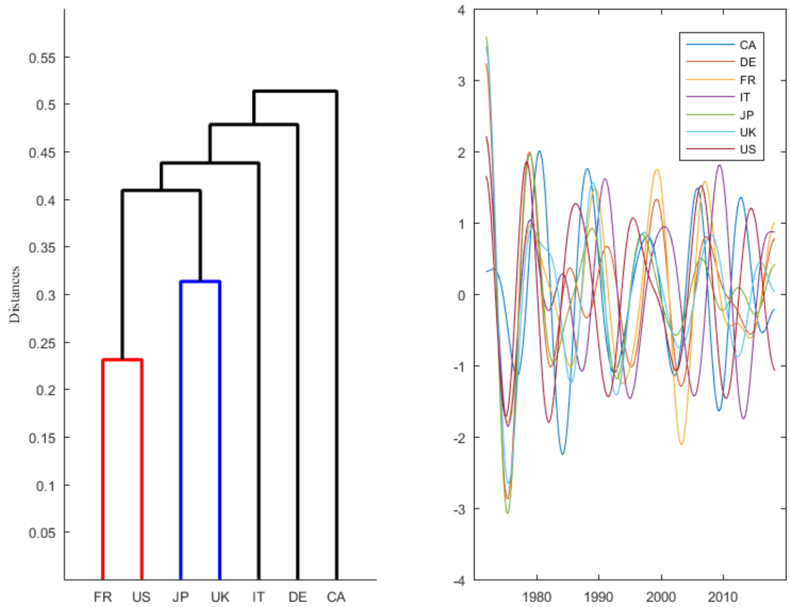

20
15
10
5
0
-5
-10
1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020
CA DE FR IT JP UK US

Appendix C: Dendograms and filtered series

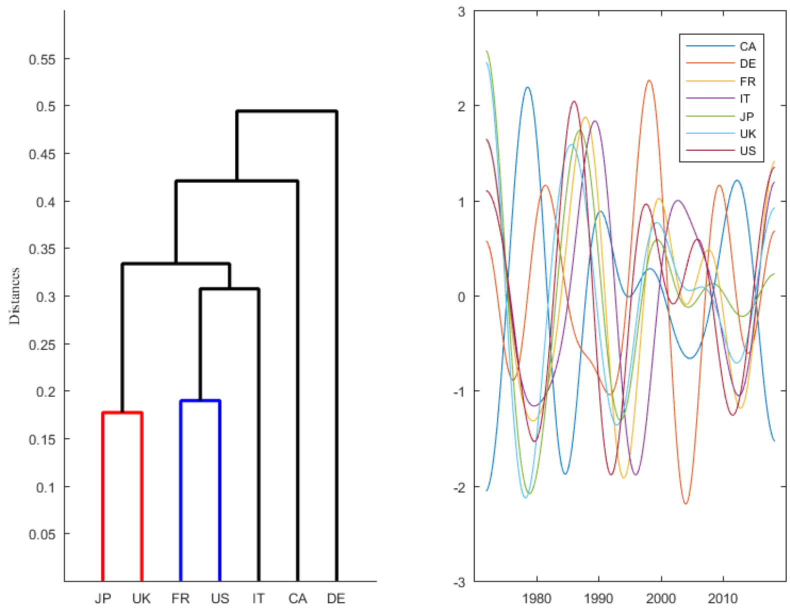
The left panels of Figures D1-D7 show the results of the distance and cluster analysis using dendograms derived from the cross-country distances of the wavelet power spectra for each variable. For most variables we have split the frequency band into cycles with length of six to ten and ten to 16 years. This enables us to capture the important cycles visible in the wavelet power spectra and allows for possible differences in the cross-country relationship across frequencies. For equity prices we look at cycle durations over the full range between six and 16 years because of the high degree of cross-country association of this broad range of cycles shown in the cohesion estimates. The colours represent the clusters resulting from the algorithm described above. Countries with black vertical lines are not part of any cluster. The y-axes indicate the average distances between the power spectra of the connected countries (13). The Figures' right panels show for all countries' the cyclical components of the (standardized) time series of the relevant frequency band. Figure D9-D15 show the dendograms for using the second half of the sample only.

Figure C1: Filtered cycles and dendogram for bank credit to the domestic non-financial private sector (BCN) – full sample

6-10 years



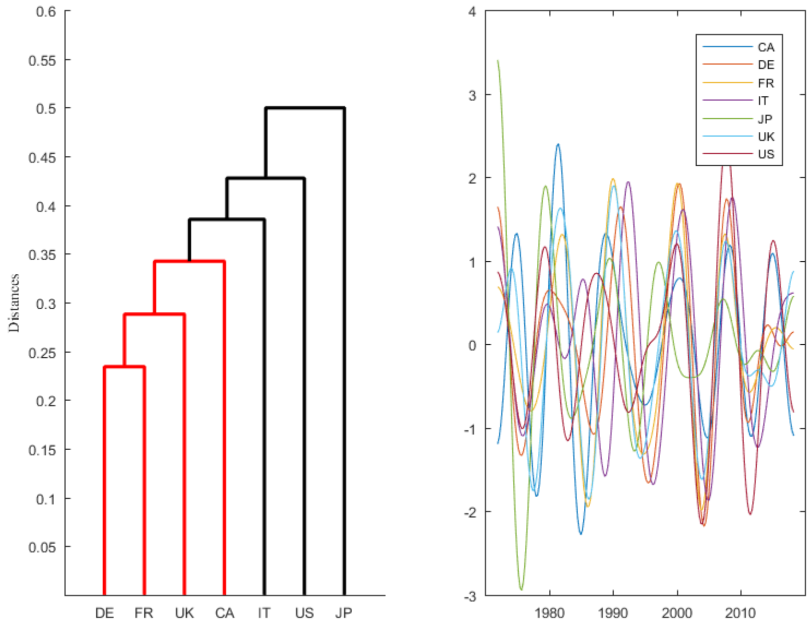
10-16 years



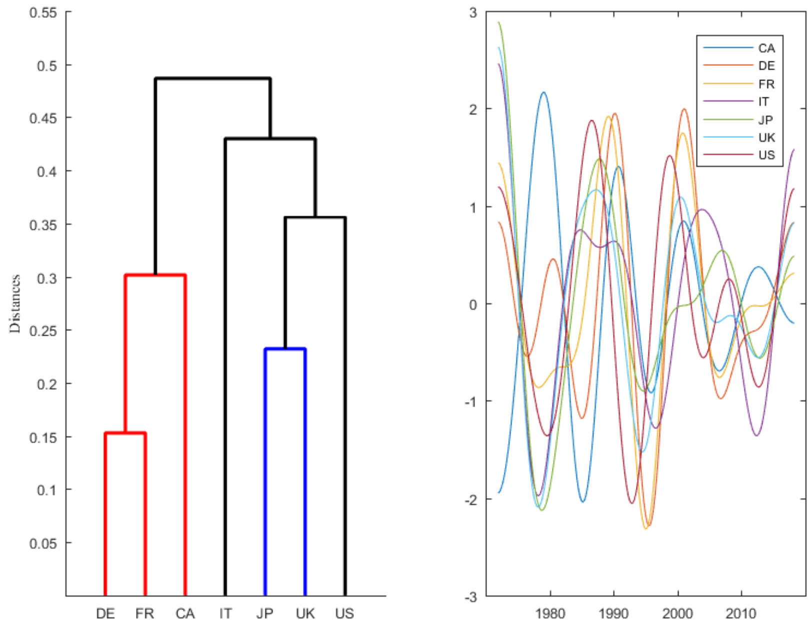
LHS: dendogram constructed from distance matrix of wavelet power spectra for indicated frequency range; colours indicate country clusters at the 10%-significance level, countries with black lines are not included in a cluster. RHS: filtered time series for indicated frequency range obtained from inverting the wavelet transformation.

Figure C2: Filtered cycles and dendogram for credit no non-financial corporations (CNF) – full sample

6-10 years



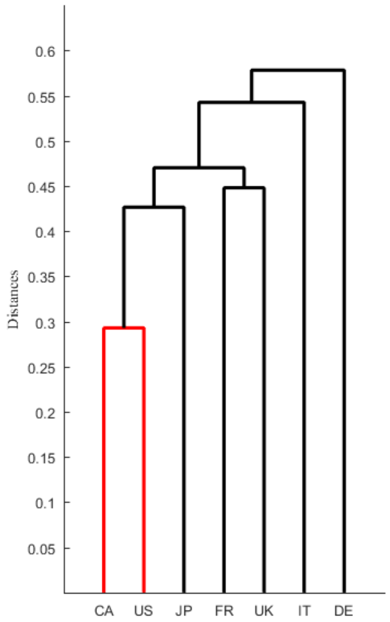
10-16 years

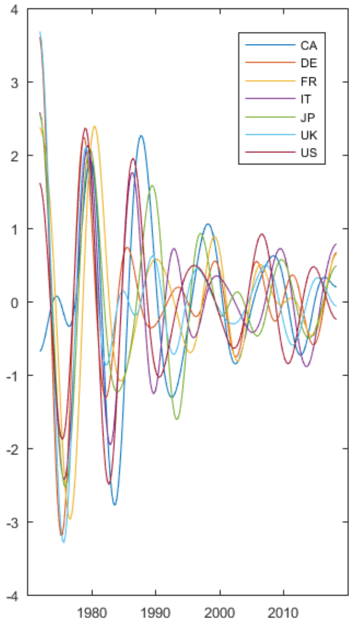


LHS: dendogram constructed from distance matrix of wavelet power spectra for indicated frequency range; colours indicate country clusters at the 10%-significance level, countries with black lines are not included in a cluster. RHS: filtered time series for indicated frequency range obtained from inverting the wavelet transformation.

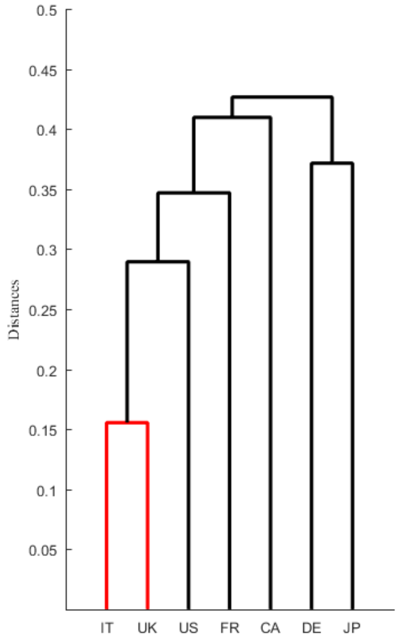
Figure C3: Filtered cycles and dendogram for credit no households (CHH) – full sample

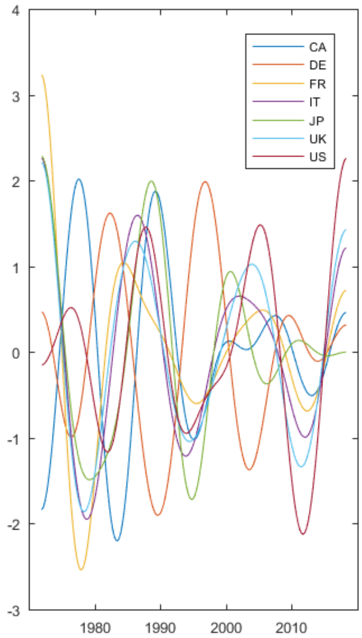
6-10 years





10-16 years

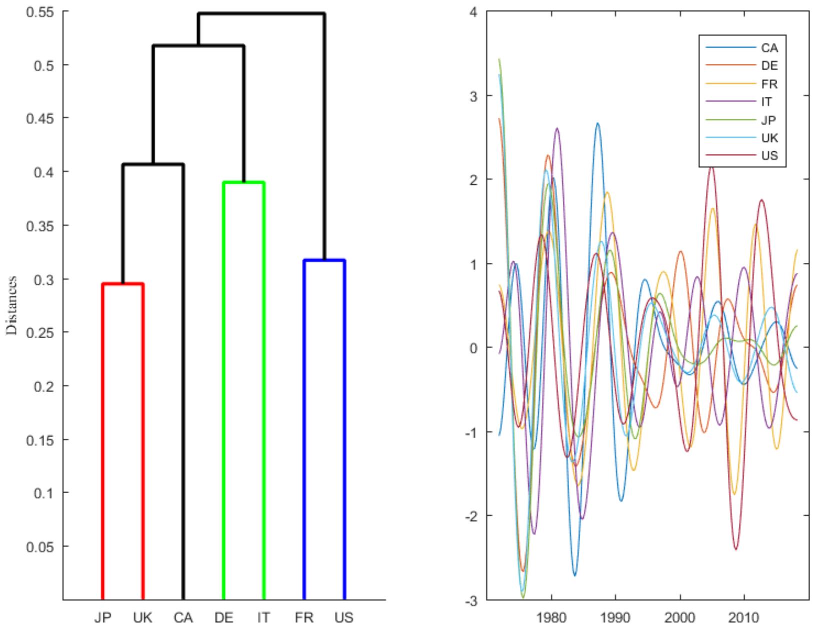




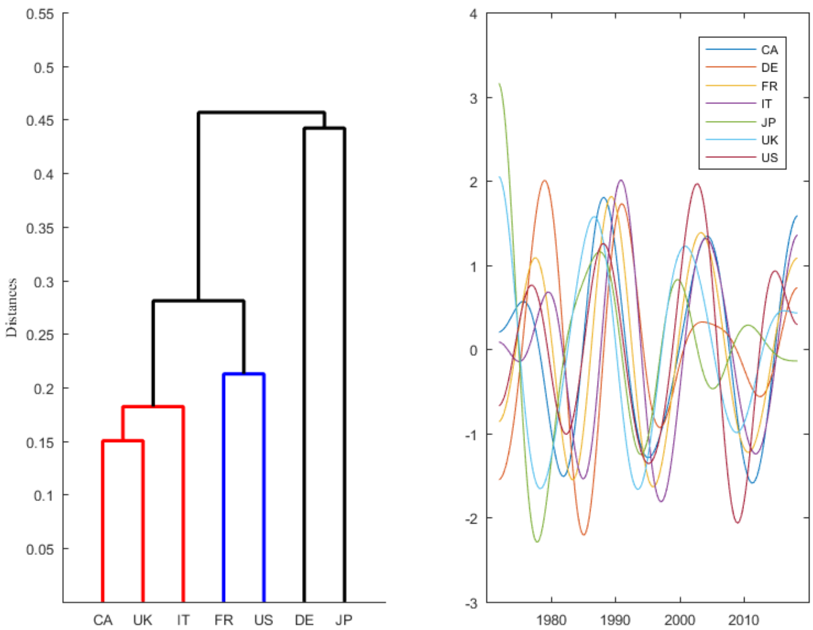
LHS: dendogram constructed from distance matrix of wavelet power spectra for indicated frequency range; colours indicate country clusters at the 10%-significance level, countries with black lines are not included in a cluster. RHS: filtered time series for indicated frequency range obtained from inverting the wavelet transformation.

Figure C4: Filtered cycles and dendogram for residential property prices (RPP) – full sample

6-10 years



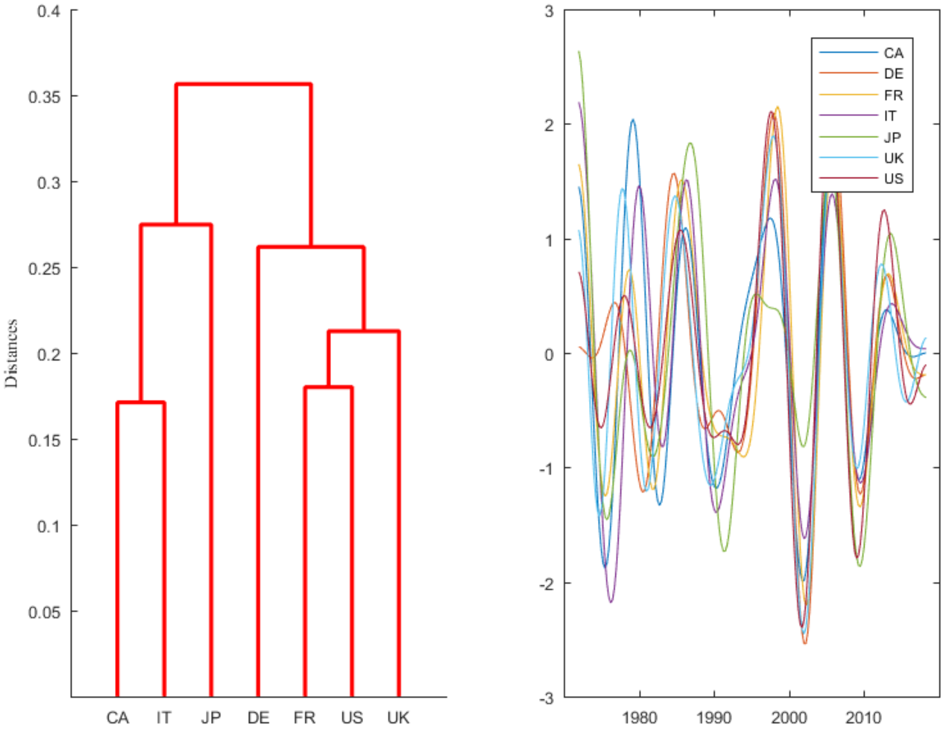
10-16 years



LHS: dendogram constructed from distance matrix of wavelet power spectra for indicated frequency range; colours indicate country clusters at the 10%-significance level, countries with black lines are not included in a cluster. RHS: filtered time series for indicated frequency range obtained from inverting the wavelet transformation.

Figure C5: Filtered cycles and dendogram for equity prices (EQP) – full sample

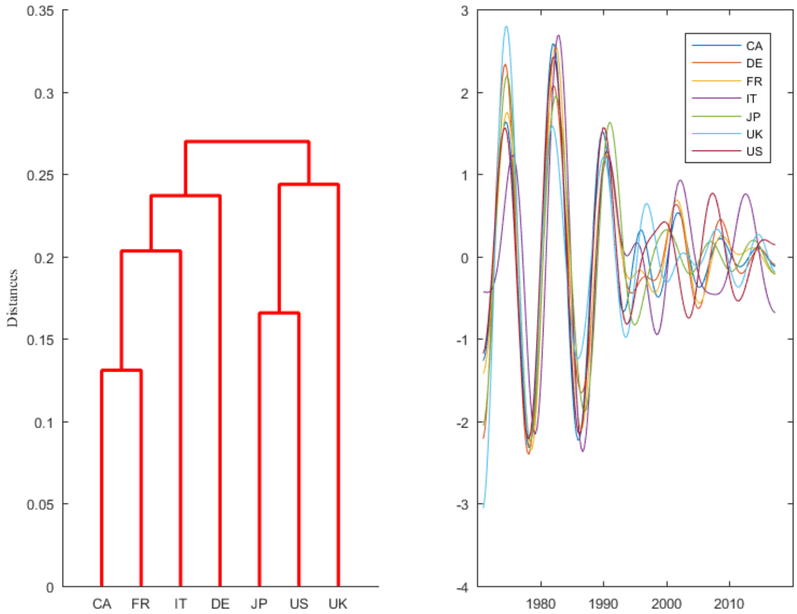
6-16 years



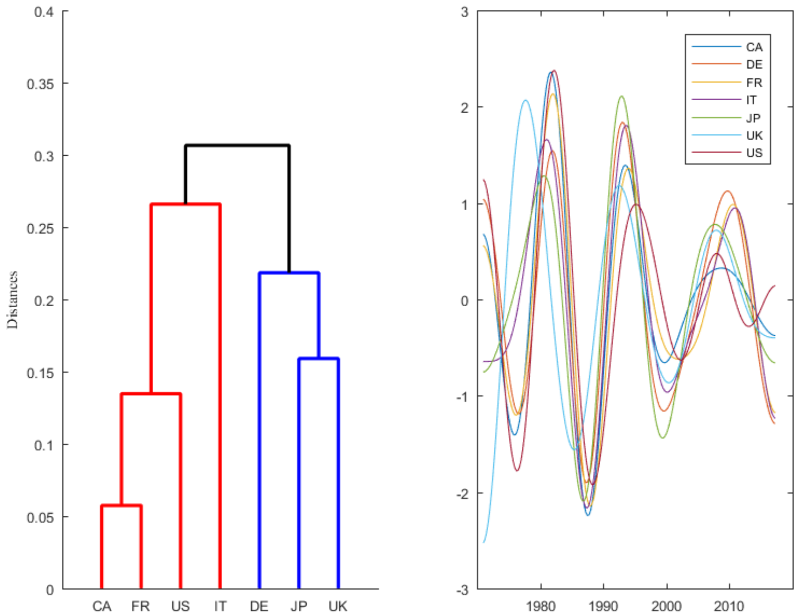
LHS: dendogram constructed from distance matrix of wavelet power spectra for indicated frequency range; colours indicate country clusters at the 10%-significance level, countries with black lines are not included in a cluster. RHS: filtered time series for indicated frequency range obtained from inverting the wavelet transformation.

Figure C6: Filtered cycles and dendogram for long-term interest rates (LTN) – full sample

6-10 years



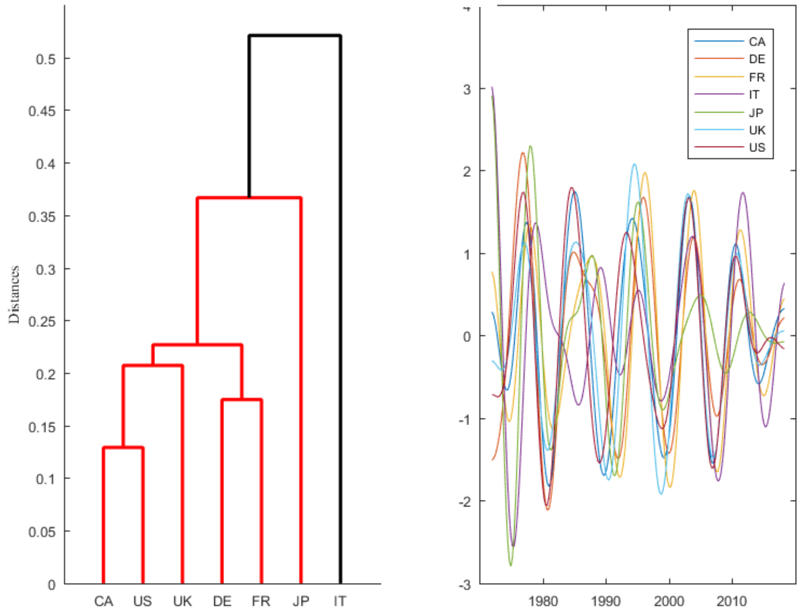
10-16 years



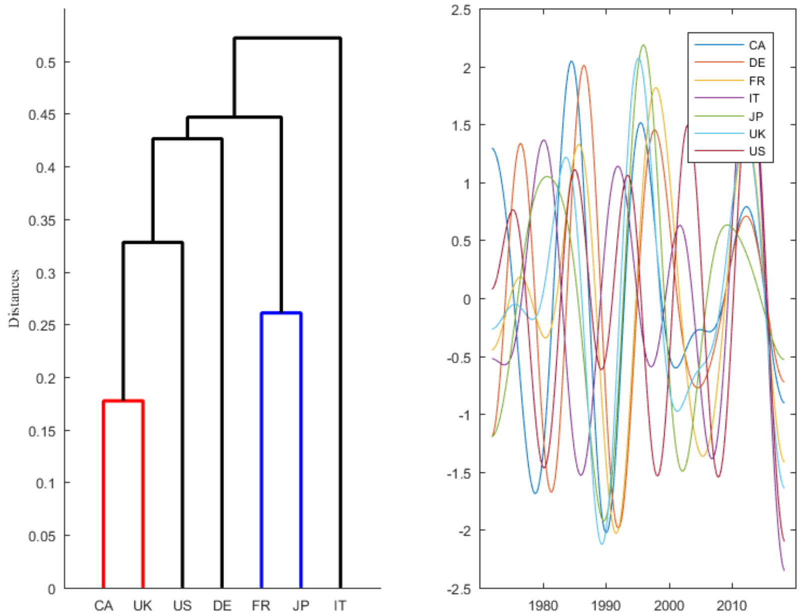
LHS: dendogram constructed from distance matrix of wavelet power spectra for indicated frequency range; **all countries are assigned to a single cluster**. RHS: filtered time series for indicated frequency range obtained from inverting the wavelet transformation.

Figure C7: Filtered cycles and dendogram for nominal term spread (SPN) – full sample

6-10 years



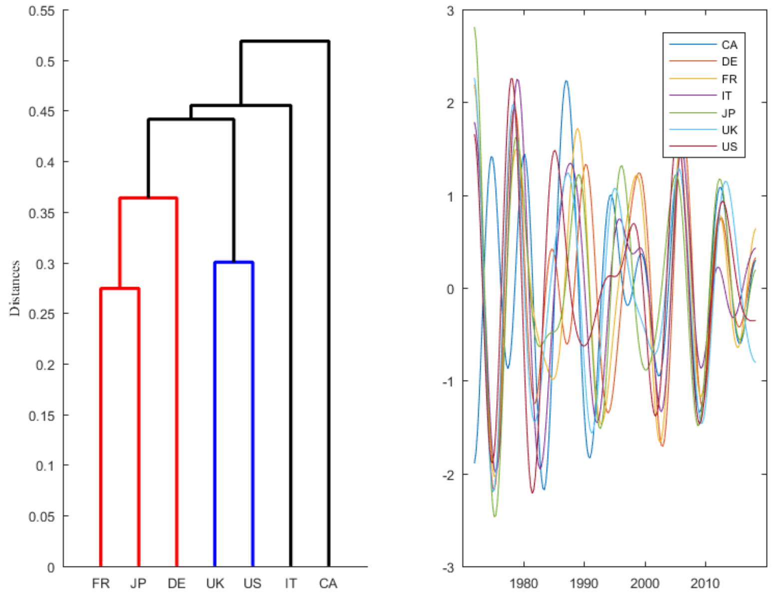
10-16 years



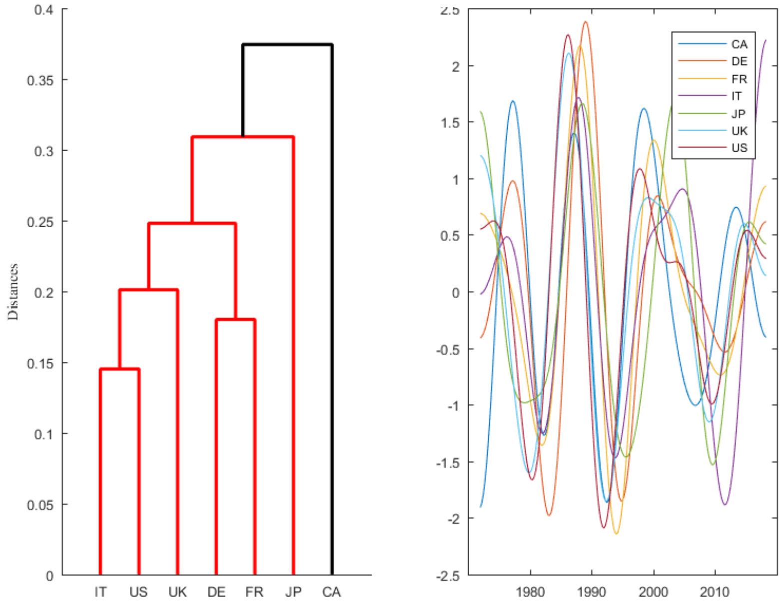
LHS: dendogram constructed from distance matrix of wavelet power spectra for indicated frequency range; colours indicate country clusters at the 10%-significance level, countries with black lines are not included in a cluster. RHS: filtered time series for indicated frequency range obtained from inverting the wavelet transformation.

Figure C8: Filtered cycles and dendogram for real GDP (YER) – full sample

6-10 years



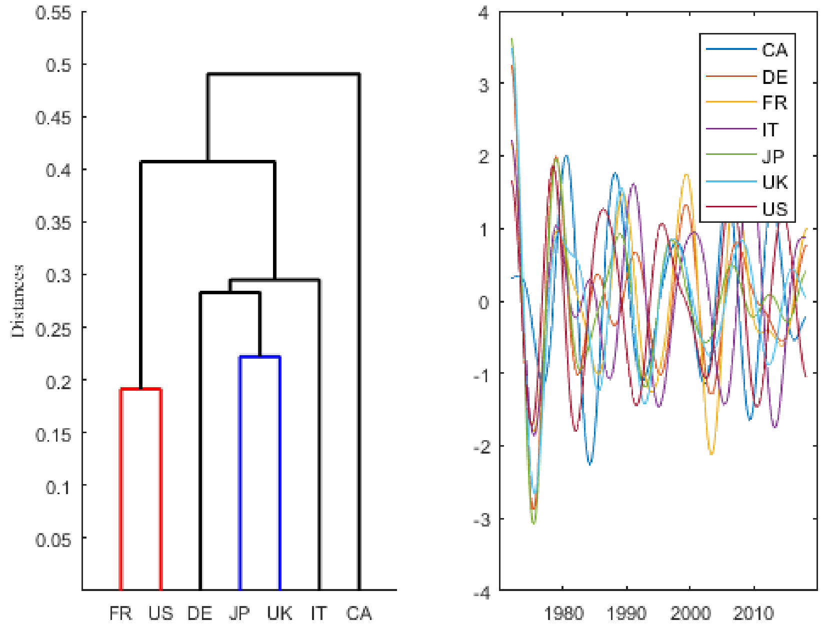
10-16 years



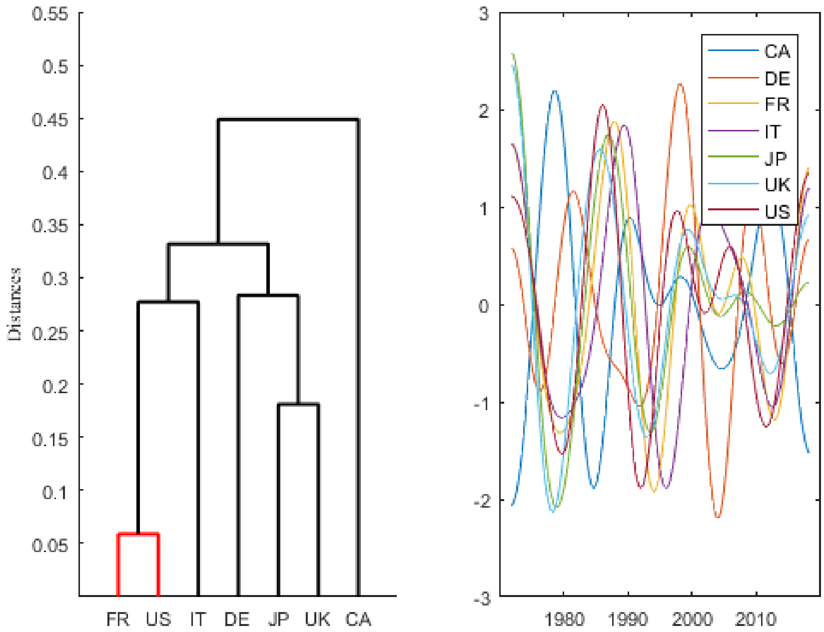
LHS: dendogram constructed from distance matrix of wavelet power spectra for indicated frequency range; colours indicate country clusters at the 10%-significance level, countries with black lines are not included in a cluster. RHS: filtered time series for indicated frequency range obtained from inverting the wavelet transformation.

Figure C9: Filtered cycles and dendogram for bank credit to the domestic non-financial private sector (BCN) – sample 1995Q1-2018Q2

6-10 years



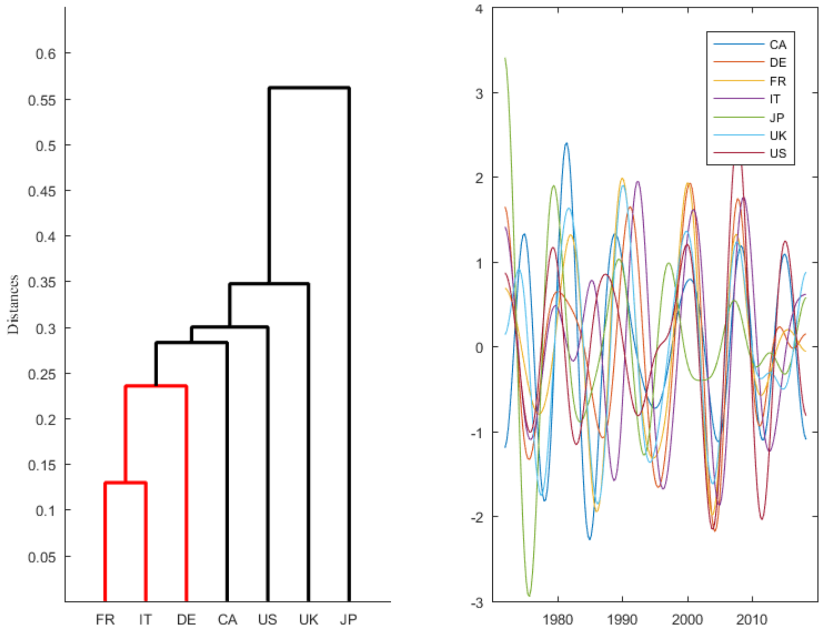
10-16 years



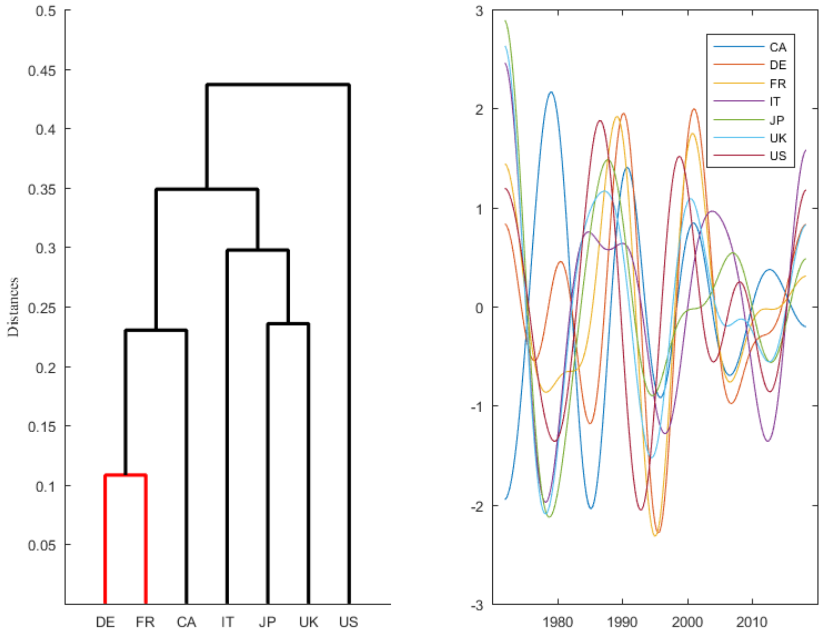
LHS: dendogram constructed from distance matrix of wavelet power spectra for indicated frequency range; colours indicate country clusters at the 10%-significance level, countries with black lines are not included in a cluster. RHS: filtered time series for indicated frequency range obtained from inverting the wavelet transformation.

Figure C10: Filtered cycles and dendogram for credit no non-financial corporations (CNF) – sample 1995Q1-2018Q2

6-10 years



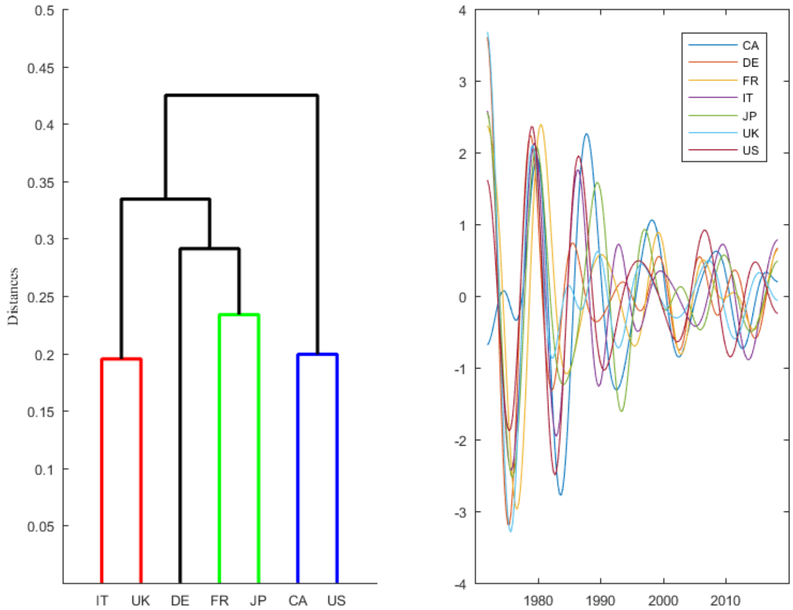
10-16 years



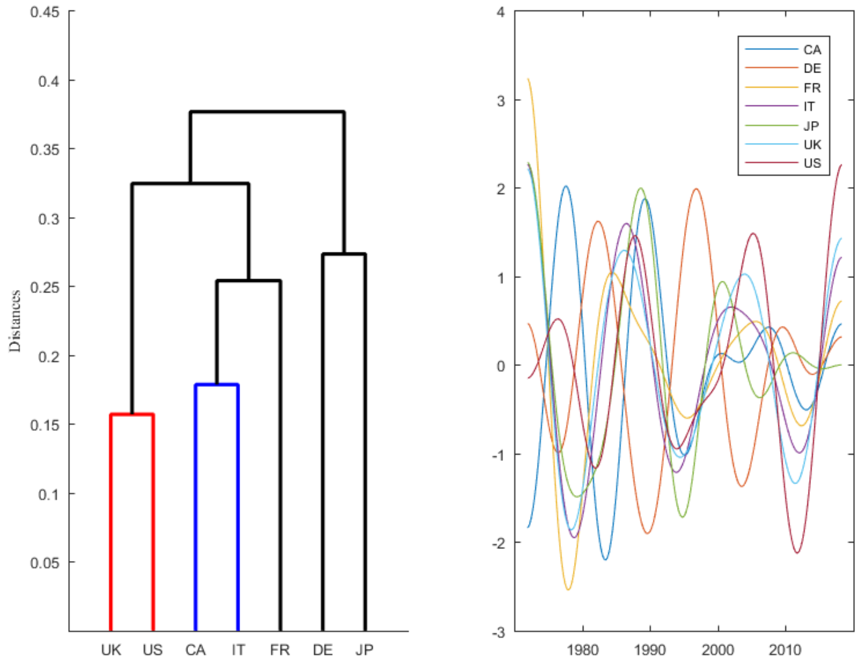
LHS: dendogram constructed from distance matrix of wavelet power spectra for indicated frequency range; colours indicate country clusters at the 10%-significance level, countries with black lines are not included in a cluster. RHS: filtered time series for indicated frequency range obtained from inverting the wavelet transformation.

Figure C11: Filtered cycles and dendogram for credit no households (CHH) – sample 1995Q1-2018Q2

6-10 years



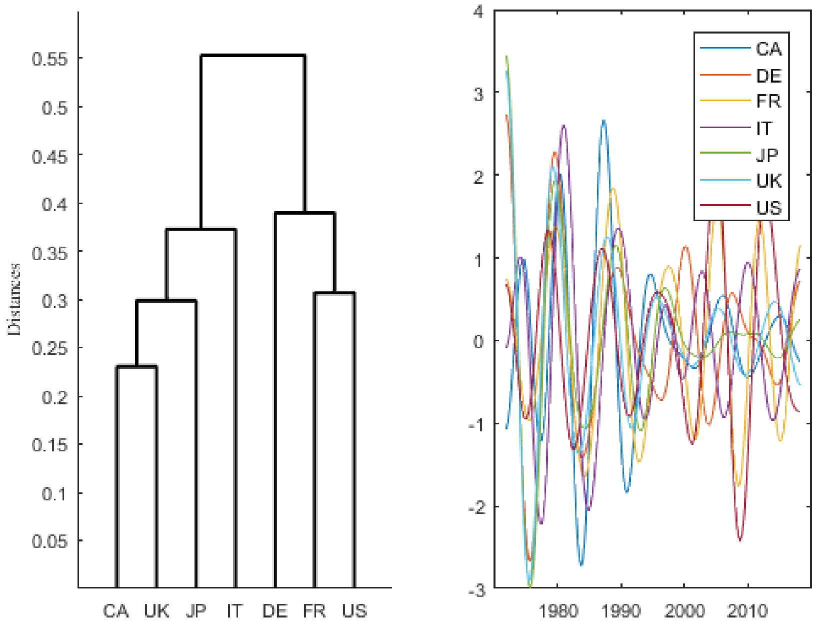
10-16 years



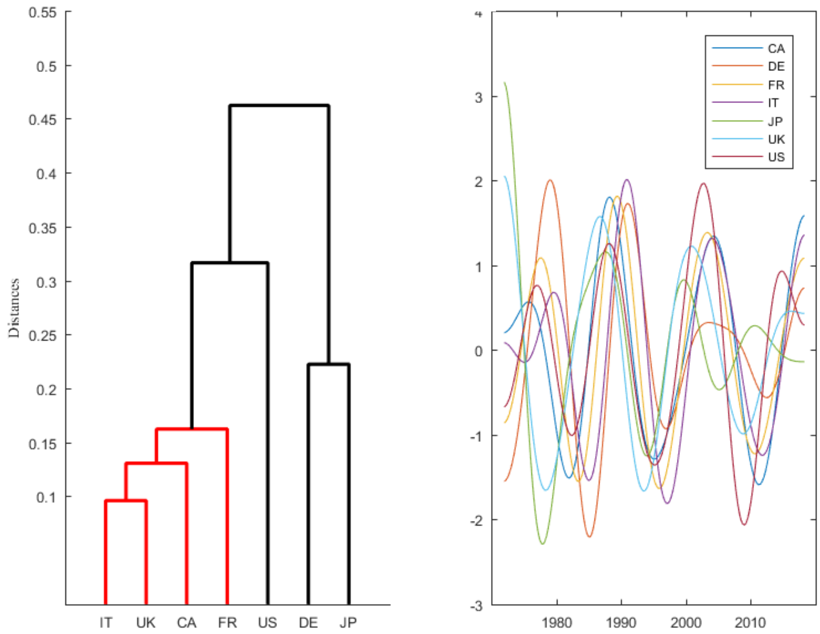
LHS: dendogram constructed from distance matrix of wavelet power spectra for indicated frequency range; colours indicate country clusters at the 10%-significance level, countries with black lines are not included in a cluster. RHS: filtered time series for indicated frequency range obtained from inverting the wavelet transformation.

Figure C12: Filtered cycles and dendogram for residential property prices (RPP) – sample 1995Q1-2018Q2

6-10 years



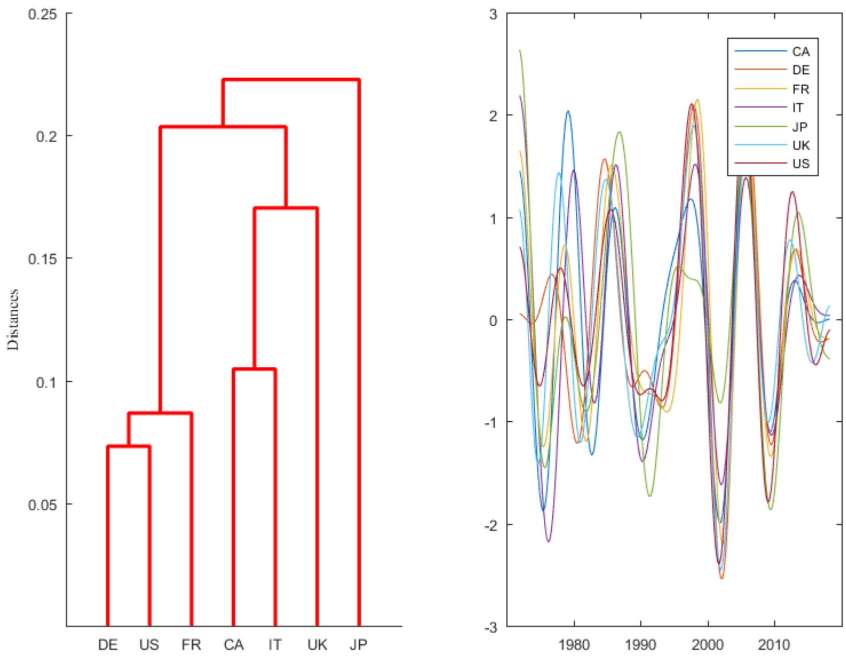
10-16 years



LHS: dendogram constructed from distance matrix of wavelet power spectra for indicated frequency range; colours indicate country clusters at the 10%-significance level, countries with black lines are not included in a cluster. RHS: filtered time series for indicated frequency range obtained from inverting the wavelet transformation.

Figure C13: Filtered cycles and dendogram for equity prices (EQP) – sample 1995Q1-2018Q2

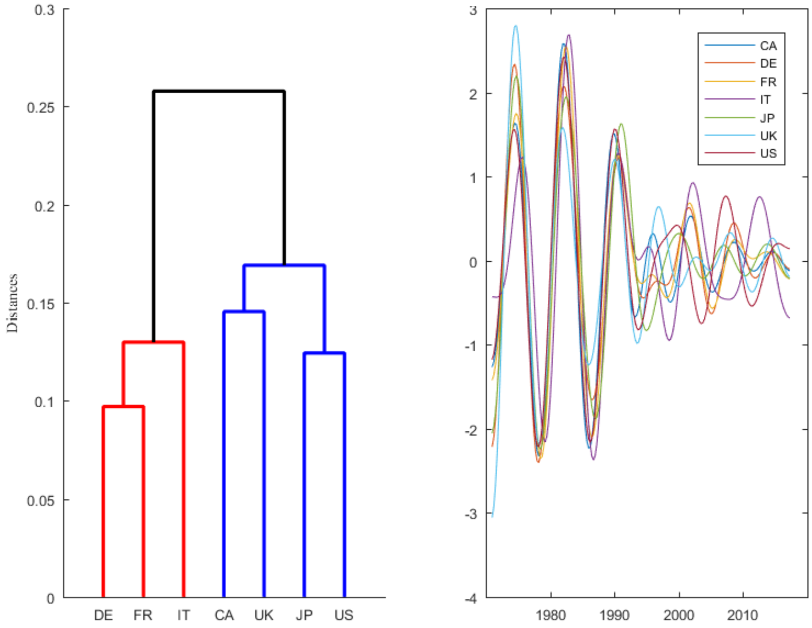
6-16 years



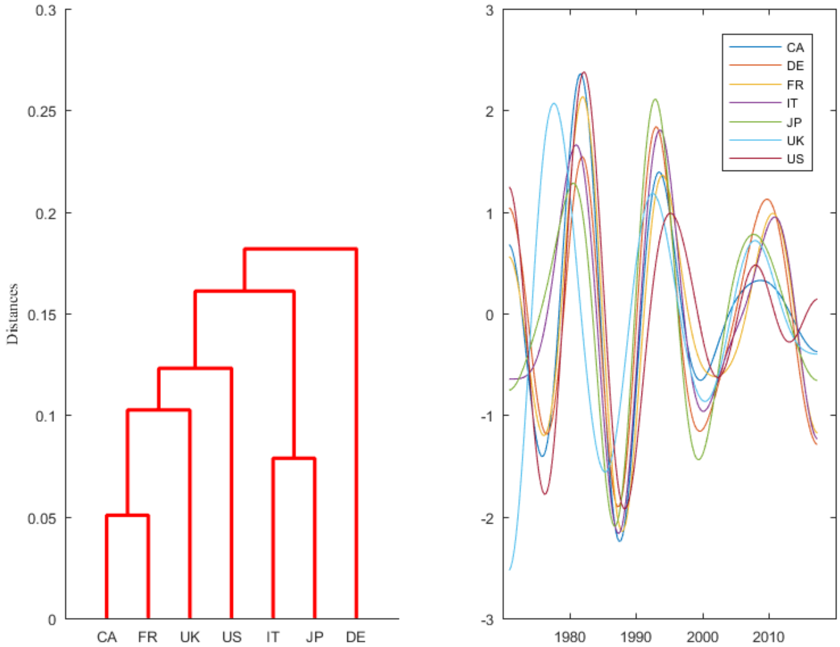
LHS: dendogram constructed from distance matrix of wavelet power spectra for indicated frequency range; colours indicate country clusters at the 10%-significance level, countries with black lines are not included in a cluster. RHS: filtered time series for indicated frequency range obtained from inverting the wavelet transformation.

Figure C14: Filtered cycles and dendogram for long-term interest rates (LTN) – sample 1995Q1-2018Q2

6-10 years



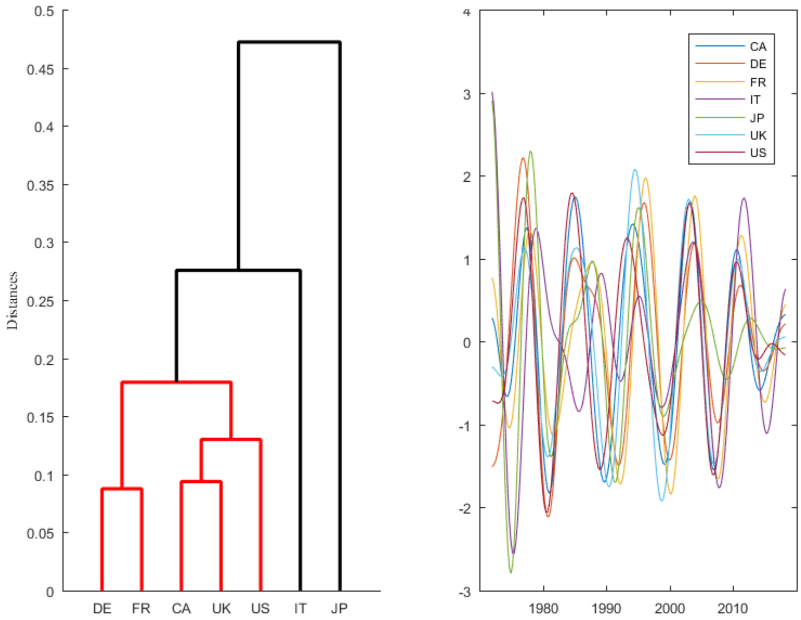
10-16 years



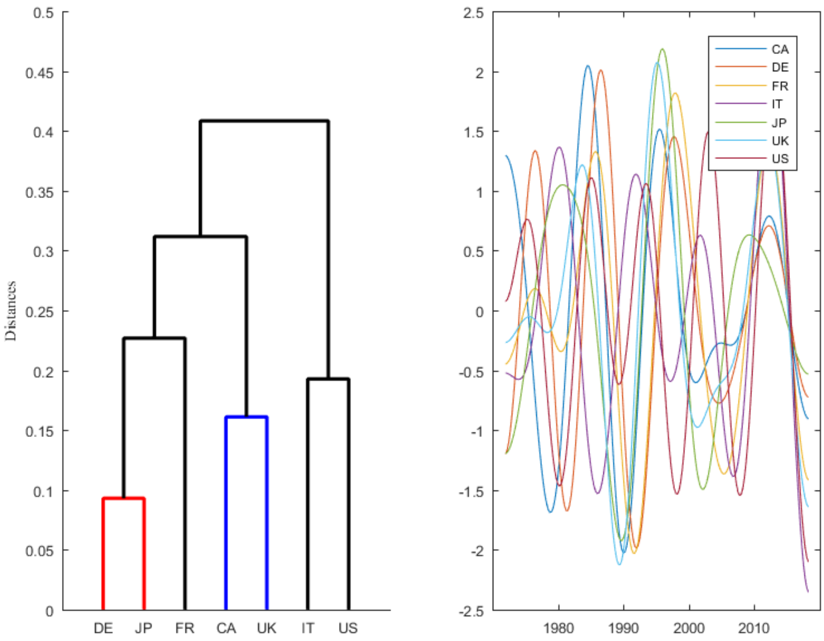
LHS: dendogram constructed from distance matrix of wavelet power spectra for indicated frequency range; **all countries are assigned to a single cluster**. RHS: filtered time series for indicated frequency range obtained from inverting the wavelet transformation.

Figure C15: Filtered cycles and dendogram for nominal term spread (SPN) – sample 1995Q1-2018Q2

6-10 years



10-16 years



LHS: dendogram constructed from distance matrix of wavelet power spectra for indicated frequency range; colours indicate country clusters at the 10%-significance level, countries with black lines are not included in a cluster. RHS: filtered time series for indicated frequency range obtained from inverting the wavelet transformation.