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Characterising the financial cycle: a multivariate and time-varying approach

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Abstract

We introduce a methodology to characterise financial cycles combining a novel multivariate spectral approach to identifying common cycle frequencies across a set of indicators, and a time varying aggregation emphasising systemic developments. The methodology is applied to 13 European Union countries as well a synthetic euro area aggregate, based on a quarterly dataset spanning 1970-2013. Results suggest that credit and asset prices share cyclical similarities, which, captured by a synthetic financial cycle, outperform the credit-to-GDP gap in predicting systemic banking crises on a horizon of up to three years. Financial cycles tend to be long, particularly in upswing phases and with important dispersion across country cases. Concordance of financial and business cycles is observed only $2/3$ of the time. While a similar degree of concordance for financial cycles is apparent across countries, heterogeneity is high – whereby a cluster of countries tends to exhibit a high synchronisation in their financial cycle phases.

Keywords: Financial cycle · Spectral analysis · Power cohesion · Macroprudential policy

JEL-**Codes**: E30 · E40 · C54

Non-technical summary

The recent global financial crisis provided a vivid illustration of the real effects of the materialisation of systemic risk that was related to a build-up of various macro-financial imbalances and vulnerabilities that can be related to excesses in the financial cycle.

Beyond enhancing financial system resilience, attenuating financial cycles is one of the two fundamental goals of macroprudential policy. Despite the prominence of this goal in macroprudential policy, there is no generally agreed definition of the financial cycle. Moreover, existing analyses on characterising financial cycles remain scarce, and are in many ways not yet suitable for policy use. Limitations include the geographic coverage of the analysis (in that it tends to focus on a limited number of countries) and a lack of consensus on the mechanics of measurement, such as the choice of indicators and the method used to construct them. Ideally, a unique synthetic measure of the financial cycle would summarise the (co-)movements over time of a range of financial sector variables, covering quantities and prices. In practice, however, over-reliance on a single composite measure is not advisable as each constituent variable contains relevant information for macroprudential policy-making.

Measuring financial cycles has become critical for macroprudential policymaking in the EU countries in the context of new macroprudential tools included in the European Union legislation, as well as due to the launch of the Single Supervisory Mechanism (SSM) with new macroprudential role for the European Central Bank (ECB). Thus, there is an urgent need to obtain a robust view on capturing financial cycles – balancing cross-country consistency with individual country relevance. However, as financial cycles are not directly observable, they must be inferred. Against this backdrop, we present a methodology aimed at furthering the basis for country-specific macroprudential policymaking.

More specifically, we suggest a methodological framework for capturing financial or, in general, economic cycles across a set of indicators, consisting of two main building blocks. First, a novel multivariate spectral measure of power cohesion is introduced. This method allows for discovery of common cycle frequencies across a set of indicators, on the basis of correlations of estimated (cross-)spectral densities. Second, a time-varying aggregation method is presented which allows for a unique composite cycle constructed from constituent indicators capturing economic fluctuations of a systemic nature.

The above method is applied to characterise and extract country financial cycles for 13 European

Union (EU) countries and a euro area aggregate for a quarterly dataset spanning 1970-2013. As indicators we employ series typically used in the growing body of literature to capture the financial cycle, which are total credit and measures for different asset markets (residential property prices and equity prices). We complete this set, i.e., the portfolio choice faced by economic agents, by including benchmark bond yields as a proxy for bond market pricing. To contrast the characteristics of financial and business cycles, we characterise business cycles applying the same methodology on a set of business cycle indicators, which are economic output, unemployment rate, consumer price inflation, and benchmark bond yields.

Our main empirical findings are threefold. First, credit and asset prices are marked by cyclical similarities. That is, credit, residential property prices, equity prices and – to a lesser extent – bond yields, exhibit common cycle frequencies, which, captured by a synthetic financial cycle, outperform the credit-to-GDP gap in predicting financial crises at a horizon of one to three years ahead. Second, financial cycles tend to be long, particularly in upswing phases. On average financial cycles last 7.2 years – though with important dispersion across countries. While financial cycles exhibit co-movement only $2/3$ of the time across the countries analysed, the co-movement of some EU country clusters is considerable – with the degree of co-movement among the six most synchronised financial cycles at 78% contrasting with 53% for the least synchronised one with the entire set of cycles. Third, country level financial cycles are not strongly aligned with their business cycle counterparts (67% on average).

Overall, results suggest a need for careful implementation of macroprudential policy, taking into account specificities in country level cycles, the possibility of cross-country co-movement of cycles, and the need for mapping of macroeconomic and macroprudential policies to potentially diverging economic and financial developments.

"The following definition seems to capture what experts refer to as the business cycle: The business cycle is the phenomenon of a number of important economic aggregates [...] being characterized by high pairwise coherences [...]. This definition captures the notion of the business cycle as being a condition symptomizing the common movements of a set of aggregates."

(Sargent, 1987, p. 282)

1 Introduction

Attenuating financial cycles is one of the main goals of macroprudential policy. Indeed, recent experience of euro area country stress, in a broader context of the global financial crisis, has vividly illustrated systemic risk inherent in the build-up and correction phases of ebullient financial cycles. At the same time, financial cycles remain considerably less studied than their business cycle counterparts, despite a rapid ongoing expansion of research. While previous studies on financial cycles have, in many ways, been seminal in establishing the literature on the empirical measurement of financial cycles, still many open questions remain; especially with respect to country characteristics relevant for applying macroprudential policies at the national level.

In this context, this paper addresses the following questions: i) Do credit and asset price indicators embed cyclical similarities which can be exploited to construct a notional composite financial cycle that helps in the prediction of financial crises? ii) What are the characteristics of financial cycles, and how do they differ across countries? iii) What is the relation of these financial cycles to business cycles?

To answer these questions, we propose a methodological framework for capturing financial and business cycles across a set of indicators, consisting of two main building blocks. First, a novel multivariate spectral measure of power cohesion is introduced. This method allows for discovery of common cycle frequencies across a set of indicators, on the basis of correlations of estimated (cross-)spectral densities. Second, a time-varying aggregation method is presented which allows for a unique composite cycle constructed from constituent indicators capturing fluctuations of a systemic nature.

The above method is applied to characterise and extract country financial cycles for 13 European Union (EU) countries and a euro area aggregate for a quarterly dataset spanning 1970-2013.[1] Country-specific financial cycle frequencies are captured by common contemporaneous cyclical movements of total credit and representative asset prices from all major market segments (property, equity, and bond), irrespective of phase differences, which in turn allow for extraction of country-specific financial cycles. To benchmark financial cycle characteristics, we compare specificities to

[1] The countries are Austria (AT), Belgium (BE), Germany (DE), Denmark (DK), Spain (ES), Finland (FI), France (FR), Ireland (IE), Italy (IT), the Netherlands (NL), Portugal (PT), Sweden (SE), and the United Kingdom (UK).

business cycles analogously derived from economic output, unemployment, consumer price inflation, and benchmark bond yields.

Our main empirical findings are threefold. First, credit and asset prices are indeed marked by cyclical similarities. That is, credit, residential property prices, equity prices and – to a lesser extent – bond yields, exhibit common cycle frequencies, which, captured by a synthetic financial cycle, outperform the credit-to-GDP gap in predicting systemic banking crises at a horizon of one to three years ahead and also enhance the predictability of crises for longer horizons. Second, financial cycles tend to be long, particularly in upswing phases. On average financial cycles last 7.2 years – though with important dispersion across countries; shortest being around four (AT and PT) and longest around 17 years (ES). Further, while financial cycles exhibit co-movement only $2/3$ of the time, such co-movement is quite considerable for many, but not all, of the countries analysed. Concordance among the six most synchronised financial cycles is 78% (BE, UK, SE, FI, ES, IE). Germany has the weakest link to cycles of other countries (53% on average). Third, country level financial cycles are not strongly aligned with their business cycle counterparts (67% on average), suggesting an important role for macroprudential policy.

The finding that financial cycles are generally longer than business cycles is consistent with the existing literature on financial cycles. Claessens et al. (2012), for a set of 43 countries and taking a cross-country perspective, find that financial cycles as separately measured by credit, house, and equity prices, are long and asymmetric. Focusing on measures of credit, Aikman et al. (2015) observe that, in contrast to business cycles, credit cycles have an important medium term dimension. Likewise, findings regarding the synchronisation of cycles and their relation to business cycles is in line with Breitung and Eickmeier (2014), Claessens et al. (2012), and Hiebert et al. (2014).

Our findings differ from the existing literature, however, in highlighting country specificities in cycle length as well as importance of individual contributing asset price series. While the aggregate findings regarding cycle length are broadly in line with previous research, our study suggests a need for caution in country attribution – given heterogeneity in features of underlying estimated country cycles. Indeed, while we find that financial cycles tend to be long, there exist important fluctuations at shorter cycles given asymmetries and irregularities of indicator cycles – contrasting with the finding by Drehmann et al. (2012) that financial cycles derived on the basis of credit and house prices are only characterised by fluctuations in the range of 8 to 30 years and last on average 16 years. In this way, there is the possibility of serious bias in extrapolating benchmark cycle estimates for a broader group of countries. The same holds true in considering relevance of individual financial series at the country level, whereby equity and bond markets share important common cycle characteristics with credit and residential property prices.[2]

[2]From a different perspective and with respect to equity, the cyclical importance of these markets, in addition to credit and property prices, stems from their role in presaging systemic crises – as emphasised by Claessens et al. (2012) or Schüler

The empirical findings of our study contribute to this recent strand of literature in several other ways. First, while previous research has suggested that cross-checking many indicators is important for characterising financial cycles, we provide a multivariate treatment. Second, we broaden asset prices used to characterise the financial cycle to encompass government bond markets (and not only property and equity), which constitute a major asset class, and, thus, completes the portfolio choice faced by economic agents. Third, we derive a composite indicator of financial cycles, one which allows for a time-varying importance of constituent indicators. In addition, given the preponderance of year on year transformations in previous studies (e.g. Drehmann et al. (2012)), we examine the implications of different transformations of financial and business cycle indicators for their spectral properties, which is vital to understand differences between cyclical fluctuations in the real economy versus the financial sector.[3]

The paper is organised as follows. Section 2 discusses methodology and Section 3 presents the application to European Union countries and the euro area aggregate. Section 4 concludes.

2 Methodology

Financial cycles are characterised by exploiting common movements of indicator series that pertain to the financial sector. The exposition of the methodology can be broken down into two main parts. First, we detail the spectral approach for obtaining country-specific financial cycle frequencies across a set of variables, which we call power cohesion. Second, a time-varying aggregation method for this set of variables to a unique composite financial cycle measure is described.

2.1 *Power cohesion - Discovering financial cycle frequencies across a set of indicators*

For identifying financial cycle frequencies common to a set of variables, we propose a novel multivariate spectral measure that we call power cohesion (PCoh). It can be formulated as

$$\mathrm{PCoh}_X(\omega) = \frac{1}{(M-1)M} \sum_{i \neq j} |f_{x_i x_j}(\omega)|, \tag{1}$$

where $1 \leq i \leq M, 1 \leq j \leq M, X = (X_1', \ldots, X_T')'$ is a $T \times M$ matrix and $X_t = (x_{1,t}, \ldots, x_{M,t})$ $(1 \times M)$. Further, $t = 1, \ldots, T$ and $M \geq 2$ reflect the time dimension and number of variables respectively, and $\omega \in [-\pi, \pi]$ denotes the cycle frequency. X_t is assumed to contain stationary stochastic processes with well-defined normalised cross spectral densities, which can be written as

$$f_{x_i x_j}(\omega) = \frac{s_{x_i x_j}(\omega)}{\sigma_{x_i}\sigma_{x_j}} = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \frac{\mathrm{Cov}[x_{i,t}, x_{j,t+k}]}{\sigma_{x_i}\sigma_{x_j}} e^{-\mathrm{i}k\omega}, \tag{2}$$

(2014), who show that recessions accompanied with equity market busts are more severe than without.

[3] See Appendix A.2.

where σ_{x_i} and σ_{x_j} are the standard deviations and $s_{x_i x_j}(\omega)$ is the cross-spectrum of $x_{i,t}$ and $x_{j,t}$. $\text{Cov}[x_{i,t}, x_{j,t+k}]$ reflects the cross-covariance between $x_{i,t}$ and $x_{j,t+k}$ and i is the imaginary unit.

Phase shifts of cycles across variables should in principle not alter a notion of frequency common to a set of variables. As such, they are discarded using PCoh by considering the absolute values of the cross-spectra. Recall that the cross-spectrum may be written as $s_{x_i x_j}(\omega) = c_{x_i x_j}(\omega) - \mathrm{i} q_{x_i x_j}(\omega)$, where the real part is captured by the co-spectrum $c_{x_i x_j}(\omega)$ and the imaginary part by the quadrature spectrum $q_{x_i x_j}(\omega)$. The real part describes the covariance in phase, whereas the imaginary part the one out of phase.[4] Using the modulus operation in Equation (1), we can see that

$$|f_{x_i x_j}(\omega)| = \frac{|s_{x_i x_j}(\omega)|}{\sigma_{x_i}\sigma_{x_j}} = \frac{\sqrt{c^2_{x_i x_j}(\omega) + q^2_{x_i x_j}(\omega)}}{\sigma_{x_i}\sigma_{x_j}}. \tag{3}$$

This implies that, using the PCoh methodology, both covariances (in phase and out of phase) are preserved.

Further, we use the normalised cross-spectral densities to construct our measure of power cohesion since the normalised measures are mapped into the same support which allows for a reasonable averaging of densities. That is, the support of PCoh(ω) when integrating from $-\pi$ to π lies within 0 and 1. Recall that the cross spectrum integrates to the unconditional covariance between $x_{i,t}$ and $x_{j,t}$ (see e.g. Hamilton (1994, p. 271)),

$$\int_{-\pi}^{\pi} s_{x_i x_j}(\omega) d\omega = \text{Cov}[x_{i,t}, x_{j,t}]. \tag{4}$$

From this it follows that

$$-1 \leq \int_{-\pi}^{\pi} f_{x_i x_j}(\omega) d\omega \leq 1. \tag{5}$$

Further, taking the absolute value of the normalised cross-spectrum, i.e., $|f_{x_i x_j}(\omega)|$ and integrating it from $-\pi$ to π leads to the support

$$0 \leq \int_{-\pi}^{\pi} |f_{x_i x_j}(\omega)| d\omega \leq 1. \tag{6}$$

The upper bound of 1 in Equation (6) holds as the covariance in phase and out of phase cannot exceed the product of the standard deviations of both variables.

Since the normalised cross-spectra indicate the contribution of different cycle lengths or frequencies to the overall co-variance, power cohesion depicts the importance of common fluctuations across cycle frequencies over a set of indicators. Of course, the importance given to each cross-spectrum, reflected by the weight used for averaging may vary; in our setup these are assumed to be equal (see Equation (1)) in order to be agnostic about the importance of specific indicators considered.

[4] Out of phase refers to cycles that are not contemporaneous. As a possible example consider two cosine waves that are identical, just that one is shifted by $\pi/2$. The usual correlation coefficient between the two series is zero, while the underlying cycles are the same.

Contrasting power cohesion with squared coherency cohesion

To better understand our proposed measure, we contrast power cohesion to cohesion derived from a comparable traditional measure of squared coherency. More specifically, we show that power cohesion should be preferred over the common spectral dependency measures if one is interested in detecting cycle frequencies that contribute most strongly to overall (co-)variance.

Squared coherency differs in that it relates the cross-spectrum to the auto-spectra at each frequency ω. Squared coherency is a textbook quantity, which has been used for researching on cyclical similarities of business cycles across countries (see, e.g., A'Hearn and Woitek (2001)) and has important parallels to other measures mentioned in the literature proposed for analysing cyclical similarities across variables, as cohesion based on dynamic correlation (see Croux et al. (2001)). Dynamic correlation similarly relates the co-spectrum to the autospectra at different frequencies and, thus, suffers from a similar disadvantage.[5] Let squared coherency cohesion be denoted by SCoh. It is defined as

$$\mathrm{SCoh}_X(\omega) = \frac{1}{(M-1)M} \sum_{i \neq j} \frac{|s_{x_i x_j}(\omega)|^2}{s_{x_i x_i}(\omega) s_{x_j x_j}(\omega)}. \tag{7}$$

SCoh(ω) of one, at frequency ω, indicates linear equivalence of processes and zero implies linear unrelatedness. As can be seen, squared coherency cohesion relates each cross-spectrum, $s_{x_i x_j}$, to the respective auto-spectra, $s_{x_i x_i}(\omega)$ and $s_{x_j x_j}(\omega)$, at frequency ω. On the other hand, power cohesion relates each cross-spectrum to the unconditional standard deviations, σ_{x_i} and σ_{x_j}. For power cohesion this implies that frequencies, which do not contribute to the average covariance are mitigated. On the contrary, in the case of squared coherency cohesion these frequencies may be emphasised. For detecting important cyclical fluctuations across a set of indicators this case has to be excluded and, thus, we argue power cohesion should be preferred.

To further clarify this point, consider the following data generating process (DGP):

$$x_{i,t} = \psi_{i,t} + \varepsilon_{i,t}, \tag{8}$$

which is characterised by a cyclical component

$$\psi_{i,t} = \alpha_{i,t} \cos(\lambda t). \tag{9}$$

$\alpha_{i,t}$ denotes a random amplitude, which may follow a stationary autoregressive process of order one, λ is the cycle frequency.[6] The idiosyncratic component, $\varepsilon_{i,t}$, is white noise with possible contemporaneous covariance.

[5] Dynamic correlation is defined as $c_{x_i x_j}(\omega)/(s_{x_i x_i}(\omega) s_{x_j x_j}(\omega))$. With this measure, the authors analyse the cohesion of business cycles in Europe and the US.

[6] A more realistic DGP would also include a phase shift of the cosine wave depending on i and t, however, as both PCoh as well as SCoh measure by definition cyclical fluctuations irrespective of phase shifts, we exclude this case for ease of exposition.

A common cycle is present if $\alpha_{i,t} = \gamma_i \alpha_t$, where γ_i is assumed to be some nonzero constant. Then, writing $\psi_t = \alpha_t \cos(\lambda t)$, $\gamma' = (\gamma_1, \ldots, \gamma_M)$, $\varepsilon'_t = (\varepsilon_{1,t}, \ldots, \varepsilon_{M,t})$, and stacking equations yields

$$X_t = \gamma \psi_t + \varepsilon_t. \tag{10}$$

Since ψ_t is uncorrelated with ε_t for all t and k, it follows that the spectrum of X_t is the sum of the two spectra of ψ_t and ε_t, i.e.,

$$s_X(\omega) = \gamma s_\psi(\omega)\gamma' + s_\varepsilon(\omega). \tag{11}$$

For this DGP SCoh can be written as

$$\text{SCoh}_X(\omega) = \frac{1}{(M-1)M} \sum_{i \neq j} \frac{|s_{x_i x_j}(\omega)|^2}{s_{x_i x_i}(\omega) s_{x_j x_j}(\omega)} \tag{12}$$

$$= \frac{1}{(M-1)M} \sum_{i \neq j} \frac{(\gamma_i \gamma_j s_\psi(\omega) + s_{\varepsilon_i \varepsilon_j}(\omega))^2}{(\gamma_i^2 s_\psi(\omega) + s_{\varepsilon_i \varepsilon_i}(\omega))(\gamma_j^2 s_\psi(\omega) + s_{\varepsilon_j \varepsilon_j}(\omega))} \tag{13}$$

To illustrate the important difference between power cohesion and squared coherence cohesion, two extreme cases are considered in the following: (1) The case of no white noise and (2) the case of perfectly correlated white noise. In the first case SCoh becomes:

$$\text{SCoh}_X(\omega) = \frac{1}{(M-1)M} \sum_{i \neq j} \frac{\gamma_i^2 \gamma_j^2 s_\psi^2(\omega)}{\gamma_i^2 \gamma_j^2 s_\psi^2(\omega)} = 1 \tag{14}$$

The last equality holds as, due to the random amplitude α_t, $s_\psi(\omega)$ has nonzero power for all frequencies. The result implies that SCoh cannot be used to detect the common cycle, as SCoh indicates a one for all frequencies. In contrast, PCoh captures the common cycle, since it does not relate the cross-spectra to the autospectra.

Adding white noise to $\psi_{i,t}$ induces a trade-off between variances, i.e., if the white noise process has greater variance contribution at each frequency then $\psi_{i,t}$, the common cycle, will not be apparent using any of the two measures, PCoh or SCoh. In case it is smaller, the capturing of the cycle in case of SCoh depends on the correlation between the noise components, $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$. This can be noted by considering case (2). It implies that $s_{\varepsilon_i \varepsilon_j}(\omega) = s_{\varepsilon_i \varepsilon_i}(\omega) = s_\varepsilon(\omega)$ and yields

$$\text{SCoh}_X(\omega) = \frac{1}{(M-1)M} \sum_{i \neq j} \frac{(\gamma_i \gamma_j s_\psi(\omega) + s_\varepsilon(\omega))^2}{(\gamma_i^2 s_\psi(\omega) + s_\varepsilon(\omega))(\gamma_j^2 s_\psi(\omega) + s_\varepsilon(\omega))} \tag{15}$$

$$\lim_{s_\psi(\omega \neq \lambda) \to 0} \text{SCoh}_X(\omega \neq \lambda) = 1 \tag{16}$$

Thus, even in situations in which the white noise spectrum has a relatively small contribution to the overall variance of the process, but is highly correlated, SCoh potentially does not capture a common cycle. This result implies that if another common cycle with lower variance contribution is present, it receives the same importance as the cycle with greater variance contribution. Contrarily, PCoh reports cycles relative to their variance contribution. Note that this type of misleading conclusion can also arise if spectra are close to zero, which may follow as a consequence of overdifferencing or seasonal adjustment.

The use of power cohesion

Power cohesion serves the purpose of identifying most important financial cycle frequencies. In this paper we follow three different ways for locating these frequencies:

First, we identify the peak to locate the cycle lengths of maximum co-movement of indicators capturing financial cycles, building on A'Hearn and Woitek (2001) who identify peaks of single spectra in the context of business cycles. This identification of a peak is not necessarily consistent with average cycle length in the presence of strong asymmetries and irregularities in variables capturing financial cycles.

Second, a window of cycle frequencies around the above peak to capture a certain percentage of most important co-movements is specified. We use this range to filter the composite financial cycle and its underlying indicators. Since the major characteristics of financial cycles are less established than the ones of business cycles, we argue that the choice of percentage range around an estimated peak is preferable to an exogenously fixed frequency window for band-pass filtering such as that assumed in existing studies (e.g., Drehmann et al. (2012)).

Third, we identify a *highest density region* in the spirit of Hyndman (1996), that is especially appropriate for summarising multimodal distributions. We report this highest density region in Section 3.2 and use it to compare characteristics of financial and business cycles. We do not use it for filtering the composite cycle, as highest density regions cannot always be summarised by one continuous range. That is, highest density regions do not necessarily overlap.

Empirical issues

We estimate the (cross-)spectral densities through cross-correlations. Further, a Parzen window with a bandwidth of $\sqrt{T} \cdot 5$ is used, which compared to the bandwidth used in Aikman et al. (2015) is slightly larger and emphasises our aim to have rather unbiased spectral density estimates; at the cost of a higher variance. As is common, we only consider the frequency window 0 to π, which suffices to determine the cyclical properties of variables when considering the absolute value of the spectral densities.

Confidence intervals for spectral densities are bootstrapped (see Figure 15). As suggested in Croux et al. (2001) and described in Franke and Härdle (1992) as well as in Berkowitz and Diebold (1998), we bootstrap the individual (cross-)spectra, rather than the time series. For each cross-spectrum we resample from a χ^2_2-distribution using 5000 replications and use a Gaussian kernel for smoothing each periodogram.[7]

We calibrate the frequency window around the peak of power cohesion using available knowledge on business cycles. First and as is standard in the literature on turning points, we require that the minimum cycle length considered is 5 quarters and the maximum cycle length remains unrestricted. Not restricting the maximum cycle length may lead to ultra long cycles or trends being included in the final frequency window. However, we ascertain stationarity of indicators and, thus, argue not to capture trend components; further, given that very long cycles are imprecisely estimated and filtered using spectral methods, upper limits should be interpreted with care.[8] Second, capturing 2/3 of total co-movements across indicators leads to frequency windows for business cycle indicators for which the median of the highest frequencies is around 2 years, which is often used as an input to band pass filters when smoothing business cycle indicators.

Specifically, we propose to endogenously select a frequency window by determining the maximum (ω_1) and minimum (ω_2) cycle lengths ($\omega_2, \omega_1 \in [0, 2\pi/5] \wedge \omega_2 \geq \omega_1$) through

$$\min_{\omega_2 - \omega_1} \frac{\int_{\omega_1}^{\omega_2} \text{PCoh}_X(\omega) d\omega}{\int_0^{\pi} \text{PCoh}_X(\omega) d\omega} \geq p. \tag{17}$$

where p is defined to be in the range [0,1], such that the frequency band contains $p \cdot 100\%$ of common variation excluding variation with a frequency below 1.25 year.[9] In our setup we assume $p = 2/3$. By finding the maximum and minimum cycle length that minimises the distance $\omega_2 - \omega_1$, we assure to pick the most important common fluctuations across indicators around the peak.

At last, the frequency window, which we identify, serves as an input to the asymmetric specification of the band pass filter proposed by Christiano and Fitzgerald (2003) when smoothing composite financial cycles as well as individual series. In applying the band pass filter, we elect for the specification that does not correct for unit roots or drifts/time trends in the variables in order to keep distorting effects of the filter to a minimum. To minimise endpoint problems, we forecast the composite index as well as the indicators 10 years ahead using an AR(p) process with intercept where the maximum lag length is set to 8 and the optimal number is selected via BIC. To further minimise endpoint problems we fit the obtained filtered series optimally to the unfiltered series by transforming its mean and variance such that squared deviations are minimised.

[7] This bootstrapping procedure assumes independence of cross-spectra, however, to the best knowledge of the authors, research in this area is still ongoing and no solution for this exact problem has been proposed.

[8] We conduct a robustness analysis using the duration of Kondratiev waves as a maximum cycle length, which is 50 to 60 years. Excluding cycles of longer duration yields equivalent results. Findings are available from the authors upon request.

[9] An unrestricted range would select ultra-high frequencies, which can be related to the high amplification that occurs using the quarter-on-quarter filter.

2.2 *Time-varying aggregation of indicators – Constructing a composite index of the financial cycle*

The combination of indicators to a composite synthetic financial cycle is obtained through time-varying aggregation weights that exploit changing correlation structures between indicators. We restrict time-varying weights to emphasise alike (and therefore systemic) developments in the system.

Our approach is related to the methodology followed by Holló et al. (2012) for constructing an indicator of systemic financial stress. Apart from its advantage of time-varying weights in aggregation, it emphasises robustness properties; also related to real-time updating.[10]

In a first step, we pre-multiply indicators such that a rise in each contributing variable relates to an upswing of the final composite index.

In a second step and following Holló et al. (2012), we transform underlying indicators using their empirical distribution function, i.e., each value of a single indicator is mapped into a unit free ordinal scale in (0,1].

Third, we linearly combine indicators using time-varying weights, that exploit time-varying correlations between indicator pairs. In capturing cyclical swings to construct a macroprudential notion of the cycle, we would like to emphasise directional developments of a systemic nature, or put differently, movements of a set of indicators that are in a similar direction, i.e., indicators that are positively correlated. In a situation in which there is a lack of models to describe the build-up of imbalances in the financial sector our procedure reflects an easy and tangible possibility. Technically we achieve this by restricting correlations to be positive; negative correlations are assumed to be zero. While all series enter the final index by construction, it implies that movements of positively related series are emphasised.[11]

More specifically, let $(x_{i,[1]}, x_{i,[2]}, \ldots, x_{i,[T]})$ denote the ordered sample of variable $x_{i,t}$. The transformed indicators are derived by

[10] One alternative approach for aggregating common information contained in several variables is through principal component analysis. This approach has, however, at least two drawbacks. First, cross-country comparability issues arise due to a possible different selection of indicators across countries that explain most important contemporaneous movements. Second, real-time updating is an issue in that new data points might alter the selection of indicators most relevant for common fluctuations. Indeed, a principal component analysis is static by definition and thus does not allow for capturing changing trends in the interdependence between financial indicators.

[11] To illustrate, consider the case of three indicators: if two of the series remain above (or below) their historical medians and the third series is located below (or above) for an extended period of time, using our method, the final signal tends to reflect the location of the first two series, since the third series is negatively related and negative correlations are assumed to be zero. As a consequence, the overall aggregation weight of the third series is lower relative to the first two; but still larger than zero. Employing unrestricted correlations, negative and positive correlations would cancel each other out and the aggregation would be similar to a simple average. In this case, the location of the financial cycle would not emphasise the build-up or correction of imbalances. Especially, for an early detection of imbalances or corrections visible in the majority of indicators, we argue that our approach is the more favourable one.

$$y_{i,t} = F_{i,T}(x_{i,t}) = \begin{cases} \frac{r}{T} & \text{for } x_{i,[r]} \leq x_{i,t} < x_{i,[r+1]}, \quad r = 1, 2, \ldots, T-1 \\ 1 & \text{for } x_{i,t} \geq x_{i,[T]}, \end{cases} \tag{18}$$

where $F_{i,T}$ denotes the empirical cdf. Let $Y_t = (y_{1,t}, \ldots, y_{M,t})$ and ι be a vector of ones of dimension $1 \times M$. The single transformed indicators are aggregated in the following way

$$\zeta_t = \frac{1}{\iota' C_t \iota} \cdot \iota' C_t Y_t',$$

where C_t is the time-varying cross-correlations matrix, i.e., the typical element of C_t, c_{ij}, is $\rho_{ij,t} = \sigma_{ij,t}/(\sqrt{\sigma_{ii,t}\sigma_{jj,t}})$. We follow Holló et al. (2012), who propose to obtain the time-varying cross correlations on the basis of an exponentially-weighted moving average process, where

$$\sigma_{ij,t} = \lambda \sigma_{ij,t-1} + (1-\lambda)(y_{i,t} - 0.5)(y_{j,t} - 0.5). \tag{19}$$

In this setup the transformed variables $y_{i,t}$ are centered using the median and λ represents the decay factor. Due to the aggregation method $\zeta_t \in (0, 1]$ as well. ζ_t is then called the unfiltered composite indicator.

Updating ζ_t, similarly to Holló et al. (2012), is done by applying Equation (18) recursively over expanding samples, i.e., "old" observations are fixed and new ones are added to the existing distribution.

Time-varying correlations are modelled using a decay factor λ of 0.89. This is slightly smaller than in Holló et al. (2012), who use 0.93. We employ a smaller decay factor since we have quarterly (instead of daily) data with, thus, fewer observations. Using 0.89 starting conditions become negligible at a faster rate. Further, covariances are initialised using the first 8 quarters of observations for each variable.

3 Application: European financial cycles

This section contains an application of the methodology to a set of European Union countries. After an exposition on data, their transformations, and descriptives on spectral properties, the application of the methodology mirrors the two steps described in Section 2. First, the selection of financial cycle frequencies using power cohesion is detailed and, second, results for the composite indicators of European financial cycles are presented.

3.1 Data, transformations, and summary of cross-spectra

Data and transformations

Absent a single summary measure for the state of the financial sector, we argue that a multivariate approach that relies on a range of macro-financial indicators provides the best-suited method for obtaining a financial cycle estimate.

In conceptualising the determinants of the financial cycle suitable for macroprudential analysis, we elect for a set of explanatory variables which build on the traditional set contributing to the build-up and propagation of systemic risk. Studies to date have focused predominantly on various measures of credit (generally transformations of total or bank based credit, either in changes in credit or ratios to GDP), as well as prices for a subset of non-financial sector balance sheet assets (real estate and equity). Indeed, the choice of these variables can be thought of as corresponding to systemic externalities underpinning the cycle such as those outlined in Claessens (2014) – that is, the scope for strategic complementarities in asset allocations in financial cycle upswings as well as fire sale potential for asset prices in cyclical downswings. At the same time, leverage (captured, for instance, by the simple proxy of broad credit for which long time series of country data are available) plays a key role in systemic risk propagation, the operationalisation of systemic risk monitoring (see, for instance, European Systemic Risk Board (2014)). To include all main asset markets in our measure of a synthetic financial cycle, we amend this set of variables by benchmark government bond yields.

Thus, estimation is based on a parsimonious set of four variables relevant for the financial cycle – measuring credit, as well as prices in the main asset market segments (house prices, equity prices and benchmark government bond yields). Further, we construct our measure of a reference business cycle through indicators on economic activity (real GDP), labour markets (unemployment rate), consumer price inflation, and the government benchmark bond yields as an available proxy for the price of intertemporal substitution of real variables such as consumption and investment. The above variables draw from a dataset covering 13 EU countries (AT, BE, DE, DK, ES, FI, FR, IE, IT, NL, PT, SE, and UK) and the euro area aggregate, at a quarterly frequency spanning from 1970Q1 until 2013Q4.[12] Variables are expressed in real terms (with the only exception of the unemployment rate). Long term yields on government bonds are adjusted for inflation, i.e., they reflect real long term yields.

In this study, we analyse cycles in growth rates, rather than classical cycles or growth cycles (Harding and Pagan (2005)). So as to preserve cyclical turning points, a quarter-on-quarter differencing is implemented – in keeping with the well-established NBER methodology (and CEPR in Europe) for identifying peaks and troughs of the business cycle on the basis of quarterly changes in GDP. Thus, total credit, house prices, equity prices, and GDP are measured in quarterly growth rates. bond yields, unemployment, and inflation reflect quarterly percentage point changes. The exact details on the vari-

[12] Starting dates vary for BE and FI (1970Q4), ES (1971Q1), IE (1971Q2), AT (1986Q3), EA (1987Q1), and PT (1988Q1).

ables and their unit root properties are provided in Appendix A.1.[13] Note that cycles identified by Drehmann et al. (2012) are recovered from annual growth rates – however, this transformation lacks precision for identifying turning points. We contrast the implications of both year on year (yoy) and quarter-on-quarter (qoq) transformations for the resulting spectral properties in Appendix A.2.[14]

Table 1: Pre-multiplication of indicators: Financial cycle and business cycle index

Financial Cycle				Business Cycle			
Δc	Δp_h	Δp_e	Δr	Δq	Δu	$\Delta \pi_p$	Δr
$\times$	$\times$	$\times$	$-$	$\times$	$-$	$\times$	$-$

Notes: $-$ indicates that indicators have been multiplied by -1 before applying the transformation from Equation (18). $\times$ denotes no pre-multiplication. Δc refers to percentage changes in total credit, Δp_h to percentage changes in house prices, Δp_e to percentage changes in equity prices, Δr to percentage point changes in bond yields, Δq to percentage changes in GDP, Δu to percentage point changes of the unemployment rate, and $\Delta \pi_p$ to percentage point changes in inflation.

For deriving the composite indices, two further transformations are carried out. First, variables are pre-multiplied to ensure that increases in their values correspond to an improvement of financial conditions. For the financial cycle, this implies a pre-multiplication of benchmark government bond yields by -1. An analogous pre-multiplication is also conducted for those business cycle indicators which negatively relate to improving economic conditions, i.e. the unemployment rate in addition to the bond yield – see Table 1 summarising all such restrictions. Second, indicators are transformed using their ecdf-function as mentioned in Section 2.2 - thereby mapping series to a $0/0.5/1$ scale.

Summary of cross-spectra

Figure 1 shows absolute cross-spectra across countries that are normalised, such that the maximum value is one. Solid blue lines denote the median, lower dashed lines portray the 10th percentile and the upper ones the 90th percentile. A small distance between the two dashed lines indicates that that the cyclical properties of the respective indicator at that frequency is similar across countries, while a long distance refers to the case where properties differ strongly.

The results indicate that there are strong cyclical commonalities between credit, house prices, and equity prices for medium term frequencies that range between 8 and 20 years, that are consistent over country cases, which can be seen by the relative small distance between the dashed lines. Considering pairs involving bond yields, the evidence is not as strong, however, in the case of credit and house prices, still, there are most important cycles located in the medium term region as the distribution is most elevated compared to other part of the distribution. Co-movement of equity prices and bond

[13] Note that for ES and IE industrial production is employed. Details are provided in Appendix A.1.

[14] Summarising the results of this exercise, we draw the conclusion that the annual transformation removes the higher frequency cycles, while the quarterly transformation emphasises them. Importantly, this does not change the relative significance of longer term cycles in the case of financial indicators; however it does for the business cycle ones, i.e., transformation of indicators matter for the business cycle but not for the financial cycle. In contrast to financial cycle indicators, business cycle indicators have important variance located at short term frequencies, which vanish using the yoy filter.

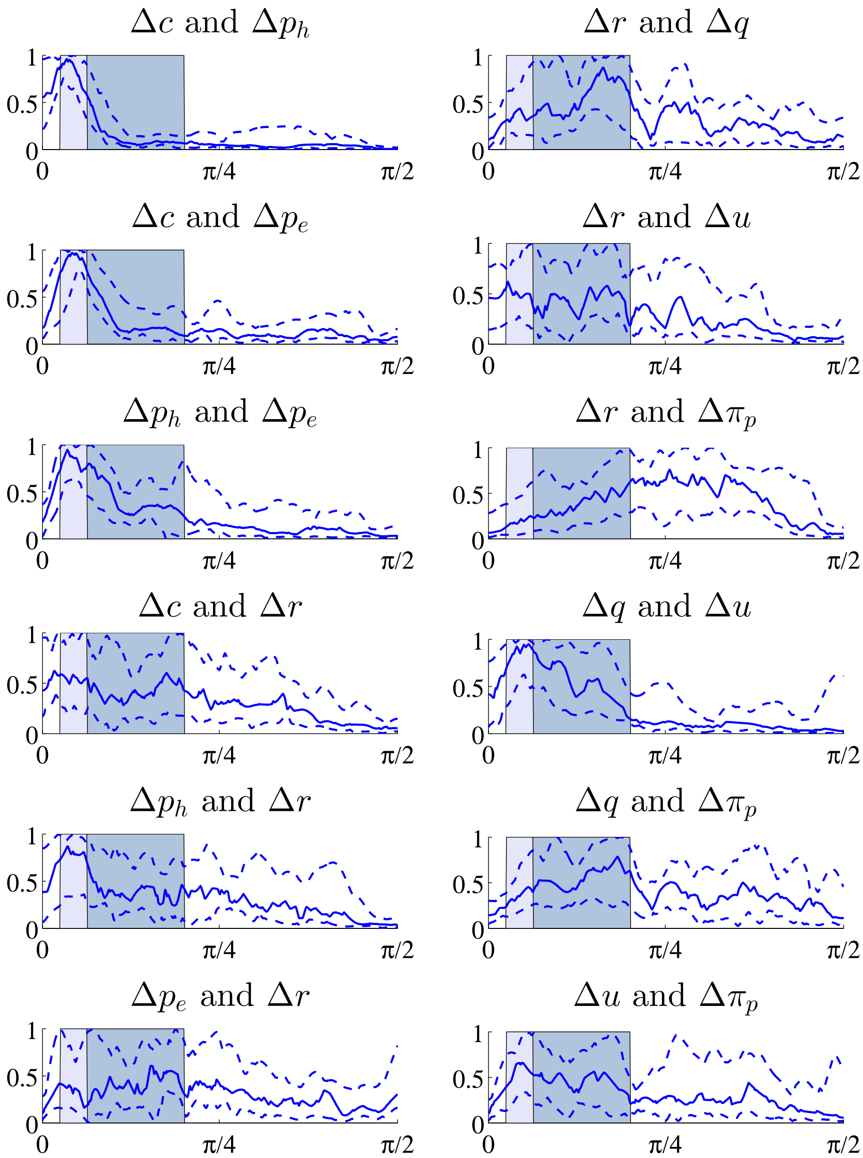


Figure 1: Absolute normalised cross-spectra of indicators across countries

Notes: This panel shows the absolute and normalised cross-spectra of the financial and business cycle indicators. The x-axis measures the frequencies of cycles in radians from 0 - $\pi/2$. The blue area depicts business cycle frequencies, i.e., cycles with durations of 2.5-8 years and the purple area marks medium term cycles (8-20 years). Δc refers to percentage changes in total credit, Δp_h to percentage changes in house prices, Δp_e to percentage changes in equity prices, Δr to percentage point changes in bond yields, Δq to percentage changes in GDP, Δu to percentage point changes of the unemployment rate, and $\Delta \pi_p$ to percentage point changes in inflation.

yields are most important over short term cycles that range within 2.5 to 8 years. Considering the respective univariate spectra (see Figure 13 in Appendix A.2), we note that for credit and house prices the highest amount of variance is also located in the medium term where most co-movement is located. Equity prices have the greatest amount of variance at cycles exactly around 8 years, i.e., at the border of short and medium term. Cycles contributing strongest to the overall variance of bond yields are located around 2.5 years, while part of the variable's variance can also be allocated to medium term frequencies.

The cross-spectra on business cycles suggest that most important co-movements are located in the short term when compared to the medium term, except for unemployment and GDP, in which case cycles are located in the region around 8 years. Bond yields and inflation have most important common fluctuations located at cycles shorter than 2.5 years. Again comparing cycle frequencies to the variables' variances (see Figure 13 in Appendix A.2), bond yields, GDP, and the unemployment rate have important cycles in the short term, while unemployment has more important cycles at the medium term. For GDP medium and short term cycles seem to be equally important. Inflation, however, has most variance located at movements of duration below one year.

Thus, while credit, house prices, and equity prices share cyclical frequencies that explain much of their individual overall variances, benchmark bond yields exhibit a medium term component less important relative to their overall variance. As cyclical fluctuations in benchmark bond yields are, in this way, attributable to both shorter and medium term frequencies, it can be justified that such an indicator might be relevant for both (longer frequency) financial and (shorter frequency) business cycles. In the case of business cycle indicators most important co-movement is located in the short term, while, still, some medium term cycles exist. At last, in contrast to all pairs, credit, house prices, and equity prices have the strongest agreement of cyclical fluctuations across countries as indicated by the short distance between the dashed lines.

3.2 Selecting financial cycle frequencies through power cohesion

Figure 2 shows power cohesion for the financial and business cycle indicators for the euro area. It suggests that co-movement of financial indicators is higher for financial cycle indicators in the medium term than for business cycle variables, as, first, the peak of power cohesion is located in the purple region, while for the business cycle it is not; second, the distribution of power cohesion in this frequency region is above the one of power cohesion for business cycle indicators.

Across countries and again compared to business cycles (see Figure 3), we find that financial cycles have homogeneously an important medium term cyclical component, which is on average 1.94 times relatively more important (see Table 2); in 11 out of 13 country cases the most important cycle even falls into the medium term range of 8 to 20 years (see purple region in Figure 3). In the case of business cycles, all country cases are characterised by important short run fluctuations; in 9 out of 13 country cases the most important cycle is shorter than 8 years. However, as suggested in the literature (e.g., Comin and Gertler (2006) or A'Hearn and Woitek (2001)), we also find in more than half of the country cases important fluctuations in the medium term.

The frequency windows identified using power cohesion cover short run as well as medium term

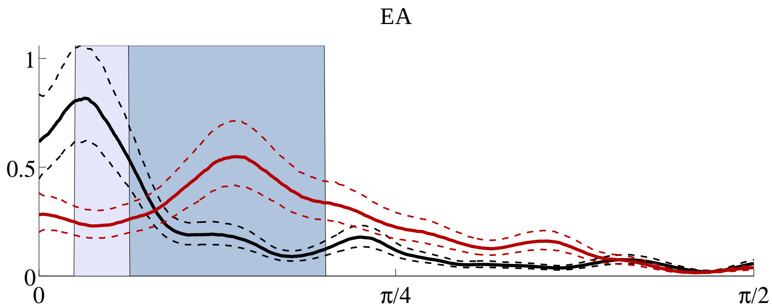


Figure 2: Power cohesion of financial (black) and business (red) cycle indicators for the euro area
Notes: This graph shows the power cohesion of the financial (black lines) and business cycle indicators (red lines). The dashed lines indicate the 68% bootstrapped confidence intervals. The x-axis measures the frequencies of cycles in radians from 0 to $\pi/2$. The blue area depicts business cycle frequencies, i.e., cycles with durations of 2.5-8 years and the purple area marks medium term cycles (8-20 years).

fluctuations for both financial and business cycle indicators (see Table 2). In the case of financial cycles, however, this window tends to cover lower frequencies.

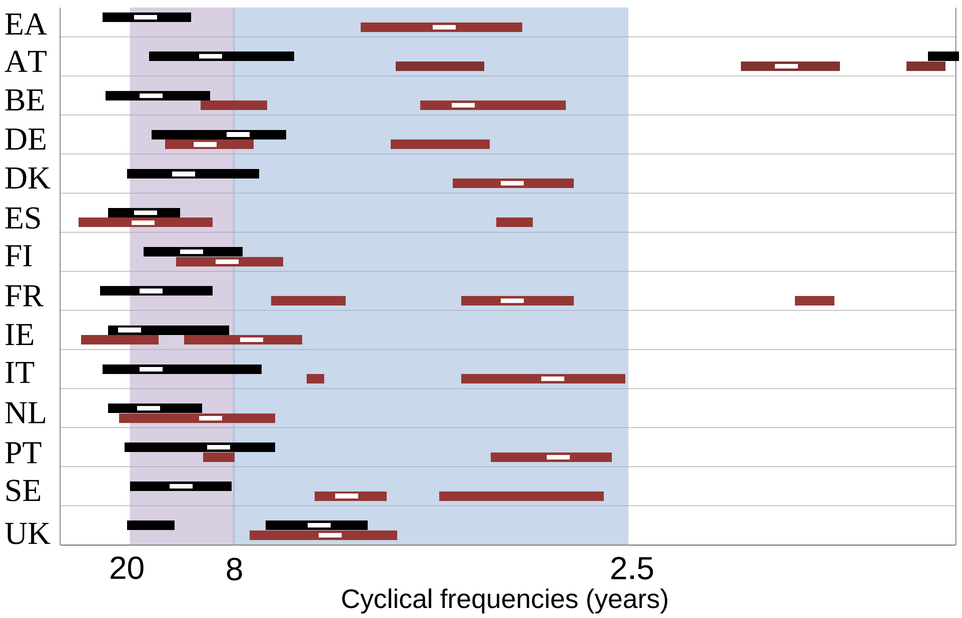


Figure 3: Highest density graph of power cohesion of financial (black) and business (red) cycle indicators
Notes: This graph depicts the 25% highest density region of power cohesion excluding cycles lower than 5 quarters for financial and business cycle indicators. The purple region marks medium term frequencies, i.e, in the range of 8 to 20 years, while the blue area short term fluctuations, i.e., 2.5 to 8 years. The white dash locates the peak of power cohesion.

The peak estimate of power cohesion for the financial indicators reveals that most important cycles range from 20.5 to 5.4 years. The median cycle is 11.6 (SE) and average 12.7 years indicating a relatively symmetric distribution of cycle length peaks across countries, which however is quite dispersed with a standard deviation of 4.2 years. There is a group of countries that has a relatively long most important cycle which is in the range of 20.5 and 15.5 years (IE, ES, NL, BE, FR, IT). DK is found to be slightly shorter than SE with 11.4 years. FI (10.7 years), AT (9.3 years), PT (8.8 years), and DE (7.9) have shorter most important financial cycles. UK has the shortest most important financial cycle that is reported to be 5.4 years. However looking at the UK highest density region in Figure 3, we see that for the UK important cycles are also located in the medium term.

For a group of countries (BE, DE, ES, FI, IE, NL, and PT), Figure 3 suggests that important business cycles are located in the medium term. Further and in the business cycle case, in nine out of 13 countries there are at least two separate regions of most important frequencies, whereas for financial cycles in only two country cases (AT and UK). Thus, financial cycle characteristics tend to be more homogeneous across countries compared to business cycle characteristics. The relevant country graphs of power cohesion for the financial and business cycles are reported in Appendix A.3.

Table 2: Importance of cyclical variation (left) and frequency band in years (right)

	Variance financial/business		Financial cycle		Business cycle	
Country	Medium term	Short term	ω_{low}	ω_{high}	ω_{low}	ω_{high}
EA	3.79	0.58	∞	4.6	8.4	2.0
AT	3.19	0.97	512.0	1.9	4.4	1.5
BE	2.36	0.82	∞	3.0	14.2	1.8
DE	1.43	0.83	128.0	2.3	11.9	2.0
DK	2.15	0.80	30.0	2.5	26.9	2.3
ES	1.95	0.60	∞	4.4	512.0	2.6
FI	1.29	0.85	39.4	3.1	24.4	2.9
FR	2.07	0.73	512	2.6	30.1	2.1
IE	1.65	0.95	∞	3.2	∞	2.2
IT	1.96	0.73	42.7	2.1	7.0	1.8
NL	1.57	0.96	∞	4.2	∞	2.3
PT	1.39	0.87	128.0	2.4	46.5	2.2
SE	2.78	0.85	34.1	2.6	6.0	1.7
UK	1.38	0.93	128.0	2.5	17.1	2.1
Mean	1.94	0.84	∞	2.8	∞	2.2
Median	1.93	0.88	128.0	2.6	24.4	2.1

Notes: Columns two and three report the relative share of co-movement of the financial cycle indicators in comparison to the co-movement of business cycle indicators scaled to the same total amount of co-variance over all cycle frequencies. Shares are reported for medium term cycles (20-8 years) and short term cycles (8-2.5 years). More specifically, figures reflect the ratio: $(\int_{f_1}^{f_2} \text{PCoh}_{\text{Financial}}(\omega)d\omega / \int_0^{\pi} \text{PCoh}_{\text{Financial}}(\omega)d\omega)(\int_{f_1}^{f_2} \text{PCoh}_{\text{Business}}(\omega)d\omega / \int_0^{\pi} \text{PCoh}_{\text{Business}}(\omega)d\omega)^{-1}$, where f_1 and f_2 reflect the lower and upper frequencies for the medium and short term cycles.
Columns four to seven report the frequency band around the peak of power cohesion that is obtained by capturing 2/3 of the common variance as described in Section 2.1.

In support of results from Figure 3, statistics in Table 2 indicate that the variance located in the medium term is on average 1.94 times more important for financial than for business cycles indicators, with 3.19 (AT) and 1.38 (UK) times being the maximum and minimum of the analysed country cases. Within the short term range, business cycle indicators have on average 1.19 times more important variances, with 1.67 (ES) and 1.03 (AT) being the maximum and minimum respectively.

Conclusively, the medium term component for financial cycle indicators is by far more distinct from business cycle characteristics than is the short term one, as share for the short term do not differ as strongly.

The identified frequency window ranges from 128 to 2.6 years for financial cycle indicators (see median Table 2) and, thus, covers longer cycles when compared to the one for business cycle indicators, which is 24.4 to 2.1 years. The highest frequencies included in the window are quite homogenously spread for the business cycle case, where the minimum is 1.5 (AT) and maximum 2.9 (FI) years. In contrast, there is more heterogeneity reported for financial indicators as the minimum is 1.9 (AT) and maximum 4.4 (ES) years. For the lower frequencies included in the frequency window, financial cycle figures are by far larger, with the exceptions of DK, IE, and NL. In IE and NL both endpoints are ∞ and in the case of DK the difference is only 3.1 years – 30 (financial cycle) and 26.9 (business cycle) years.

3.3 A composite index of the financial cycle

This section first discusses the early warning properties of financial cycles for systemic banking crises. Second, the euro area financial cycle and individual European country financial cycles are discussed. Third, we provide a comparison of financial and business cycles. The last part offers several robustness checks.

For the analyses in this section we use among other things the method on turning points as suggested by Bry and Boschan (1971) and extended to quarterly frequency by Harding and Pagan (2002). The turning point analysis is conducted on the aggregated composite cycle indices.[15]

3.3.1 Early warning exercise

This section motivates the construction of a financial cycle index by analysing its early warning properties of financial crises. In this, we build on the seminal work by Frankel and Rose (1996), Kaminsky and Reinhart (1999), and Schularick and Taylor (2012). We find that the filtered composite financial cycle outperforms the single indicators and the credit-to-GDP gap in predicting systemic banking crises at a horizon of one to three years ahead, while it also enhances the predictability of crises at longer horizons.

More specifically, we use a logit model estimated on a pooled data set to explain two vulnerability horizons preceeding systemic banking crises as defined by Laeven and Valencia (2012).[16] The

[15] The Matlab code has been gratefully adapted from Canova and Schlaepfer (2015). Since turning points are defined by local minima and maxima in the level of series we aggregate our composite cycles. To this end, we first subtract the median from each composite cycle and then cumulatively sum up the respective index.

[16] As is common in the early warning literature, we focus on predicting vulnerable periods preceding systemic banking crises instead of the banking crises themselves. This is because vulnerabilities can be triggered into crises by hardly predictable or unforeseen events. Further, note that crisis dummies can only be defined on a yearly basis using dates provided in Laeven and Valencia (2012). It implies that the link of a starting date of a crisis and vulnerability period cannot be exact

Table 3: Early warning exercise

Financial indicators	Vulnerability horizon: 4 to 12 quarters				Vulnerability horizon: 12 to 20 quarters			
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Δc	**0.21**				0.07			
	[0.07]				[0.07]			
Δp_h	**0.14**				**0.18**			
	[0.05]				[0.06]			
Δp_e	**0.03**				0.00			
	[0.01]				[0.01]			
Δr	-0.09				**-0.01**			
	[0.07]				[0.07]			
Filt. financial cycle		**3.30**		**3.24**		**2.04**		**1.98**
		[0.80]		[0.85]		[0.81]		[0.80]
Credit-to-GDP gap			**0.03**	**0.03**			**0.03**	**0.03**
			[0.01]	[0.01]			[0.01]	[0.01]
McFadden adj. R^2	0.05	0.09	0.03	0.12	0.03	0.04	0.02	0.06
AUROC	0.72	0.73	0.64	0.79	0.67	0.65	0.68	0.74
Type I error	0.19	0.25	0.71	0.27	0.21	0.35	0.25	0.40
Type II error	0.42	0.33	0.07	0.27	0.53	0.36	0.43	0.24
Observations	2030	2030	2030	2030	2030	2030	2030	2030

Notes: Country clustered standard errors are reported in square brackets. Coefficients in bold indicate significance at least at the 10% significance level. Filt. denotes filtered and adj. to adjusted. Type I/II errors are derived by minimising the policy makers loss function using equal preferences for missing a crises (no signal but crisis, type I error) and false alarms (signal but no crisis, type II error) with respect to some signalling threshold level separating predicted crises and non-crises. Loss is defined as $L = \frac{\text{Quarters no signal}}{\text{Quarters crisis}} + \frac{\text{Quarters signal}}{\text{Quarters no crisis}}$. Sample lengths have been equalised at the country level for comparative purposes.

vulnerability horizons explored are 4 to 12 as well as 12 to 20 quarters. Variables considered are the unfiltered indicators as well as the filtered financial cycle that has been derived on an expanding sample.[17] These are contrasted with the credit-to-GDP gap that is constructed employing the HP-filter with a smoothing parameter of 400000, again, on an expanding sample.[18] We choose to compare our financial cycle measure with the credit-to-GDP gap measure, as the latter has been assigned a prominent role for setting countercyclical capital buffers in the Basel III regulations and the EU Capital Requirements Directive (CRD IV). Further, studies have suggested that the latter variable ranks among the variables with the best early warning properties for banking crises (see e.g., Behn et al. (2013)). To assess early warning properties, we report the adjusted R^2 suggested by McFadden, the area under the receiver operator curve (AUROC) and the type I and II errors derived by equal preferences of a policy maker between type I and II errors. For further details please refer to the caption of Table 3 or Behn et al. (2013).

Within the vulnerability horizon of one to three years the filtered financial cycle is found to have the best early warning properties among the selected variables in at least three dimensions (see Equa-

when using quarterly data. This, however, does not impair the comparison of indicators provided.

[17]The standardisation using the ecdf is carried out employing the complete data set, as such a standardisation is only reasonable for a large number of observations.

[18]This reflects the exact specification as laid down in the Official Journal of the European Union (2014/C 293) “Recommendation of the European Systemic Risk Board of 18 June 2014 on guidance for setting countercyclical buffer rates”.

tion (ii) in Table 3). First, the AUROC is 0.73, which is higher than the one for the single indicators (Equation (i)) and by far larger than the AUROC reported for the credit-to-GDP gap (0.64, Equation (iii)). Further, the R^2 suggests that Equation (ii) has the best model fit. Second, besides having a relatively low type I error of 25%, the sum of both type I and II errors is lowest for Equations (i) to (iii). The credit-to-GDP gap has the highest type I error of 0.71, i.e., it misses 71% of economically costly crises. Third, the financial cycle improves the AUROC of the credit-to-GDP gap by 15 percentage points (Equation (iv)).

Considering the longer horizon of three to four years, the credit-to-GDP gap slightly outperforms the financial cycle measure (Equation (vi) vs. (vii)). Still, the financial cycle improves the AUROC of the credit-to-GDP gap by 6 percentage points (Equation (viii)).

The estimated signs of statistically significant coefficients are in line with theoretical considerations. An increase in the filtered financial cycle, similarly to a rise in the credit-to-GDP gap, elevates the predicted probability of systemic banking crises at both vulnerability horizons. In the models with individual unfiltered series, an increase in credit, residential property prices, or equity prices predicts a rise of the crisis probability. In contrast, a decrease in bond yields, which mirrors an increase in bond prices, predicts an elevation of the crisis probability. At last, while the coefficients of credit, equity prices, and bond prices are not found to be statistically significant in all of the specifications, the ones for residential property prices are.

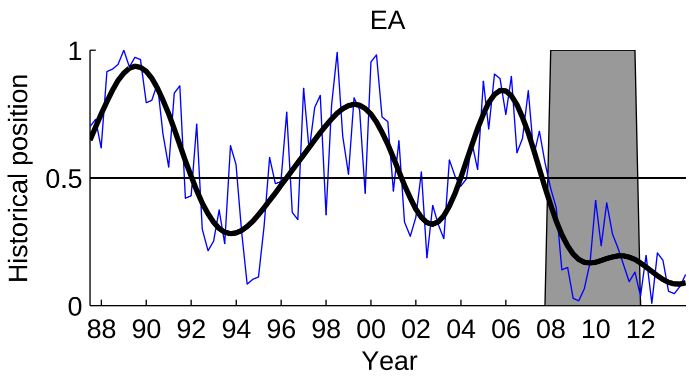
In sum, results provide strong support for our proposed financial cycle measure, which can help policy makers to predict systemic banking crises also beyond the credit-to-GDP gap measure prominent in the Basel III and the equivalent European legislation.

3.3.2 Financial cycles

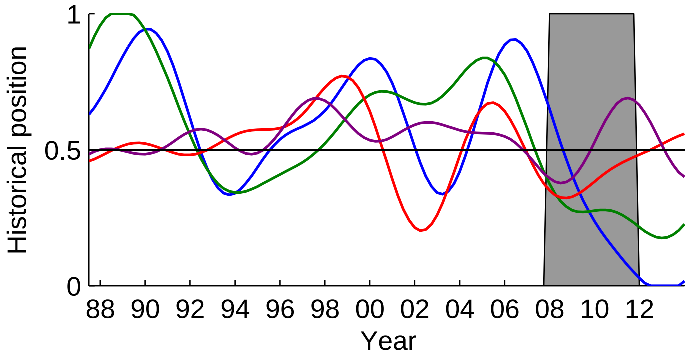
An examination of the financial cycle for an euro area aggregate suggests a particularly pronounced boom-bust phase around the onset of global financial crisis in 2008. This notably includes an unusually stark suppressed phase of the cycle since the outbreak of the global financial crisis. This down phase follows a pronounced up phase prior to its onset (Figure 4a). Both phases are mainly explained by movements in credit, house, and equity price variables, as indicated by the higher aggregation weights (Figure 4c).

This latter finding is consistent with the finding over the entire sample period, whereby the unfiltered financial cycle index correlates highest with house prices (0.76), then credit (0.72), equity prices (0.43), and bond yields (-0.30).

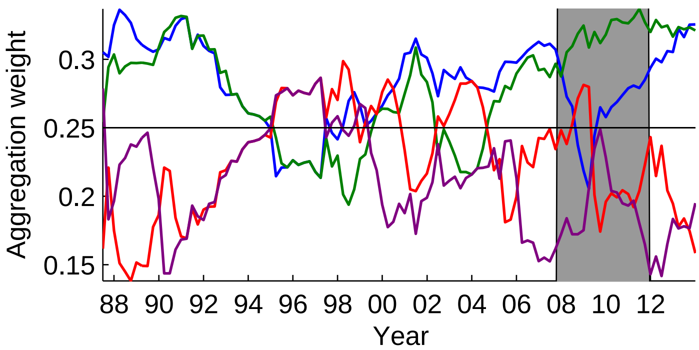
Indeed, credit appears to also account for the other two prior downturns since 1987 – in conjunction with house prices in the early 1990s in contrast to equity prices in the early 2000s. Looking at the graph of filtered indicators (Figure 4b) and the time-varying weights (Figure 4c), both credit and



(a) Unfiltered (blue) and filtered (black) composite financial cycle



(b) Filtered indicator series: Δc (blue), Δp_h (green), Δp_e (red), and $-\Delta r$ (purple)



(c) Time-varying aggregation weights: Δc (blue), Δp_h (green), Δp_e (red), and $-\Delta r$ (purple)

Figure 4: Euro area financial cycle, 1987Q2-2013Q4

Notes: The upper (a) and middle (b) panel show the unfiltered and filtered composite financial cycle as well as its indicators using the frequency band presented in Table 2. The x-axis measures the date and the y-axis the relative historical position, where 0/1 represents the min/max and 0.5 is the historical median. The lower panel (c) depicts the time-varying aggregation weights exploiting time-varying correlations between indicators. The 0.25 line indicates equal weighting. Date is indexed on the x-axis and the aggregation weight on the y-axis. The grey shaded area marks a systemic banking crisis as identified by Laeven and Valencia (2012).

Table 4: Correlation of unfiltered indicators with unfiltered composite financial cycle

Country	Δc	Δp_h	Δp_e	Δr
AT	0.41	0.39	0.47	-0.27
BE	0.53	0.61	0.52	-0.22
DE	0.59	0.57	0.35	-0.23
DK	0.63	0.77	0.66	-0.11
ES	0.70	0.65	0.56	-0.26
FI	0.38	0.72	0.74	-0.24
FR	0.46	0.62	0.47	-0.40
IE	0.54	0.70	0.58	-0.10
IT	0.59	0.50	0.42	-0.30
NL	0.65	0.65	0.37	-0.13
PT	0.61	0.56	0.54	-0.26
SE	0.50	0.72	0.44	-0.16
UK	0.60	0.65	0.44	-0.09
Mean	0.55	0.62	0.50	-0.21

Notes: Table shows the correlation between each unfiltered indicator and the unfiltered composite financial cycle across the longest available sample in each country case. Δc refers to percentage changes in total credit, Δp_h to percentage changes in house prices, Δp_e to percentage changes in equity prices, Δr to percentage point changes in bond yields.

house prices are below their historical median and second, the weight attached to both series is higher than the one to equity prices and bond prices. The second suppression of the euro area financial cycle commences in 2001Q2 and is explained by movements in equity prices as well as credit. The weight for credit is high throughout this period and equity is second highest beginning in 2002Q2.

It is also striking to what extent the unfiltered composite euro area financial cycle exhibits a strong cyclical tendency (Figure 4a). Indeed, its movement is well described by the filtered financial cycle, that follows closely the unfiltered index' low frequency variation. There is some volatility around this low frequency fluctuations, as exemplified for instance in the rapid upward spike in 2010 that is not reflected in the filtered series – though the endpoint of the filtered index respects that of the unfiltered series in this case.

For single country cases (see Table 4), Δc is represented strongest in the composite index of DE, ES, IT, NL (of similar magnitude as Δp_h), and PT. Δp_h is most important in the case of BE, DK, FR, IE, NL, SE, and UK. In the case of AT and FI, Δp_e is found to be most important. In contrast, in none of the country cases is bond yield series the most important one.[19]

Concordance across countries

Concordance of financial cycles ranges from 0.42 (DE with UK and FR) to 0.91 (ES with UK) suggesting important differences in cycle synchronisation across countries (see Table 9 in Appendix A.4.1). In general, DE has the lowest concordance with 0.53 and BE the highest with 0.75 both on average. The heterogeneity of cycle synchronisation is illustrated by the differing colours in Fig-

[19]The individual country financial cycles, their indicators, and aggregation weights are depicted in Appendix A.4.1.

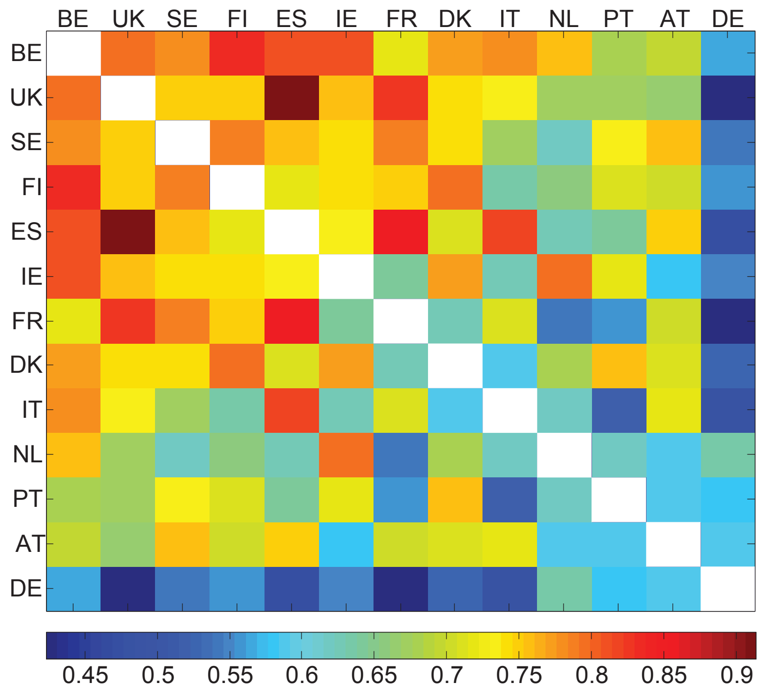


Figure 5: Concordance of financial cycles
Notes: Concordance is obtained on the maximum common sample, i.e., 1988Q1-2013Q4, using the turning point algorithm on the aggregated filtered financial cycles as indicated in Section 3.3.

ure 5, in which countries are ordered from top to bottom by highest to lowest average concordance respectively.[20]

3.3.3 A comparison to business cycles

As inherent in the data, the composite euro area financial cycle is longer than its business cycle counterpart constructed on a conceptually equivalent basis (see Figure 6).[21] Moreover, the financial cycle appears to have leading properties ahead of the global financial crisis, whereby subsiding financial cycle vigour occurs well in advance of the turning point in the business cycle (2005Q4 vs. 2007Q3). In contrast, the business cycle recovers strongly after the first trough in response to the financial crisis, while the financial cycle remains suppressed for a prolonged period of time.

These observations are consistent with more formalised turning point analysis across countries,

[20] In support of these results, a principal component analysis (not reported in this study) of filtered financial cycles from 2000-2013 suggests that 12 out of 13 country financial cycles, i.e., all but DE, correlate strongly and positively with the first principal component that explains 67% of total variation. The second principal components captures a factor related strongly and positively to the DE financial cycle, but not the other countries. Interestingly this second principal component relates negatively to UK and ES, which showed strongest concordance of country cycles. A rise in the second principal component is likely to be followed by rise of the DE financial cycle, but a fall in the cycle of ES or UK, which have a correlation of -0.55 and -0.58 respectively. Of course, a principal component analysis does not offer a structural interpretation of interdependencies, nonetheless, common sources of variation may be described.

[21] The respective charts for the individual countries and the unfiltered business cycle composite indices can be found in Appendix A.4.2.

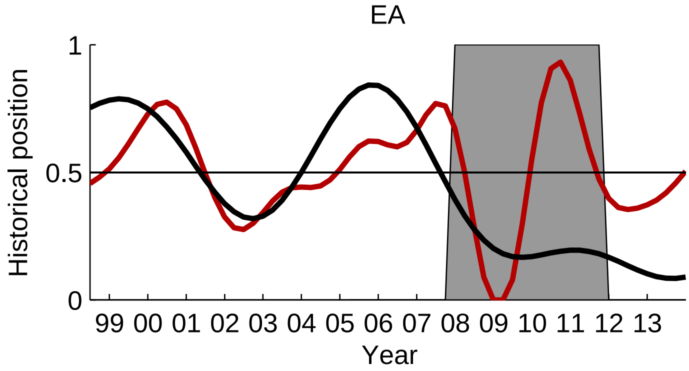


Figure 6: Euro area financial (black) versus business (red) cycle
Notes: The x-axis measures the date and the y-axis the relative historic position, where 0/1 represents the min/max and 0.5 is the historic median. The grey shaded area indicates a systemic banking crisis as identified by Laeven and Valencia (2012).

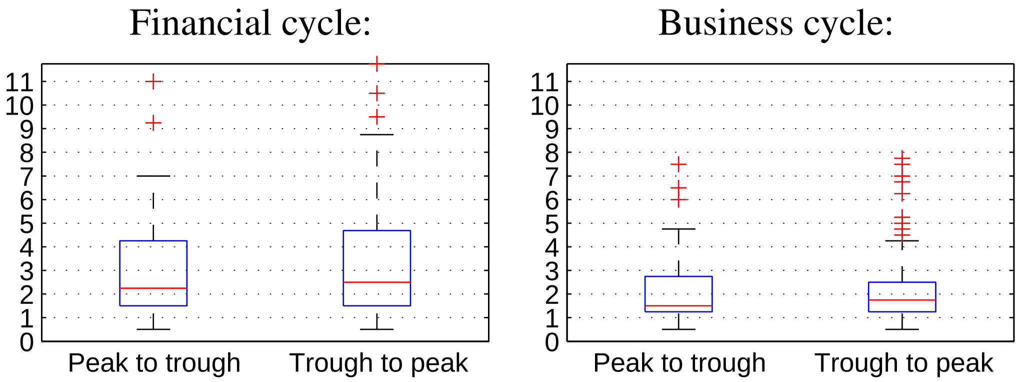
which suggests longer and less symmetric financial cycles.

First, financial cycles tend to be longer than their business cycle analogue (Table 5). The average financial cycle length derived from the unfiltered indicator is 7.2 years versus an average business cycle length of 4.7 years in the case of the filtered business cycle indicator. While the comparison of the means for the unfiltered indicators does not provide as strong evidence (4.5 versus 4.1 years) we find that financial cycles are longer in nine out of 13 country cases.

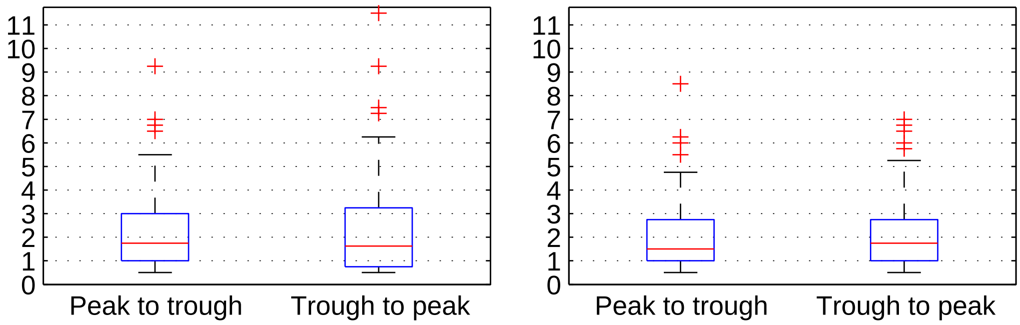
Second, financial cycles also tend to be much more asymmetric than their equivalently calculated business cycle counterparts (see Figure 7). In particular, the distribution of upturns in financial cycles, i.e, trough to peak, has a fatter tail with respect to downturns. Further, the median and the upper quantile of the filtered composite financial cycle index is above that of downturns – and the mean for upturns is larger than for downturns (see Table 5). In contrast, distributions of durations of the composite business cycle indicator for up- and downturns appear to be rather symmetric – and the median is slightly higher for upturns, while the mean of the upper quantile is about equal (or even smaller, for that matter).

Regarding synchronisation of business with financial cycles (see Table 5), on average 67% of the country cases are in phase. Above average concordance is found for DK (0.74), ES (0.79), FI (0.73), FR (0.72), and IE (0.81). Lowest concordance exists between the financial and business cycle in NL (0.59) and SE (0.59), closely followed by DE (0.60).

Turning to the cross-country distributions of financial and business cycles synchronisation respectively (Figure 8), results suggest greater financial than real economy heterogeneity, albeit with correlated financial cycle peaks. The concordance of financial cycles across the European Union countries analysed is more heterogeneous than that of business cycles (inherent in the variance of the distributions). That said, for most countries the synchronisation of financial cycles is higher than for



(a) Filtered



(b) Unfiltered

Figure 7: Duration of cyclical phases across European countries in years
Notes: The upper panel (a) shows boxplots describing the distribution of duration from peak to trough and trough to peak for the filtered composite financial and business cycle in years. The lower panel (b) depicts the latter statistics for the unfiltered composite indices. The statistics are derived by excluding the euro area aggregate and using the turning point algorithm as indicated in Section 3.3.

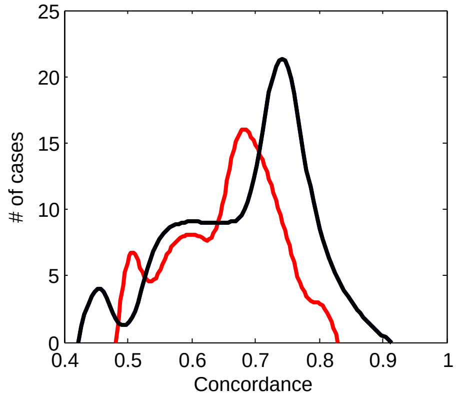


Figure 8: Synchronisation of financial cycles (black) versus synchronisation of business cycles (red)
Notes: Figure shows smoothed histogram depicting distribution of bilateral concordance of financial versus business cycles for all analysed EU countries (excluding euro area aggregate). Concordance is obtained on the maximum common sample, i.e., 1988Q1-2013Q4. Statistics are produced using the turning point algorithm as indicated in Section 3.3.

Table 5: Duration of down- and upturns (P-T and T-P) and concordance (Conc.) of financial and business cycles in years

	Filtered:					Unfiltered:				
	Financial cycle		Business cycle			Financial cycle		Business cycle		
	P-T	T-P	P-T	T-P	Conc.	P-T	T-P	P-T	T-P	Conc.
EA	3.4	4.4	2.5	2.6	0.79	1.4	2.6	1.4	1.8	0.79
	(0.9)	(1.2)	(1.4)	(1.2)		(0.7)	(2.1)	(0.6)	(1.0)	
	[2]	[2]	[2]	[2]		[4]	[4]	[3]	[3]	
AT	2.4	1.8	1.2	1.3	0.64	2.1	2.1	1.6	1.5	0.77
	(1.1)	(1.4)	(0.5)	(0.5)		(1.5)	(1.1)	(0.8)	(1.1)	
	[5]	[5]	[16]	[17]		[6]	[6]	[13]	[14]	
BE	2.9	4.0	2.4	1.7	0.63	2.4	2.8	2.3	2.3	0.66
	(2.2)	(1.3)	(1.3)	(0.8)		(2.0)	(1.7)	(1.8)	(1.2)	
	[5]	[5]	[10]	[9]		[7]	[8]	[8]	[8]	
DE	3.3	3.7	1.9	2.6	0.60	2.3	2.1	2.3	1.9	0.58
	(3.2)	(2.2)	(0.8)	(1.6)		(1.8)	(1.5)	(1.7)	(1.8)	
	[6]	[5]	[9]	[9]		[9]	[9]	[10]	[10]	
DK	2.6	2.1	2.3	2.4	0.74	2.0	2.1	1.8	1.5	0.61
	(1.9)	(1.2)	(1.9)	(1.5)		(2.0)	(1.6)	(0.8)	(1.4)	
	[9]	[9]	[9]	[9]		[9]	[9]	[13]	[13]	
ES	7.9	8.6	3.3	4.3	0.79	2.6	3.0	2.3	2.4	0.77
	(4.4)	(4.4)	(2.4)	(3.0)		(1.2)	(4.4)	(2.7)	(2.3)	
	[2]	[2]	[5]	[5]		[6]	[6]	[8]	[8]	
FI	2.8	3.3	2.4	3.4	0.73	2.3	2.3	2.4	2.5	0.70
	(1.2)	(1.5)	(1.2)	(1.9)		(1.6)	(1.2)	(1.6)	(2.0)	
	[6]	[7]	[7]	[7]		[8]	[9]	[8]	[8]	
FR	4.0	3.4	2.5	2.1	0.72	1.9	1.9	2.1	2.5	0.71
	(2.4)	(3.4)	(1.8)	(1.3)		(1.3)	(1.2)	(1.9)	(1.4)	
	[5]	[6]	[8]	[8]		[10]	[11]	[8]	[8]	
IE	4.3	4.9	3.2	3.8	0.81	1.7	1.7	1.7	1.4	0.65
	(2.3)	(2.7)	(1.3)	(2.9)		(1.6)	(1.8)	(1.1)	(0.7)	
	[5]	[4]	[5]	[4]		[12]	[12]	[10]	[10]	
IT	2.4	3.2	1.5	1.9	0.62	1.8	3.0	1.6	1.7	0.68
	(1.8)	(1.9)	(0.6)	(0.9)		(1.6)	(2.8)	(1.3)	(1.1)	
	[6]	[7]	[11]	[12]		[7]	[8]	[11]	[11]	
NL	3.8	5.6	2.8	2.9	0.59	1.8	2.2	2.5	3.2	0.65
	(2.9)	(4.3)	(1.3)	(2.1)		(1.4)	(1.7)	(1.2)	(1.9)	
	[3]	[3]	[7]	[7]		[8]	[8]	[7]	[7]	
PT	2.0	1.7	2.3	2.3	0.63	2.0	1.7	2.1	2.1	0.76
	(0.7)	(1.9)	(1.3)	(2.0)		(1.1)	(2.1)	(1.6)	(1.7)	
	[6]	[6]	[9]	[8]		[7]	[6]	[10]	[9]	
SE	2.5	2.7	1.4	1.8	0.59	3.3	2.7	2.1	2.5	0.63
	(1.7)	(1.7)	(0.6)	(1.1)		(2.9)	(2.2)	(1.3)	(1.3)	
	[8]	[8]	[13]	[13]		[7]	[7]	[8]	[9]	
UK	3.3	5.1	1.6	2.0	0.63	2.3	2.9	1.9	2.1	0.66
	(2.4)	(2.7)	(1.1)	(0.8)		(1.6)	(3.1)	(1.4)	(1.5)	
	[4]	[4]	[12]	[11]		[7]	[7]	[11]	[10]	
Mean	3.4	3.8	2.2	2.5	0.67	2.2	2.3	2.0	2.1	0.68
	[70]	[71]	[121]	[119]		[103]	[106]	[125]	[125]	

Notes: This table shows the mean of durations for downturns denoted by P-T (peak to trough) and upturns denoted by T-P (trough to peak). Standard deviations are reported in round brackets and number of events in square brackets. Conc. refers to concordance and measure the synchronicity of phases of country composite financial and business cycles and is obtained on the maximum common sample, i.e., 1988Q1-2013Q4. Mean is derived by averaging all country means and counting all events excluding the euro area aggregate. Statistics are produced using the turning point algorithm as indicated in Section 3.3.

business cycles (peak of distribition).

At last, there is evidence that the output of the turning point algorithm should be adapted for the analysis of unfiltered financial cycle indicators, as, e.g., is done by Claessens et al. (2012) by reporting time of recoveries, i.e., the time it takes for a variable to attain the level of the previous peak after a trough. While the algorithm does not produce largely differing results for filtered and unfiltered business cycles (see Table 5), it does in the case of the financial cycle. For business cycles, the total average length differs by 0.6 years while for financial cycles it extends to 4.7 years.

3.4 Robustness Analysis

In this section, we perform several robustness checks; first, we analyse cycles based on subsets of financial cycle indicators. Second, we highlight the effect of varying the parameter determining the frequency window. And third, we show the effect of setting a different parameter λ that controls the persistence of time-varying correlations.

3.4.1 Cycles using subsets of indicators

In this part we consider two subsets of indicators and compare outcomes of the different analyses. As the emerging literature on financial cycles has mainly focussed on measures of credit, residential property prices, and equity prices, we focus on these variables in our first subset. Further, to derive a synthetic financial cycle measure Drehmann et al. (2012) suggest to filter credit measures as well as residential property prices using a frequency window of 8 to 30 years before linearly aggregating. Therefore, we consider only credit and residential property prices for our second subset of indicators.

Three important results emerge: First, most relevant cycles are rather consistently located at similar frequencies across the different sets of indicators. Second, cycle length estimates are rather robust when excluding bond yields, but rather not when focussing only on credit and residential property prices. That is, for half of the country cases (seven out of 14) the lengths of extracted financial cycles only differ marginally, i.e., by up to one year, when only bond yields are excluded. In three country cases, cycle lengths differences are marginal for the two subsets, while more pronounced when each compared to the benchmark setup. Notably, in the case of ES, the cycle length is robust across all specifications. In further four country cases, estimates of cycle length differ across all sets. Third, when only considering credit and residential property prices for identifying financial cycles, our results suggest that shortest cycles that should be considered are well below 8 years, contrary to the argument of Drehmann et al. (2012).

The highest density graph (Figure 9) suggests that – with respect to the exclusion of bond yields and equity prices – the agreement of indicators for identified cycles that contribute strongest to the overall co-variance is rather stable, with the only major exception of PT. Further, in the case of DE

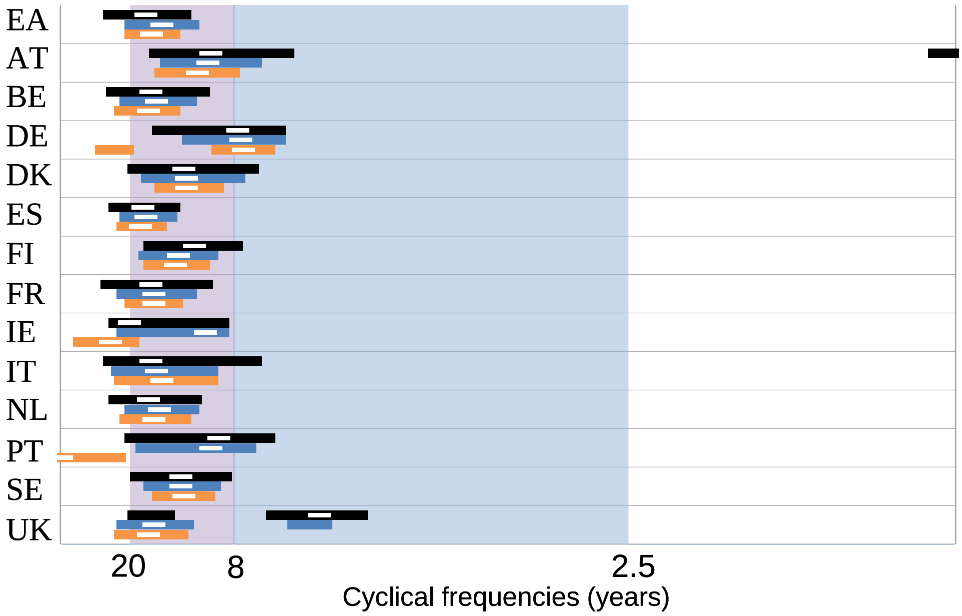


Figure 9: Highest density graph of power cohesion of all financial indicators (black), Δc, Δp_h, and Δp_e (blue), and Δc and Δp_h (orange)

Notes: This graph depicts the 25% highest density region of power cohesion excluding cycles lower than 5 quarters for financial and subsets of financial cycle indicators. The purple region marks medium term frequencies, i.e, in the range of 8 to 20 years, while the blue area short term fluctuations, i.e., 2.5 to 8 years. The white dash locates the peak of power cohesion.

and IE, longer cycles are suggested when considering only credit and residential property prices (orange bar), while in the case of AT (blue and orange bar) and UK (orange bar), important short term fluctuations disappear. Also, we find that the more asset prices dropped the denser is the region where 25% of most important cycles are located, i.e., compared to the black bars, the blue bar is shorter across country cases. Shortest is the orange bar.

The identified frequency window allows for similar conclusions (Table 6). The window identified using only credit and residential property prices is shorter than the one including equity prices as both the low and high frequency limits are include in the latter set. As stressed, while the long cycles included differ much in years, their importance with respect to cycle selection is minor. However, important differences emerge with respect to the shortest cycle length included. The mean of the shortest cycles included is 6.2 for credit and residential property prices and 4.1 years by additional considering equity prices. This is in contrast to 2.6 years employing all indicators. This result is also mirrored in the turning point analysis (Table 7), for which we find that credit and residential property price cycles last on average 10.8 years, while including equity prices leads to an average length of 8.8 years. This is in contrast to our benchmark scenario that identifies cycles of an average length of 7.2 years. However, taking a country perspective, we note that in half of the country (and region) cases the differences are only marginal, i.e., up to one year, when excluding bond yields. In four cases cycle

Table 6: Frequency band of power cohesion identified using subsets of variables

Country	Δc, Δp_h, and Δp_e ω_{low}	ω_{high}	Δc and Δp_h ω_{low}	ω_{high}
EA	256.0	6.7	56.9	8.5
AT	∞	2.8	∞	5.2
BE	∞	5.3	512.0	7.8
DE	∞	3.1	∞	4.9
DK	28.4	2.7	32.0	5.6
ES	170.7	8.3	85.3	9.5
FI	56.9	4.3	85.3	6.1
FR	∞	4.2	102.4	6.4
IE	512.0	5.6	∞	8.1
IT	64.0	2.3	85.3	2.0
NL	73.1	5.6	512.0	7.1
PT	∞	3.0	∞	6.2
SE	∞	4.1	46.5	6.8
UK	128.0	4.0	36.6	5.2
Mean	∞	4.3	∞	6.2
Median	512.0	4.1	102.4	6.2

Notes: Table reports the frequency band around the peak of power cohesion that is obtained by capturing 2/3 of the common variance as described in Section 2.1.

lengths are only marginally different for the two subset of indicators, while in 4 cases all estimates are found to be different. Most robust is our finding for ES, in which case the cycle length consistently found to be around 15 to 16 years. At last and as found previously, cycles tend to be asymmetric as the upturn lasts on average 4.7 years (6 years excluding equity) and the down turn only 4.1 years (4.8 years excluding equity). The statistics for the unfiltered series provide weaker evidence.

More specifically concerning credit and residential property prices, highest frequencies selected by our frequency window are below 8 years and the lowest well above 30 years, indicating that – using credit and residential property prices – important cycle frequencies are located in this part of the spectrum and, thus, outside of the region suggested by Drehmann et al. (2012). Even the highest density chart (see Figure 9) suggests that there are country cases in which, considering only the 25% of most important cycles, fluctuations are located outside of this 8 to 30 year window (AT, DE, IE, PT). Thus, also when considering measures of credit and house prices the latter frequency window potentially leads to a serious bias of financial cycles as fluctuations that contribute strongest to the the overall co-variance are neglected.

3.4.2 Varying the frequency window parameter

We conduct this robustness analysis for illustrative purposes on the euro area financial cycle. Next to the benchmark frequency window of 2/3, Figure 10 also shows the filtered composite financial cycle when using a window that is 10 percentage points (p.p.) larger or smaller.

Table 7: Duration of down- and upturns (P-T and T-P) of subsets of indicators in years

	Δc, Δp_h, and Δp_e				Δc and Δp_h			
	Filtered:		Unfiltered:		Filtered:		Unfiltered:	
	P-T	T-P	P-T	T-P	P-T	T-P	P-T	T-P
EA	3.0	4.9	3.3	4.5	4.5	9.1	2.5	5.5
	(1.4)	(0.2)	(1.8)	(0.0)	(0.0)	(4.1)	(2.8)	(1.0)
	[2]	[2]	[2]	[2]	[1]	[2]	[2]	[3]
AT	2.8	2.3	2.4	2.1	4.5	3.3	1.7	1.1
	(1.4)	(1.0)	(1.1)	(1.1)	(0.0)	(0.4)	(1.5)	(0.7)
	[3]	[3]	[4]	[4]	[2]	[2]	[7]	[7]
BE	4.2	4.4	2.6	3.2	5.4	8.8	3.1	3.1
	(2.3)	(0.7)	(1.8)	(1.6)	(2.3)	(4.0)	(2.1)	(2.0)
	[4]	[4]	[6]	[7]	[2]	[3]	[6]	[7]
DE	3.8	3.3	2.2	1.6	5.8	5.2	2.8	2.3
	(4.3)	(1.1)	(2.1)	(1.2)	(4.2)	(3.1)	(2.3)	(1.5)
	[6]	[5]	[11]	[10]	[4]	[3]	[8]	[7]
DK	4.2	2.8	1.9	1.8	3.9	4.3	2.5	3.2
	(2.9)	(1.4)	(0.8)	(1.4)	(2.8)	(1.4)	(2.2)	(2.5)
	[6]	[6]	[10]	[10]	[4]	[4]	[6]	[6]
ES	7.5	9.3	3.9	4.4	7.3	8.4	2.9	3.6
	(3.9)	(3.9)	(2.4)	(4.9)	(1.8)	(3.0)	(1.6)	(4.1)
	[2]	[2]	[4]	[4]	[2]	[2]	[5]	[6]
FI	4.4	3.9	2.1	2.4	4.0	7.7	3.2	3.8
	(3.0)	(0.2)	(1.8)	(1.7)	(2.8)	(2.8)	(2.9)	(2.0)
	[4]	[4]	[8]	[9]	[3]	[3]	[5]	[6]
FR	3.8	3.8	2.4	2.3	5.5	5.8	3.7	3.9
	(2.5)	(2.0)	(2.3)	(1.7)	(1.8)	(5.3)	(2.2)	(3.6)
	[5]	[5]	[8]	[9]	[3]	[3]	[5]	[5]
IE	5.3	6.7	1.6	1.8	5.1	6.9	1.7	2.3
	(1.8)	(5.5)	(1.1)	(1.9)	(2.3)	(5.9)	(2.0)	(2.3)
	[2]	[3]	[12]	[12]	[2]	[3]	[8]	[9]
IT	3.6	5.0	2.0	2.4	4.3	4.6	2.8	2.9
	(2.4)	(4.5)	(1.6)	(2.5)	(2.2	4.2)	(2.1)	(3.5)
	[4]	[4]	[8]	[9]	[4]	[4]	[6]	[7]
NL	3.7	5.8	1.6	2.2	4.4	7.1	2.3	3.1
	(2.3)	(2.9)	(1.2	1.8)	(2.7)	(1.9)	(2.3)	(2.4)
	[3]	[3]	[9]	[10]	[2]	[2]	[6]	[6]
PT	2.0	1.8	1.5	2.0	3.9	3.5	1.2	1.4
	(0.8)	(1.9)	(1.0)	(1.9)	(0.9)	(3.9)	(0.5)	(1.9)
	[6]	[6]	[7]	[7]	[2]	[2]	[7]	[8]
SE	3.6	5.5	2.6	2.5	4.3	6.0	4.4	5.4
	(2.6)	(1.3)	(1.7)	(2.0)	(3.3)	(0.2)	(2.4)	(5.7)
	[3]	[3]	[8]	[8]	[3]	[4]	[4]	[4]
UK	4.3	6.8	2.0	2.5	4.8	6.3	2.6	2.8
	(1.9)	(4.1)	(1.8)	(2.0)	(2.6)	(3.3)	(2.0)	(2.5)
	[3]	[3]	[8]	[9]	[3]	[3]	[7]	[8]
Mean	4.1	4.7	2.2	2.4	4.8	6.0	2.7	3.0
	[51]	[51]	[103]	[108]	[36]	[38]	[80]	[86]

Notes: This table shows the mean of durations for downturns denoted by P-T (peak to trough) and upturns denoted by T-P (trough to peak). Standard deviations are reported in round brackets and number of events in square brackets. Mean is derived by averaging all country means and counting all events excluding the euro area aggregate. Statistics are produced using the turning point algorithm as indicated in Section 3.3.

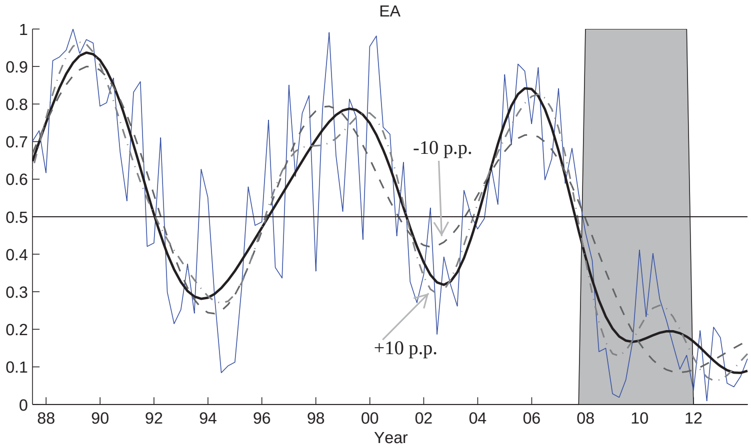


Figure 10: Filtered financial cycles using a frequency window covering 10 p.p. more and less than the benchmark setup

Notes: The x-axis measures the date and the y-axis the relative historical position, where 0/1 represents the min/max and 0.5 is the historical median. The grey shaded area indicates a systemic banking crisis as identified by Laeven and Valencia (2012).

The filtered series with the smallest parameter, i.e., 10 p.p. less, is naturally the smoothest one, only capturing an upward trend at the end of global financial crisis. The endpoints of the unfiltered series and this filtered one deviate more strongly than the other filtered cycle estimates. The specification using a larger frequency window, i.e., covering 10 p.p. more of common variation, follows the unfiltered series more closely, but has also more noise added to it. Endpoints do not deviate strongly and are similar to the benchmark setup.

Note that while we find that the peaks and troughs of growth rates differ for all frequency window specifications, we do not find such evidence for turning points, i.e., when the series passes from below median to above or vice versa. In this case the benchmark specification follows almost exactly the less smooth one. Some small bias exists for the smoother one.

In sum, we argue that 2/3 represents a good trade-off for balancing smoothness and bias.

3.4.3 Varying the correlation persistence parameter

In this section, we vary the persistence parameter, λ using 0.89 and 0.95 instead of 0.93. Further, we plot the simple average, i.e, without employing time-varying weights. Figure 11 shows the result for the unfiltered euro area financial cycle.

First, the simple average adds noise to the location of the financial cycle and, thus, time-varying weights should be preferred. In the latter case, booms and busts are well more defined, i.e., the unfiltered indicator remains above the historical median, as e.g., can be seen by the first boom phase on the sample, the upswing the before the financial crisis, and also the downturn following the financial crisis shock, where the signal has less variance. Further, the global financial crisis shock leads to a downturn before the simple average.

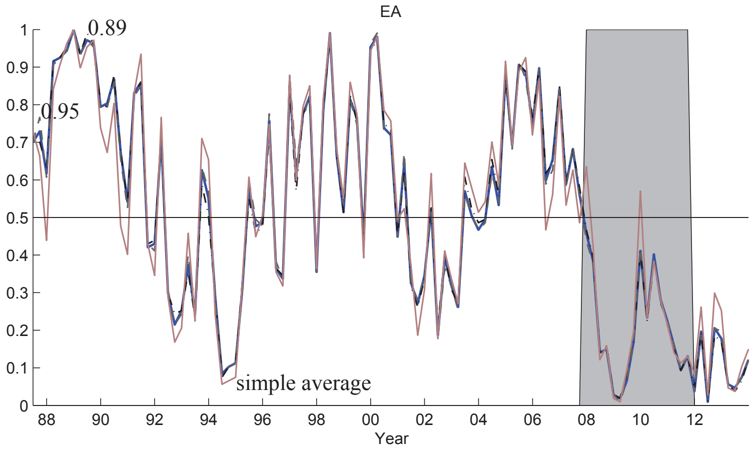


Figure 11: Unfiltered financial cycle indicator using different correlation persistence parameters and the simple average

Notes: The x-axis measures the date and the y-axis the relative historical position, where 0/1 represents the min/max and 0.5 is the historical median. The grey shaded area indicates a systemic banking crisis as identified by Laeven and Valencia (2012).

Second, the difference using the different persistence parameters is seen to be negligible.[22]

4 Conclusions

Beyond enhancing financial system resilience, one of the key objectives of macroprudential policy is to attenuate financial cycles. This paper presents an empirical methodology to characterise and extract financial cycles, which is based on a novel multivariate spectral method of deriving common cyclical frequencies for financial aggregates. Further, a time-varying aggregation method is presented which allows for a unique composite cycle constructed from constituent indicators capturing economic fluctuations of a systemic nature. We apply this method to selected European Union countries and the euro area aggregate using total credit and measures for different asset markets (residential property prices, equity prices, and benchmark bond yields) as aggregates. Quarterly cycles for credit and the above main asset prices are derived for the period of 1970-2013. The resulting synthetic country financial cycles are calculated in such a way that they summarise the (co-)movements over time of a range of financial sector variables, while still retaining information on each constituent variable relevant for informed policymaking.

The methodology introduced in this paper to construct composite financial cycles strengthens the basis for countercyclical macroprudential mandates currently being implemented around the world. The empirical application to a broad set of the EU countries emphasises how a consistent summary representation of credit and asset market developments can help in predicting financial stress, while

[22] Compared to an index using unrestricted correlations, our methodology identifies more clearly swings in the financial cycle, which, e.g., can be noted by a higher degree of persistence.

at the same time allowing for country-specific cycles drawing from frequency domain analysis of financial cycle characteristics. On the one hand, the results support the notion that countercyclical macroprudential policies in the EU need to be tailored to country-specific phases. On the other hand, considerable co-movement of financial cycles across the countries analysed suggests a strong need for coordination and reciprocity in the implementation of country-specific measures. Further, financial cycles' interaction with their business cycle counterparts – and the potential for divergence – underscores the need for policy specialisation, notably across the macroeconomic and macroprudential space.

The methodology and geographic coverage in this way contribute to a small and growing literature on financial cycles. Notwithstanding its contribution, several areas of further research remain. These include methodologies suited to structural breaks and nonlinearities inherent in underlying series, a more structural analysis of the interplay of composite financial cycles across countries, and exploration of other variables that could further enhance the precision of financial frequencies and cycles.

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A Appendix

A.1 Data, transformations, and tests on unit roots

The data are from the Bank of International Settlements (BIS), Datastream (DS), Global Financial Data (GFD), the Statistical Data Warehouse (SDW), or the OECD.

In case data is available at the yearly frequency only, it is converted to quarterly frequency using the approach suggested in Bernanke et al. (1997), which exploits state-space methods. Further, some series are backcasted using similar variables which have a longer history, chained back in time on the basis of growth rates.

All series, except for inflation and unemployment, are measured in real terms. GDP and house prices are directly obtained in real terms, while real total credit and real equity prices are deflated with the respective country consumer price index (CPI). Total credit, house prices, equity prices, and GDP are transformed to log quarter-on-quarter (or year-on-year), i.e., percentage, changes. Bond yields and unemployment are quarter-on-quarter (or year-on-year), i.e., percentage point, changes. Inflation is the first difference of log quarter-on-quarter (or year-on-year) changes in the CPI (percentage points).

The resulting sample period is 1970Q3 until 2013Q4 for the quarter-on-quarter transformation (and 1971Q2 until 2013Q4 for all results in the appendix using annual transformations), except where denoted for specific variables below.

Total Credit: Total credit is taken from the BIS data set and reflects total loans and debt securities provided by domestic banks, all other sectors of the economy and non-residents to the private non-financial sector (non-financial corporations, households, and non-profit institutions serving households). Exceptions to the above starting dates are BE (1970Q4), FI (1970Q4), and IE (1971Q2). Credit for the euro area, based on a synthetic aggregation available since 1980Q1, reflects loans to households and non-financial corporations and is taken from the balance sheet items data set (SDW: BSI.Q.U2.N.A.A20.A.1.U2.2250.Z01.E and BSI.Q.U2.N.A.A20.A.1.U2.2240.Z01.E).

House prices: This measure reflects real residential property prices as compiled by the ECB using national sources, backcasted using growth rates from OECD data. For Austria up to 2000Q1 the series only reflects house prices in Vienna. Starting dates vary for AT (1986Q3), ES (1971Q1) and PT (1988Q1). The euro area aggregate is a synthetic euro area aggregate for 17 countries (SDW: RPP.Q.I6.N.TD.00.3.00), with start date 1980Q1.

Equity prices: We employ the index from OECD main economic indicators. In the case of BE (before 1985Q2), DK (before 1983Q1), ES (before 85Q1), and PT (before 1988Q1) we use an equity index provided by GFD. The respective GFD codes are _BSPTD, _OMXCPID, _SMSID, _PSI20D. Starting date varies for PT (1977Q2). The euro area aggregate commences in 1987Q1.

Bond yields: Bond yields are measured by long term government bonds with a maturity of around 10 years and are obtained through SDW (financial market data). For DK, FI, SE we employ the relevant series of the BIS Macro-economic series database. Series for DK, FI, SE, and UK are backcasted using data form the international financial statistics database. Further, in the case of ES (before 1987Q2) and FI (before 1988Q1) we use the respective series provided by GFD: codes are IGESP10D and IGFIN10D. In the case of PT (1974Q2 - 1975Q5) and SE (1986Q1 - 1986Q2), because of missing data, we use the GFD series as a way to circumvent these data issues. Codes are IGPRT10D and IGSWE10D. The euro area aggregate commences in 1980Q1.

GDP: Real GDP is obtained from SDW and reflects the OECD/Eurostat series. In the case of IE we use industrial production, given a yearly frequency for Irish GDP most part of our sample (before 1996). DS code is IRQ66..CE. For ES, on the basis of the unit root test (see Table 8), we employ industrial production instead of GDP. The DS code is ESIPTOT.G. The euro area aggregate commences in 1995Q1.

Unemployment: Country unemployment indices are taken from the OECD Economic Outlook database and retrieved trough SDW. In the case of IE (before 1983Q1) and ES (before 1976Q3) we convert from annual to quarterly frequency. In IE, as an indicator for quarterly changes we use the persons on the life register series (DS: IRUNPBENO) and convert the annual unemployment series using GFD (GFD: UNIRLM). For ES we relate the yearly GFD (GFD: UNESPM) series to the number of registered unemployed by the relevant Spanish Ministry (DS: ESUNPTOTP). In the case of Finland we use the series by GFD (GFD: UNFINM) before 1975Q1. For DE we use the OECD Main Economic Indicators' series (DS: BDQLRT28Q). The euro area aggregate commences in 1998Q1.

Table 8: Unit root tests

Country	Augmented Dickey Fuller (ADF) Test							Philips-Perron (PP) Test						
	c	p_h	p_e	r	y	u	π_p	c	p_h	p_e	r	y	u	π_p
Level														
EA	0.725	0.567	0.320	0.627	0.441	0.209	0.850	0.869	0.794	0.352	0.383	0.342	0.640	0.914
AT	0.966	**0.001**	0.216	0.572	0.936	0.542	**0.020**	0.967	0.094	0.305	0.300	0.919	0.577	**0.001**
BE	0.999	0.879	0.482	0.469	0.872	0.058	**0.030**	1.000	0.987	0.515	0.237	0.848	0.181	**0.008**
DE	0.633	0.574	0.445	0.510	0.898	0.194	0.096	0.321	0.715	0.565	0.259	0.842	0.307	**0.000**
DK	0.836	0.551	0.911	0.056	0.758	0.162	0.128	0.983	0.632	0.940	0.062	0.758	0.162	**0.000**
ES	0.541	0.446	0.412	0.533	0.835	0.518	0.756	0.932	0.646	0.239	0.310	0.856	0.772	**0.004**
FI	0.999	0.423	0.179	0.814	0.827	0.154	0.386	0.999	0.730	0.294	0.680	0.836	0.342	0.064
FR	0.998	0.725	0.490	0.610	0.768	0.356	0.363	1.000	0.927	0.562	0.413	0.703	0.362	0.277
IE	0.905	0.356	0.371	0.113	0.933	0.254	0.249	0.997	0.665	0.427	**0.062**	0.981	0.420	**0.001**
IT	0.791	0.456	0.109	0.470	0.168	0.534	0.738	0.979	0.424	0.124	0.220	0.120	0.745	0.110
NL	0.890	0.403	0.520	0.553	0.812	0.051	0.393	0.971	0.688	0.518	0.255	0.830	0.234	**0.004**
PT	0.794	0.872	0.109	0.294	0.396	0.329	0.580	0.978	0.944	0.255	**0.035**	0.386	0.895	**0.000**
SE	1.000	0.976	0.767	0.209	0.999	0.599	0.253	1.000	0.991	0.847	0.135	0.997	**0.007**	**0.000**
UK	0.948	0.708	0.645	0.001	0.970	0.185	0.060	0.951	0.737	0.685	0.085	0.971	0.275	**0.007**
Yoy Filter														
EA	0.280	0.209	**0.018**	**0.037**	**0.015**	**0.006**	**0.000**	0.373	0.262	**0.025**	**0.044**	0.078	0.154	**0.000**
AT	**0.007**	0.123	**0.000**	**0.008**	**0.015**	**0.001**	**0.000**	0.059	**0.007**	**0.002**	**0.018**	**0.001**	**0.000**	**0.000**
BE	0.105	0.116	**0.008**	**0.000**	**0.000**	**0.003**	**0.001**	**0.007**	**0.045**	**0.006**	**0.026**	**0.035**	**0.009**	**0.000**
DE	0.401	**0.012**	**0.000**	**0.000**	**0.000**	**0.041**	**0.000**	0.115	**0.004**	**0.012**	**0.003**	**0.000**	**0.037**	**0.000**
DK	**0.023**	**0.001**	**0.000**	**0.009**	**0.015**	**0.004**	**0.000**	0.209	**0.010**	**0.015**	**0.000**	**0.000**	**0.004**	**0.000**
ES	**0.043**	0.111	**0.049**	**0.003**	0.131	**0.005**	**0.001**	0.460	**0.027**	**0.029**	**0.000**	0.054	**0.043**	**0.000**
FI	**0.037**	**0.004**	**0.003**	**0.001**	**0.049**	**0.040**	**0.000**	**0.001**	**0.011**	**0.002**	0.141	**0.003**	**0.022**	**0.000**
FR	**0.000**	0.184	**0.000**	**0.003**	**0.012**	**0.018**	**0.000**	**0.006**	**0.037**	**0.005**	**0.016**	**0.003**	**0.003**	**0.000**
IE	0.258	0.186	**0.000**	**0.000**	0.462	**0.008**	**0.000**	**0.048**	**0.045**	**0.013**	**0.001**	**0.001**	**0.018**	**0.000**
IT	0.134	**0.003**	**0.000**	**0.001**	**0.010**	0.097	**0.002**	0.076	0.138	**0.001**	**0.045**	**0.037**	**0.011**	**0.000**
NL	**0.038**	0.072	**0.010**	**0.001**	**0.016**	**0.038**	**0.000**	0.167	0.059	**0.011**	**0.000**	**0.000**	**0.037**	**0.000**
PT	0.186	0.075	**0.004**	**0.000**	**0.007**	**0.037**	**0.000**	**0.010**	**0.050**	**0.002**	**0.000**	**0.006**	**0.004**	**0.000**
SE	0.066	**0.023**	**0.000**	**0.019**	**0.000**	**0.000**	**0.000**	**0.011**	0.112	**0.017**	**0.002**	**0.000**	**0.000**	**0.000**
UK	0.644	**0.002**	**0.001**	**0.001**	**0.018**	**0.007**	**0.000**	**0.012**	**0.009**	**0.013**	**0.032**	**0.006**	**0.016**	**0.000**
Qoq Filter														
EA	0.341	0.090	**0.000**	**0.000**	**0.000**	0.083	**0.000**	**0.000**	**0.027**	**0.000**	**0.000**	**0.000**	0.061	**0.000**
AT	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
BE	**0.000**	**0.014**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DE	**0.004**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DK	**0.036**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
ES	0.244	**0.000**	**0.000**	**0.000**	**0.004**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
FI	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
FR	**0.000**	**0.011**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
IE	**0.003**	**0.005**	**0.000**	**0.000**	**0.021**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
IT	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
NL	**0.003**	0.054	**0.000**	**0.000**	**0.000**	**0.015**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.009**	**0.000**
PT	0.086	**0.001**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
SE	**0.000**	**0.006**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
UK	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**

Notes: Table depicts p-values for indicated tests on unit roots. Bold numbers indicate that test rejects the H0 of a unit root at least at the 5% level. Red numbers in the case of yoy and qoq indicate that both the ADF and PP tests indicate that for the respective series the H0 cannot be rejected given a 5% level. All tests include a constant term. Maximum lag length is 13 for the ADF test and the Schwarz Info Criterion used. In the case of the PP test the bandwidth is chosen via Newey-West. c refers to total credit, p_h to house prices, p_e to equity prices, r to bond yields, y to gdp, u to unemployment rate, and π_p to inflation.

Inflation: CPI is from OECD/Eurostat and obtained through SDW. In order to maximise our sample period we obtain this measure for IE from the national statistics office (DS: IRCONPRCF). The euro area aggregate commences in 1996Q1.

Unit root tests, as presented in the Table 8, indicate that – taking both the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) test into account (5 % significance level) – there is evidence of unit roots in the levels of the variables. This can only be rejected in the case of inflation for AT and BE. For the quarter-on-quarter filter tests results suggest compelling evidence against unit roots in all cases, with the only exception being the aggregate euro area unemployment series. [23] For ES we find

[23] For the year-over-year filter the tests indicate stationarity for most variables. However there are six cases, in which both tests cannot reject the null hypothesis of a unit root: credit for the euro area, DE, IT, and the UK as well as house prices for

evidence in the case of GDP of a unit root.[24]

A.2 Spectral properties of indicators and indicator pairs

This Appendix discusses the implications of the quarter-on-quarter and year-on-year transformations for the cyclical characteristics of the underlying indicators. First, we discuss the theoretical effects of transformations and following, we compare the estimated spectral densities across indicators.

A.2.1 The effects of transforming indicators

The spectral approach requires a stationary process, thus, raising the important task to correctly detrend the data.[25] The method for correctly detrending, i.e., without distorting the cyclical pattern of interest, depends on the nature of the non-stationarity. In the absence of a commonly agreed definition of a financial or even business cycle it is impossible to define the cyclical pattern of interest. Further, one does not know the source of non-stationarity, which further hinders a correct analysis. In this respect tests on unit roots might give an indication whether a transformation renders a series stationary, however these are known to be flawed by low power. In light of these observations we follow the procedure suggested in A'Hearn and Woitek (2001) which is to compare the power transfer functions of the filters and learn about the distortions that these filters induce into the data.[26]

To stationary transform indicators we compare two different filters. The first one reflects the standard first difference filter ($\Delta y_t = y_t - y_{t-1}$) which we call qoq filter as we use quarterly series. The second one is similar but represents a seasonal filter in order to, among other things, mute yearly seasonal cycles ($\Delta_4 y_t = y_t - y_{t-4}$). We call this filter yoy filter. In the context of quarterly data, the qoq filter is the standard one applied in business cycle studies (e.g. Comin and Gertler (2006)).[27] The yoy filter is less standard but has been used, for instance, in the study of the financial cycle by Drehmann et al. (2012).

The power transfer functions (PTFS) in Figure 12 depict the squared gain induced by each filter across frequencies. The area in blue marks business cycle frequencies (2.5-8 years) and the purple area medium term cycle periods which have been argued to be important for the financial cycle (8-20 years). The ideal filter – for the purpose of detrending – would remove the permanent fluctuations at

the euro area and NL.

[24]On the basis of the test results we decide to substitute real GDP in ES with industrial production that could have led to the evidence of unit roots. The p-values of the unit root tests for ES industrial production are – for the ADF and PP test respectively: 0.39 & 0.45 (level); 0.21, 0.00 (yoy); 0.00, 0.00 (qoq). Unfortunately, a substitute is not apparent for the financial variables or EA unemployment.

[25]For a thorough discussion on detrending in relation with business cycle analyses, please refer to Canova (1998).

[26]Note, the distortions depend on the type of non-stationarity, the following example reflects the distortion induced to a trend stationary or white noise series.

[27]There are also studies using yearly data (e.g. A'Hearn and Woitek (2001) or Aikman et al. (2015)) and applying the first difference transformation. The discussion provided here, however, exclusively depicts an exposition for quarterly data as the windows of interest (short and medium term) would vary using a different data frequency

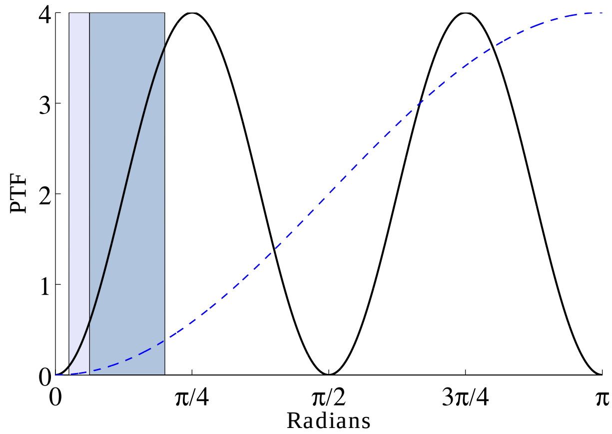

Figure 12: Power transfer function of quarter-on-quarter and year-on-year filter
Notes: The yoy filter is depicted by the solid black line; the qoq filter by the blue dashed line. The blue area marks business cycle frequencies (2.5-8 years) and the purple area medium term cycles (8-20 years).

frequency zero and leave the others untouched (meaning a squared gain of 1).[28] However, no such filter exists for all processes. The qoq filter is optimal for difference stationary processes. The yoy filter removes yearly cycles in the case of quarterly data, i.e. at frequency $\pi/2$. Further, the qoq filter dampens the frequencies which are actually suspected to drive business and financial cycles, as their gain is below one in that region. High frequency components (e.g., < one year) are intensified. In contrast, the yoy filter reduces the variance of cycles to a lesser extent and even amplifies some regions of business cycle frequencies. Moreover, the yoy filter rather suppresses high frequency components, except for cycles around $2.\bar{6}$ quarters. In this light, it can be argued that the yoy filter should be preferred as the actual frequencies of interest are not muted as strongly as in the case of the qoq filter. However it also induces distortions, i.e. overemphasises business cycle frequencies and biases the turning points properties of a series. In evaluating the spectral densities and power cohesion it is important to keep in mind at which frequencies a filter induces distortions. In the case of the yoy filter peaks around 2 years and $2.\bar{6}$ quarters could be induced by the filter. In contrast high frequency movements (< one year) for the qoq filter could be induced by the latter.

A.2.2 Univariate spectra

We use our large country setup to discuss similarities of cycle characteristics of variables across countries. The following Figure 13 reports the distribution of important cycles for all indicators considered in this study (financial and business cycle) across countries, excluding the euro area aggregate series. Spectral densities are normalised, such that the maximum value is one. Black lines depict the results

[28]The HP-filter is close the ideal one when applied to trend stationary data. However, the filter is known to induce spurious cycles when applied to the wrong data type. A'Hearn and Woitek (2001) even show that there is the potential danger that it induces a long cycle.

for the year-on-year transformation and blue line the quarter-on-quarter. Lower dashed lines portray the 10th percentile and the upper ones the 90th percentile. A small distance between the two dashed lines indicates that that the cyclical properties of the respective indicator at that frequency is similar across countries, while a long distance refers to the case where properties differ strongly across countries.

The graph confirms the result that credit and house prices are characterised by medium term cycles. Further, variables across countries seem to have similar cyclical properties as the distance between the dashed lines is small. Similarly, for equity prices the graph depicts homogeneous results across countries, however equity prices seem to have important fluctuations both at the medium as well as short term cycle frequencies.

In the case of business cycle indicators and r there is less evidence that variables have the same cyclical properties across countries. However, bond yields have most important cycles located within the window of the short term cycles skewed to 2.5 years. The qoq analysis also depicts important cycle frequencies for higher frequency components. This is also true for y, in which case the distribution of power is distributed quite equally for the qoq filter. Both transformations suggest that important fluctuations are in the short and medium term frequencies, which is in line with previous studies. In the case of the yoy filter most important cycles even appear towards longer term cycles, i.e. skewed towards the zero frequency, which would indicate that the variable is still driven by a trend.[29] Regarding u, the spectra indicate for both qoq and yoy transformations that most important cyclical variations are located in the medium term region. Nonetheless and similar to y, there are important cycle frequencies in the short term range as well. Again the yoy transformation cancels out the short term movements, while the qoq shows variation located in the higher frequency region for some countries. In the case of π_p differences between the resulting yoy and qoq spectra are strongest. Medium and short term cycles are relatively not important in the qoq case but highly in the yoy one.

Contrasting the spectra using different transformations two conclusions can be drawn: First, the yoy transformation removes the variation in the higher frequencies of the spectrum relative to the qoq filter, except for π_p. Second, the importance of the medium and short term cycle periods is robust for financial indicators (also r) with respect to the transformation across countries. Just for p_e the graph depicts that short term cycles for the qoq filter are more important relative to the short term cycles employing the yoy filter, nonetheless indicating that the cycle length on the border of medium and short term is most important. This is in contrast to the exclusive business cycle indicators (y, π_p, and u), in which case we note differences across filters within the short and medium term frequencies.

[29] Looking more specifically at the single spectra of y for each country, we note that for AT, BE, DE, DK, and SE most important cycle frequencies are located in the short term. For ES, FR, IE, IT, and NL we note that the zero frequency is most important, i.e., there is evidence that the transformed series is still governed by a long-term trend or a structural break may be present. Next to this zero frequency, however, the short term still contains the second most important cycle frequencies, except for PT. For FI and UK there is evidence of most important cycles being in the medium term.

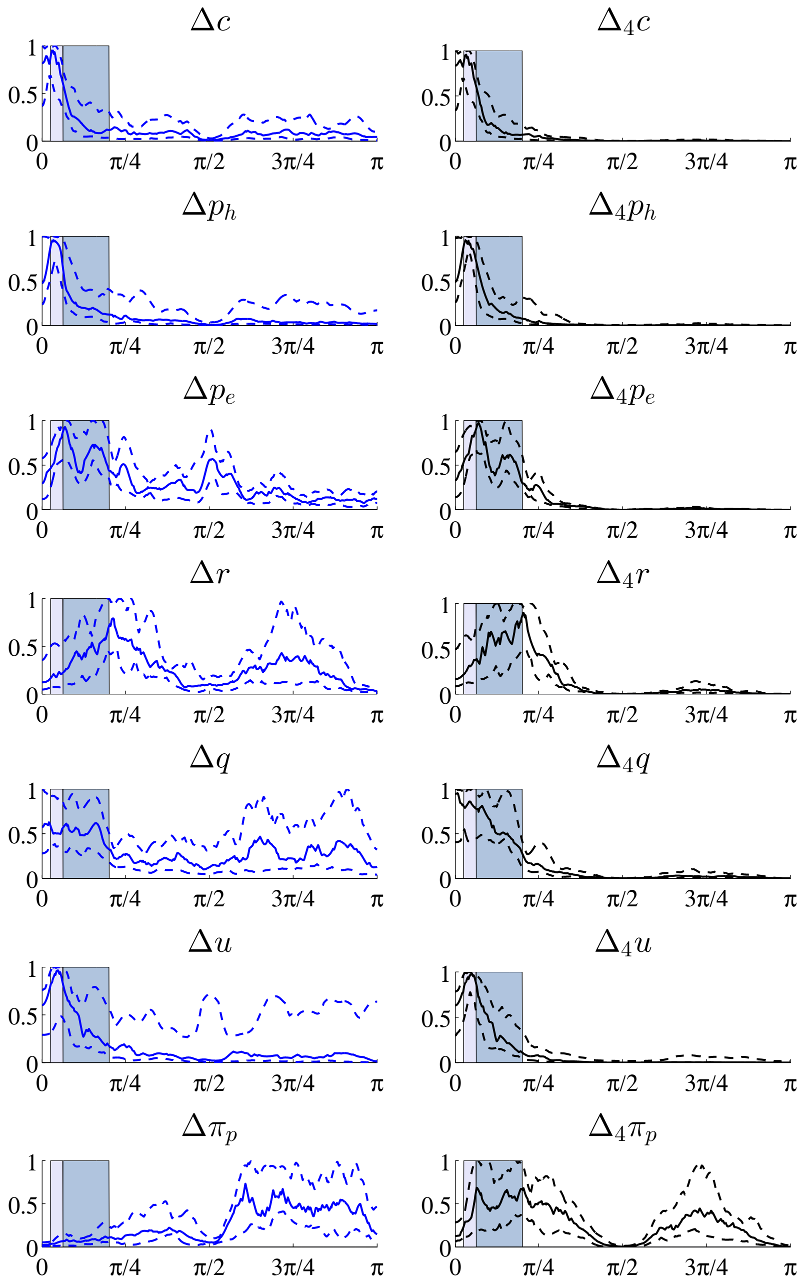

Figure 13: Normalised univariate spectra of indicators across countries

Notes: The left column depicts the graphs for qoq transformations and the right one for the yoy transformations. The x-axis measures the frequencies of cycles in radians. The maximum value of the spectral densities is normalised to one (y-axis). The blue area depicts business cycle frequencies, i.e., cycles with durations of 2.5-8 years and the purple area marks medium term cycles (8-20 years). $\Delta = 1 - L$ and $\Delta_4 = 1 - L^4$, where L denotes the lag operator. c refers to the log of total credit, p_h to the log of residential property prices, p_e to the log of equity prices, r to bond yields, q to the log of GDP, u to the unemployment rate, and π_p to the first log difference of the price level.

A.2.3 Cross-spectra

The previous subsection sheds light on the univariate spectra. For identifying economic cycles we, however, advance the idea of exploiting the co-variation between several indicators. Thus, the following analyses in detail at which cycle frequencies there is most co-movement for all pairs of indicators neglecting phase shifts. These cross-spectra are reported in Figure 14. Again, a relatively short (long) distance between the dashed lines indicates homogeneous (heterogeneous) cyclical properties of indicator pairs across countries.

We find that co-movement across indicators for the financial cycle is generally located in the medium term cycle region, while business cycle indicators are co-move in the short term as well as in the medium term region. Furthermore while financial indicators relatively agree in their cyclical properties across countries, this is less evident for business cycle indicators.

More specifically and regarding the financial indicators, we note that c shares important co-movements at the medium term cycle with p_h or p_e. This is a homogeneous result across countries. Co-movements of p_h and p_e are also most important within the medium term region which is a homogeneous result across countries. In contrast to the co-variation with credit, these graphs also depict important cyclical movements at the short term, however with less agreement across countries. The joint movement of c and p_h with r is most important towards the medium term frequencies while there exist important cycles also in the short term. For p_e and benchmark bond yields (r) important co-variation lies within the short and medium term. In all cross spectra that involve r we see that results differ relatively strong across countries. Moreover, the qoq transformation emphasises relatively strongly high frequency movements.

With respect to the business cycle indicators the yoy transformation supports common findings that important cyclical fluctuations are located within the short term, but also in the medium term region. However compared to the agreement of cyclical properties of the financial indicators (except for r), the business cycle cross spectra are relatively heterogeneous across countries. For the cross spectra that involve π_p high frequency movements are relatively more important in the qoq case.

Contrasting the yoy and qoq transformation, again, we draw the conclusion that the yoy transformation removes the higher frequency cycles, while the qoq emphasises them. This does not change the importance of longer term cycles in the case of financial indicators, however it does for the business cycle ones. This is especially evident in the cross spectra that involve inflation. We conclude from this section that the transformation of indicators matter for the business cycle but not for the financial cycle. The yoy filter has the nice property to reduce noise in the higher frequency regions, while the qoq filter emphasises those.

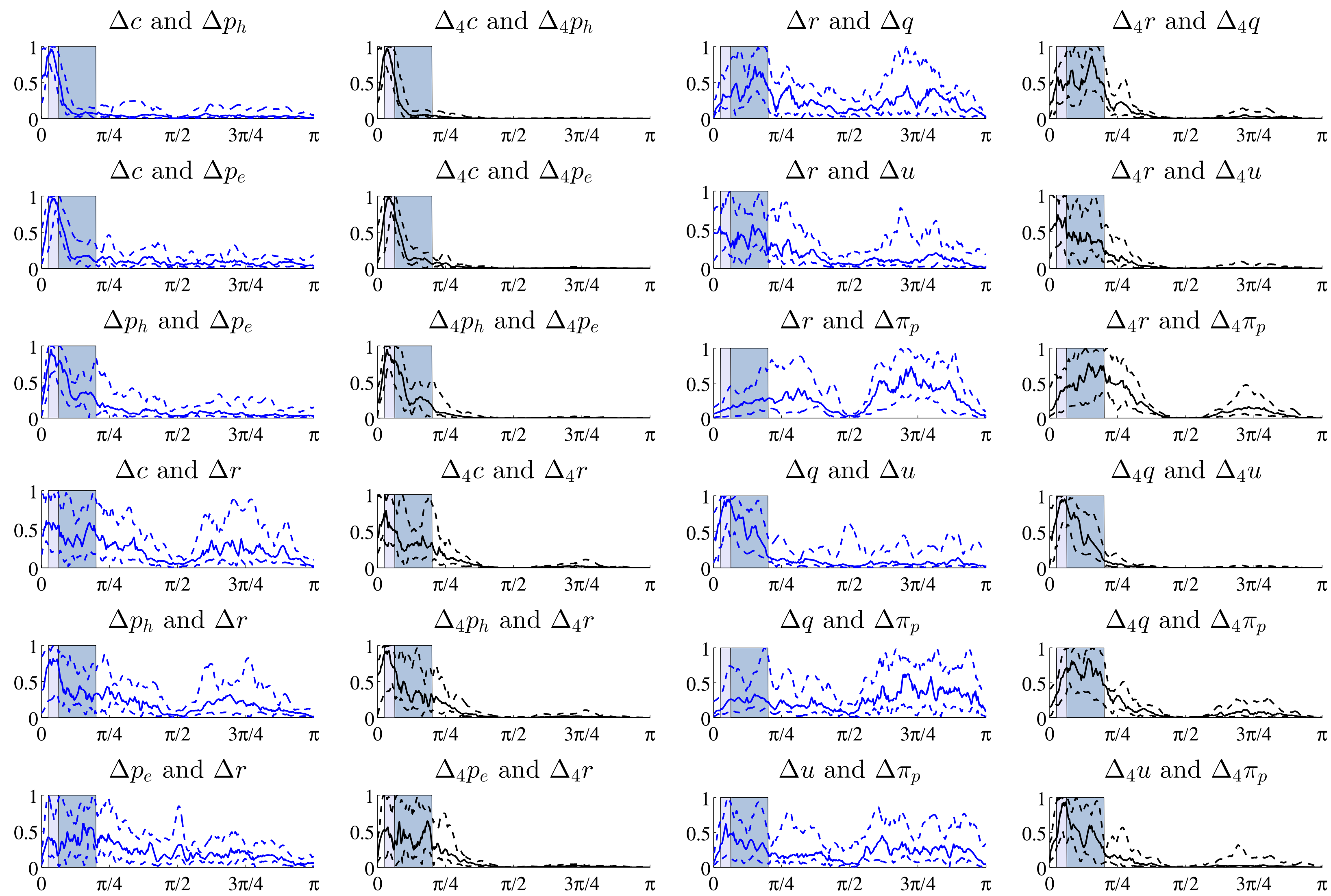

Figure 14: Absolute normalised cross-spectra between indicators across countries

Notes: The first and third columns show the cross-spectra of indicator pairs for qoq transformations across countries. The second and fourth columns depict the respective cross-spectra employing yoy transformations. The x-axis measures the frequencies of cycles in radians. The maximum value of the spectral densities is normalised to one (y-axis). The blue area depicts business cycle frequencies, i.e., cycles with durations of 2.5-8 years and the purple area marks medium term cycles (8-20 years). $\Delta = 1 - L$ and $\Delta_4 = 1 - L^4$, where L denotes the lag operator. c refers to the log of total credit, p_h to the log of residential property prices, p_e to the log of equity prices, r to bond yields, q to the log of GDP, u to the unemployment rate, and π_p to the first log difference of the price level.

A.3 Appendix to selecting financial cycle frequencies through power cohesion

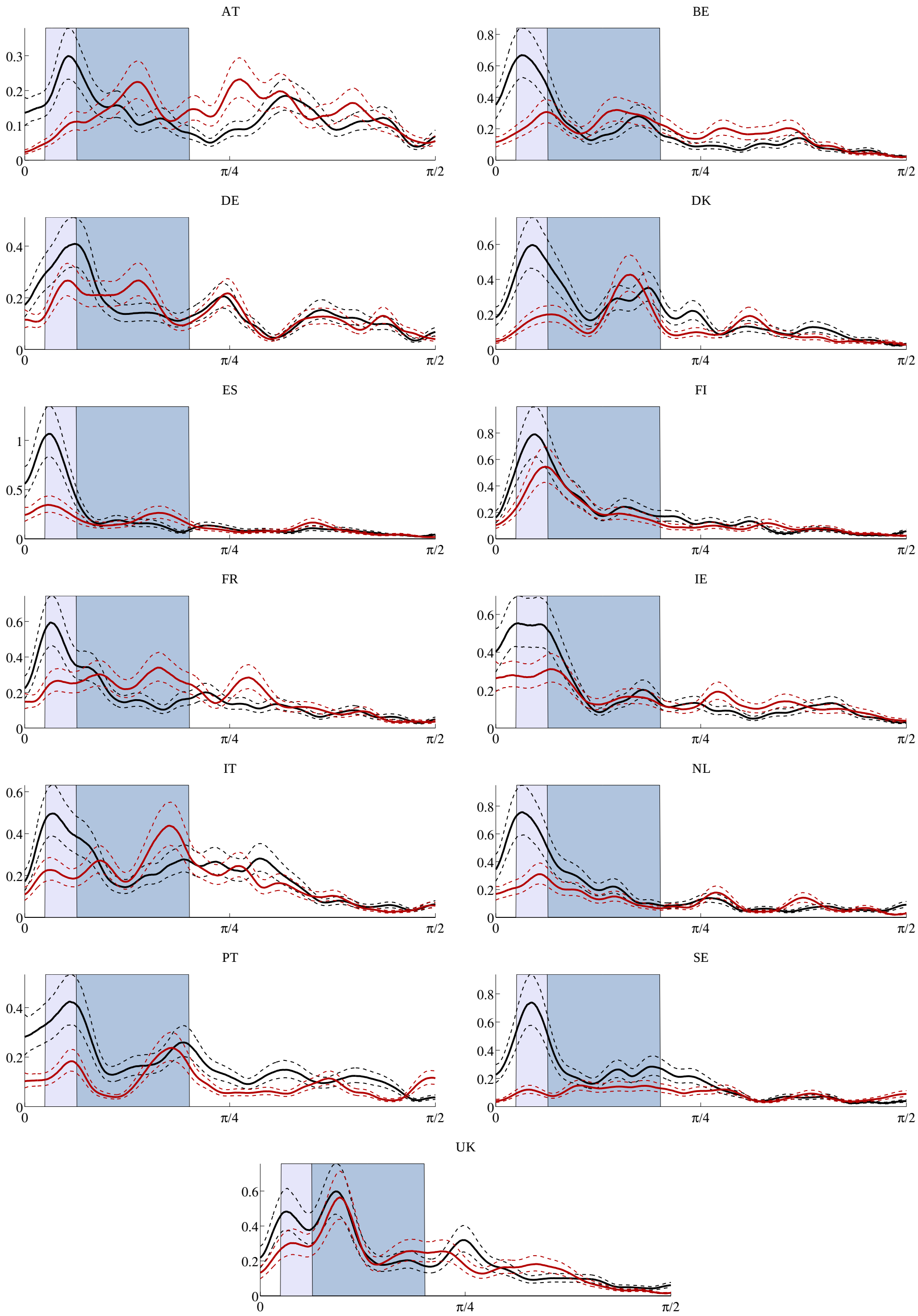

Figure 15: Power cohesion of financial (black) and business (red) cycle indicators

Notes: This panel shows the power cohesion of the financial (black lines) and business cycle indicators (red lines). The dashed lines indicate the 68% bootstrapped confidence interval. The x-axis measures the frequencies of cycles in radians from 0 to $\pi/2$. The y-axis shows the value of PCoh.The blue area depicts business cycle frequencies, i.e., cycles with durations of 2.5-8 years and the purple area marks medium term cycles (8-20 years).

A.4 Appendix to a composite index of the financial cycle

A.4.1 Financial cycles

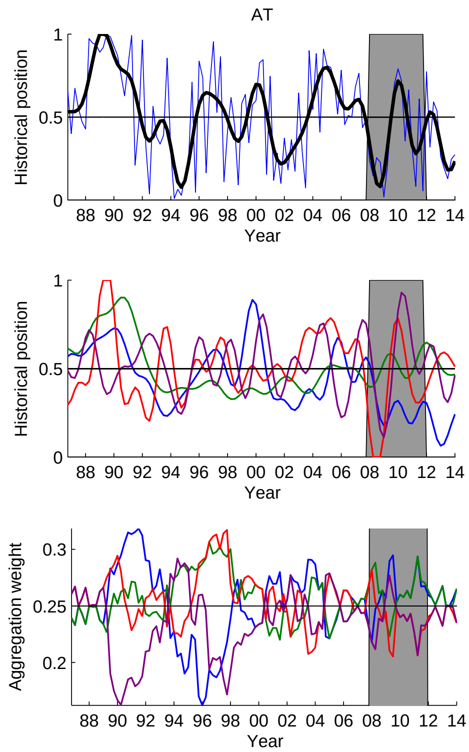

Figure 16: For each country:
1. Unfiltered (blue) and filtered (black) composite financial cycle,
2. Filtered indicator series: Δc (blue), Δp_h (green), Δp_e (red), and $-\Delta r$ (purple),
3. Time-varying aggregation weights: Δc (blue), Δp_h (green), Δp_e (red), and $-\Delta r$ (purple)

Notes: The x-axis measures the date. For each country the y-axis of the upper two graphs shows the relative historical position, where 0/1 represents the min/max and 0.5 is the historical median. The y-axis of the lower graph depicts the time-varying aggregation weights exploiting time-varying correlations between indicators, where the 0.25 line indicates equal weighting. Filtered indices use the respective frequency window as depicted in Table 2. The grey shaded area indicates a systemic banking crisis as identified by Laeven and Valencia (2012).

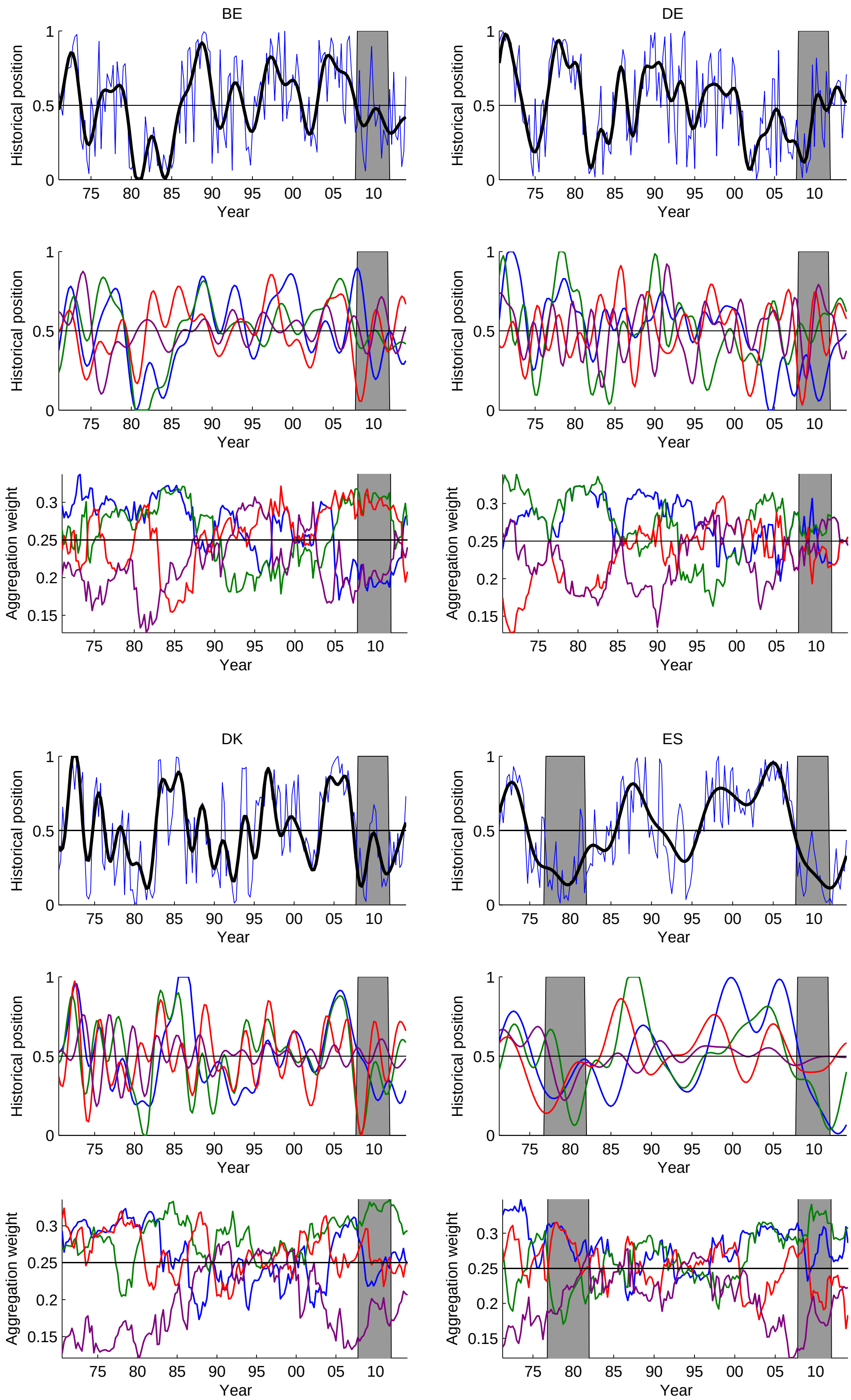

Figure 17: For each country:
1. Unfiltered (blue) and filtered (black) composite financial cycle,
2. Filtered indicator series: Δc (blue), Δp_h (green), Δp_e (red), and $-\Delta r$ (purple),
3. Time-varying aggregation weights: Δc (blue), Δp_h (green), Δp_e (red), and $-\Delta r$ (purple)

Notes: The x-axis measures the date. For each country the y-axis of the upper two graphs shows the relative historical position, where 0/1 represents the min/max and 0.5 is the historical median. The y-axis of the lower graph depicts the time-varying aggregation weights exploiting time-varying correlations between indicators, where the 0.25 line indicates equal weighting. Filtered indices use the respective frequency window as depicted in Table 2. The grey shaded areas indicate systemic banking crises as identified by Laeven and Valencia (2012).

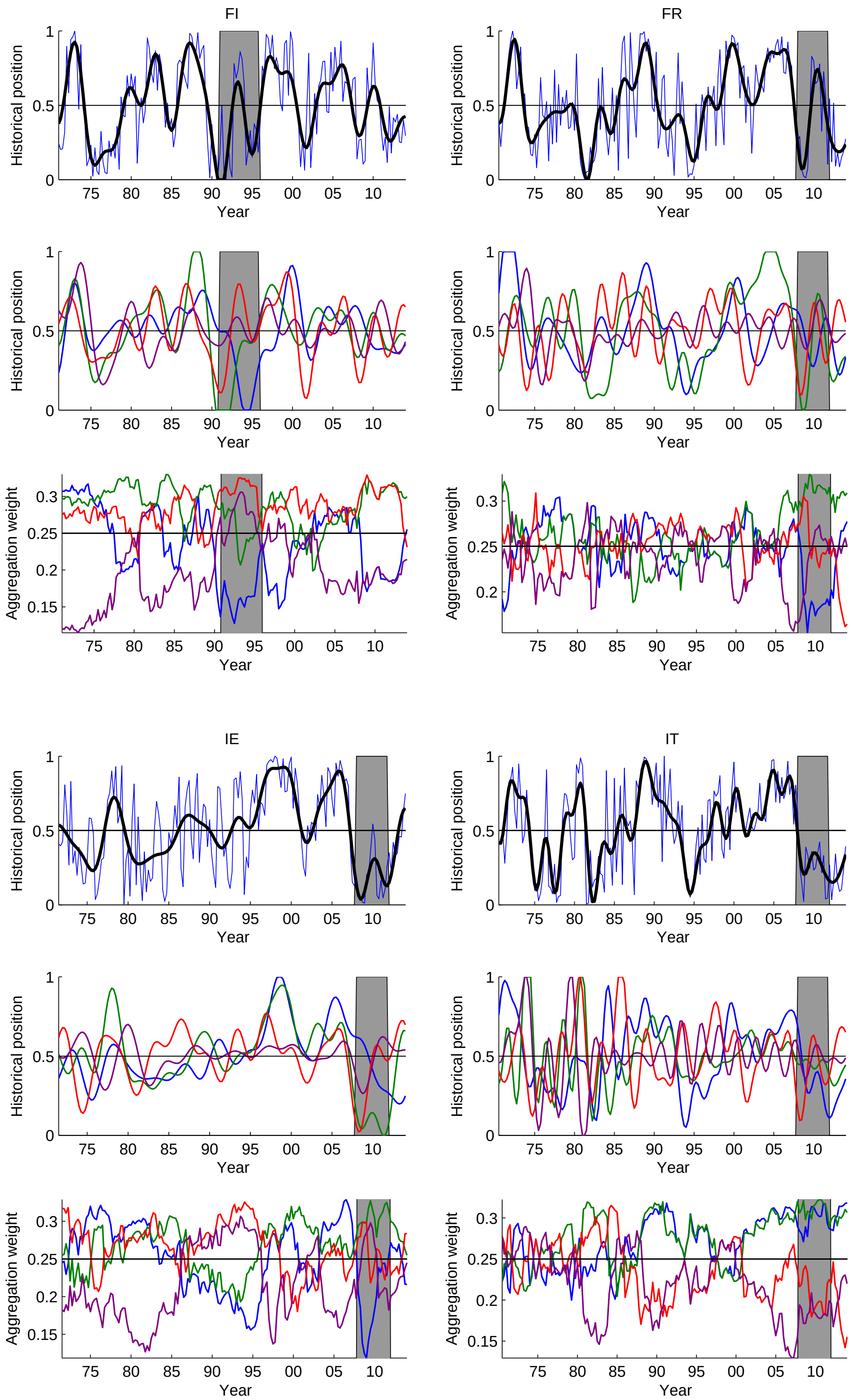

Figure 18: For each country:

1. Unfiltered (blue) and filtered (black) composite financial cycle,
2. Filtered indicator series: Δc (blue), Δp_h (green), Δp_e (red), and $-\Delta r$ (purple),
3. Time-varying aggregation weights: Δc (blue), Δp_h (green), Δp_e (red), and $-\Delta r$ (purple)

Notes: The x-axis measures the date. For each country the y-axis of the upper two graphs shows the relative historical position, where 0/1 represents the min/max and 0.5 is the historical median. The y-axis of the lower graph depicts the time-varying aggregation weights exploiting time-varying correlations between indicators, where the 0.25 line indicates equal weighting. Filtered indices use the respective frequency window as depicted in Table 2. The grey shaded areas indicate systemic banking crises as identified by Laeven and Valencia (2012).

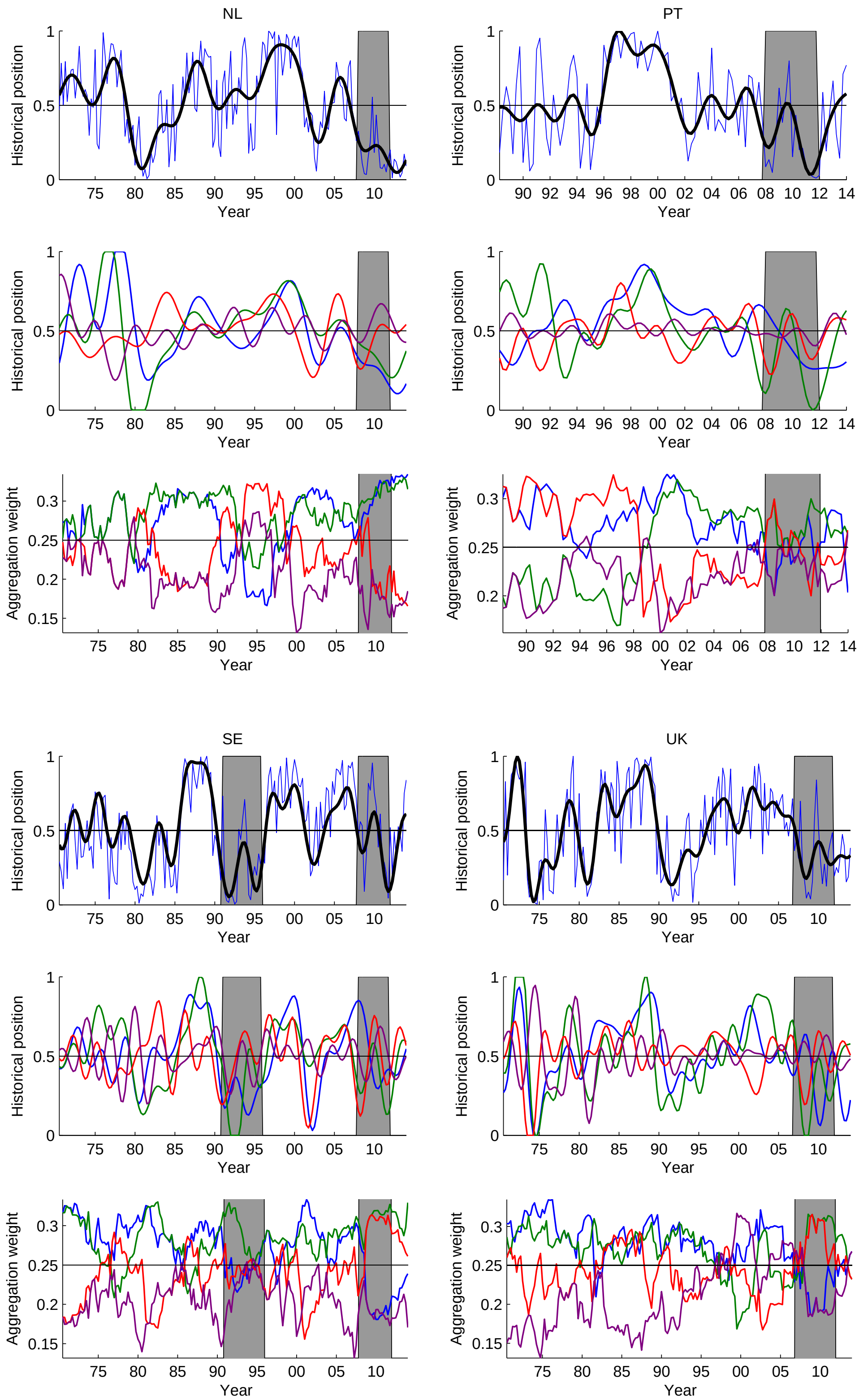

Figure 19: For each country:
1. Unfiltered (blue) and filtered (black) composite financial cycle,
2. Filtered indicator series: Δc (blue), Δp_h (green), Δp_e (red), and $-\Delta r$ (purple),
3. Time-varying aggregation weights: Δc (blue), Δp_h (green), Δp_e (red), and $-\Delta r$ (purple)

Notes: The x-axis measures the date. For each country the y-axis of the upper two graphs shows the relative historical position, where 0/1 represents the min/max and 0.5 is the historical median. The y-axis of the lower graph depicts the time-varying aggregation weights exploiting time-varying correlations between indicators, where the 0.25 line indicates equal weighting. Filtered indices use the respective frequency window as depicted in Table 2. The grey shaded areas indicate systemic banking crises as identified by Laeven and Valencia (2012).

Table 9: Concordance of filtered and unfiltered financial cycles

	AT	BE	DE	DK	ES	FI	FR	IE	IT	NL	PT	SE	UK	*Mean*
							Filtered							
AT		0.69	0.59	0.71	0.75	0.70	0.70	0.58	0.72	0.59	0.59	0.76	0.66	0.67
BE	0.69		0.57	0.77	0.81	0.84	0.72	0.81	0.78	0.76	0.68	0.78	0.80	0.75
DE	0.59	0.57		0.53	0.47	0.56	0.42	0.55	0.48	0.63	0.58	0.54	0.42	0.53
DK	0.71	0.77	0.53		0.71	0.80	0.63	0.77	0.59	0.68	0.76	0.74	0.74	0.70
ES	0.75	0.81	0.47	0.71		0.72	0.86	0.73	0.82	0.63	0.64	0.76	0.91	0.73
FI	0.70	0.84	0.56	0.80	0.72		0.75	0.74	0.63	0.65	0.71	0.79	0.75	0.72
FR	0.70	0.72	0.42	0.63	0.86	0.75		0.64	0.71	0.54	0.56	0.79	0.83	0.68
IE	0.58	0.81	0.55	0.77	0.73	0.74	0.64		0.63	0.80	0.72	0.74	0.76	0.71
IT	0.72	0.78	0.48	0.59	0.82	0.63	0.71	0.63		0.62	0.52	0.67	0.73	0.66
NL	0.59	0.76	0.63	0.68	0.63	0.65	0.54	0.80	0.62		0.62	0.62	0.67	0.65
PT	0.59	0.68	0.58	0.76	0.64	0.71	0.56	0.72	0.52	0.62		0.73	0.67	0.65
SE	0.76	0.78	0.54	0.74	0.76	0.79	0.79	0.74	0.67	0.62	0.73		0.75	0.72
UK	0.66	0.80	0.42	0.74	0.91	0.75	0.83	0.76	0.73	0.67	0.67	0.75		0.73
Mean	0.67	0.75	0.53	0.70	0.73	0.72	0.68	0.71	0.66	0.65	0.65	0.72	0.73	0.68
							Unfiltered							
AT		0.65	0.63	0.71	0.65	0.68	0.72	0.63	0.64	0.64	0.62	0.63	0.58	0.65
BE	0.65		0.60	0.83	0.75	0.80	0.68	0.78	0.66	0.78	0.74	0.75	0.75	0.73
DE	0.63	0.60		0.52	0.49	0.55	0.60	0.57	0.55	0.72	0.58	0.42	0.49	0.56
DK	0.71	0.83	0.52		0.77	0.82	0.74	0.80	0.66	0.78	0.71	0.77	0.74	0.74
ES	0.65	0.75	0.49	0.77		0.74	0.84	0.84	0.84	0.76	0.77	0.88	0.85	0.77
FI	0.68	0.80	0.55	0.82	0.74		0.74	0.71	0.62	0.74	0.72	0.80	0.68	0.72
FR	0.72	0.68	0.60	0.74	0.84	0.74		0.74	0.79	0.67	0.66	0.76	0.78	0.73
IE	0.63	0.78	0.57	0.80	0.84	0.71	0.74		0.71	0.87	0.74	0.72	0.78	0.74
IT	0.64	0.66	0.55	0.66	0.84	0.62	0.79	0.71		0.67	0.64	0.72	0.72	0.69
NL	0.64	0.78	0.72	0.78	0.76	0.74	0.67	0.87	0.67		0.80	0.66	0.72	0.73
PT	0.62	0.74	0.58	0.71	0.77	0.72	0.66	0.74	0.64	0.80		0.75	0.65	0.70
SE	0.63	0.75	0.42	0.77	0.88	0.80	0.76	0.72	0.72	0.66	0.75		0.79	0.72
UK	0.58	0.75	0.49	0.74	0.85	0.68	0.78	0.78	0.72	0.72	0.65	0.79		0.71
Mean	0.65	0.73	0.56	0.74	0.77	0.72	0.73	0.74	0.69	0.73	0.70	0.72	0.71	0.71

Notes: This table shows the bilateral concordance between indicated countries. Statistics are produced using the turning point algorithm as indicated in Section 3.3.

A.4.2 A comparison to business cycles

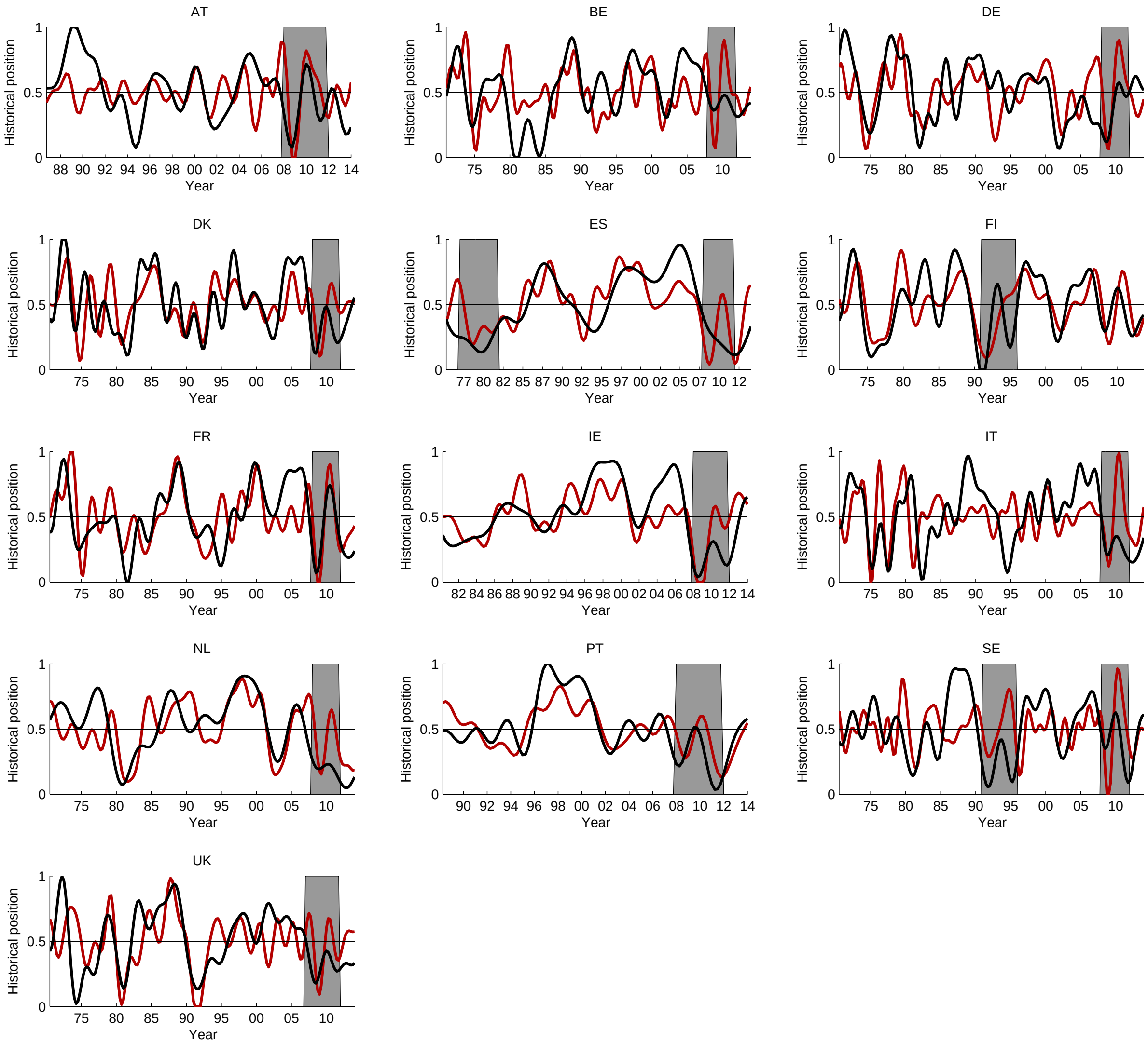

Figure 20: Financial (black) and business (red) cycles

Notes: This panel shows the filtered financial and business cycles using the frequency bands presented in Table 2. The x-axis measures the date and the y-axis the relative historical position, where 0/1 represents the min/max and 0.5 is the historical median. The grey shaded areas indicate systemic banking crises as identified by Laeven and Valencia (2012).

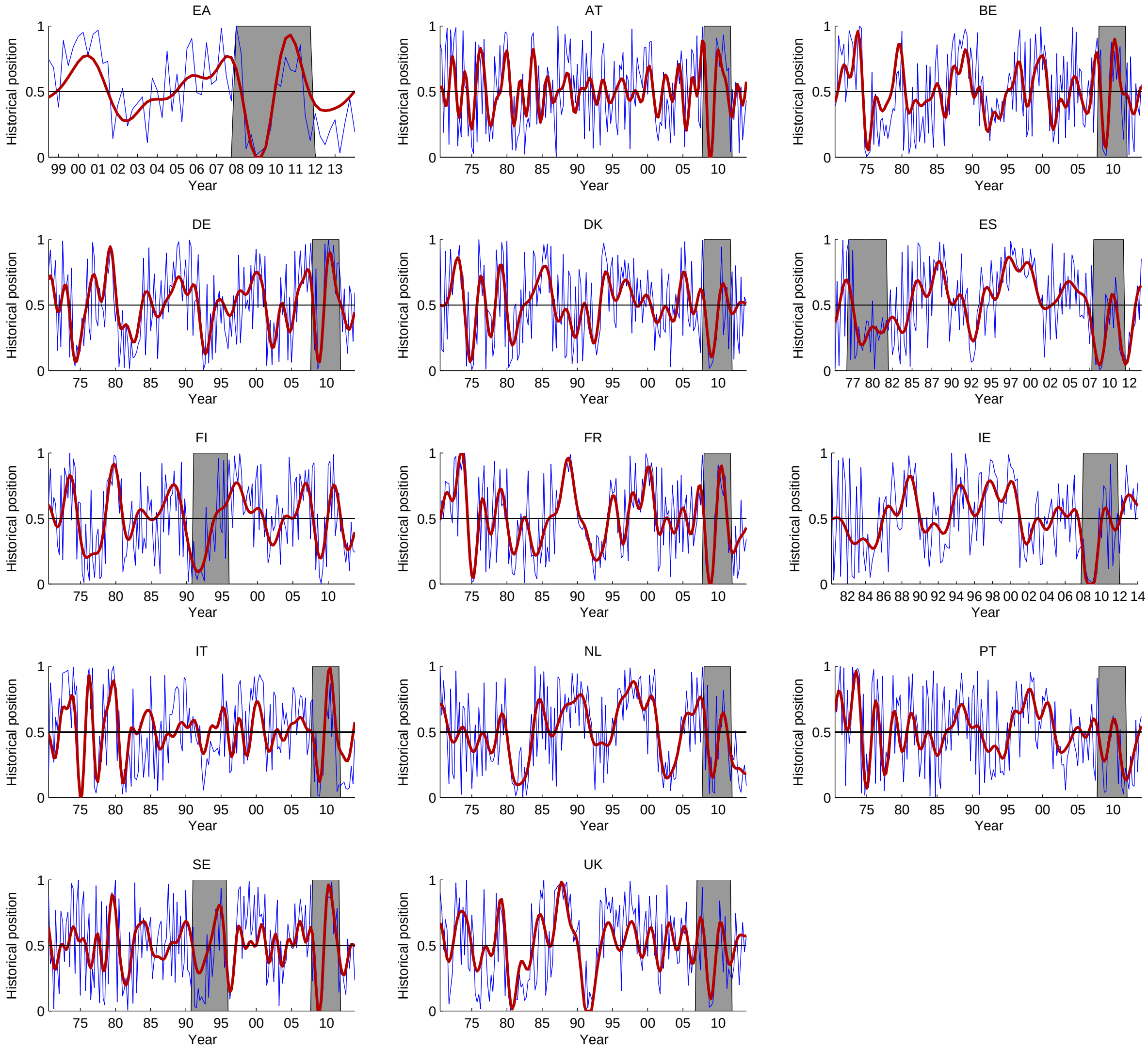

Figure 21: Unfiltered (blue) and filtered (red) business cycle composite index

Notes: This panel shows the unfiltered and filtered business cycle composite index using the frequency bands presented in Table 2. The x-axis measures the date and the y-axis the relative historical position, where 0/1 represents the min/max and 0.5 is the historical median. The grey shaded areas indicate systemic banking crises as identified by Laeven and Valencia (2012).

Table 10: Correlation of unfiltered indicators with unfiltered composite business cycle

Country	Δq	Δu	$\Delta \pi_p$	Δr
AT	0.43	-0.55	0.59	-0.63
BE	0.47	-0.53	0.67	-0.57
DE	0.44	-0.61	0.50	-0.50
DK	0.59	-0.60	0.52	-0.49
ES	0.57	-0.59	0.57	-0.62
FI	0.50	-0.63	0.59	-0.65
FR	0.58	-0.61	0.58	-0.48
IE	0.51	-0.53	0.58	-0.64
IT	0.50	-0.49	0.52	-0.50
NL	0.38	-0.60	0.60	-0.49
PT	0.50	-0.28	0.43	-0.55
SE	0.55	-0.27	0.60	-0.59
UK	0.42	-0.68	0.43	-0.38
Mean	0.50	-0.54	0.55	-0.55

Notes: Table shows the correlation between each unfiltered indicator and the unfiltered composite business cycle across the longest available sample in each country case. Δq to percentage changes in GDP, Δu to percentage point changes of the unemployment rate, $\Delta \pi_p$ to percentage point changes in inflation, and Δr to percentage point changes in bond yields.

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