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Coherent financial cycles for G-7 countries: why extending credit can be an asset

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Abstract

Failing to account for joint dynamics of credit and asset prices can be hazardous for countercyclical macroprudential policy. We show that composite financial cycles, emphasising expansions and contractions common to credit and asset prices, powerfully predict systemic banking crises. Further, the joint consideration yields a more robust view on financial cycle characteristics, reconciling an empirical puzzle concerning cycle properties when using two popular alternative methodologies: frequency decompositions and standard turning point analysis. Using a novel spectral approach, we establish the following facts for G-7 countries (1970Q1-2013Q4): Relative to business cycles, financial cycles differ in amplitude and persistence – albeit with heterogeneity across countries. Average financial cycle length is around 15 years, compared with 9 years (6.7 excluding Japan) for business cycles. Still, country-level business and financial cycles relate occasionally. Across countries, financial cycle synchronisation is strong for most countries; but not for all. In contrast, business cycles relate homogeneously.

Keywords: Financial cycle · Spectral analysis · Macroprudential policy

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“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

Financial cycles are central to systemic risk. Experience has shown that imbalances can build up in the financial system that have the propensity to lead to severe recessions, often accompanied by banking crises (e.g., Minsky (1977), Kindleberger (1978), and Reinhart and Rogoff (2009)). Though the existence of such boom-bust cycles is widely accepted and already enshrined in macroprudential mandates, assessment of such cycles remains in its infancy.

Our results suggest that research focusing in isolation on individual variables such as credit aggregates, housing, or equity prices to capture financial cycles is incomplete, and possibly misleading. We propose to combine credit with asset prices, emphasising expansions and contractions common to all series. The importance of such dynamics has not only been stressed by the theoretical construct of leverage cycles (see Geanakopolos (2010)) but also empirical studies such as Jordà, Schularick and Taylor (2015b) concerning the detrimental effects of leveraged asset price bubbles. We go beyond this, however, showing that combining credit with asset prices leads to marked accuracy of financial crisis prediction, while also reconciling empirical puzzles concerning financial cycle characteristics derived from two popular alternative methodologies: frequency decompositions and standard turning point analysis.

We offer an integrated approach to empirically identify, characterise, and evaluate financial cycles; exploiting the co-movement of credit and asset prices.[1] For *identification*, we select credit and various asset prices and present similarities in their statistical features that can be justified by the literature on leverage cycles (see Geanakopolos and Fostel (2008) and Geanakopolos (2010), as well as work by Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), Adrian and Shin (2010)) or in general by work stressing the importance economics agents’ ability to borrow (see, e.g., Iacoviello (2005) or Jermann and Quadrini (2012)). Taking this perspective, we highlight the theoretical link for the interaction of credit and asset prices; through the importance of assets as collateral for loan creation and existing feedback effects (e.g., changing margin requirements). Based on this idea we *characterise* financial cycles, i.e., we develop a spectral methodology that exploits the co-movement of credit and asset prices to capture most important common cycle frequencies – in other words, their empirical coherence. Further, we emphasise such commonality in aggregating credit and asset prices into a composite financial cycle index focussing on most important common cycle frequencies. We

[1]Important points of departure for the proposed spectral approach have been studies by A’Hearn and Woitek (2001) and Croux, Forni and Reichlin (2001) in the context of business cycles. The evaluation exercise builds on the seminal work by Frankel and Rose (1996), Kaminsky and Reinhart (1999), and Schularick and Taylor (2012).

evaluate real time composite financial cycle indices via their ability to predict known past episodes of systemic banking crises.

Three key results emerge when considering financial and business cycles of G-7 countries from 1970Q1 until 2013Q4. First, findings corroborate the rationale of modelling the joint interaction of credit and asset prices. On the one hand, their statistical features differ from business cycle indicators: credit and asset prices have higher amplitude and – with the exception of equity prices – higher persistence. Further and across countries, the correlation of credit with house prices and, in most countries, also bond prices is the strongest contemporaneously; similar to the interaction of business cycle indicators. Equity prices tend to precede credit. On the other hand, our out-of-sample signalling exercise suggests that composite financial cycle indices, exploiting the co-movement of credit and asset prices, are the best indicators for the prediction of systemic banking crises starts and vulnerability periods for G-7 economies. Predicting the start of crises, a broad index, considering the interaction of credit, housing, equity and bond prices, has an area under the receiver operating characteristic (AUROC) curve of 0.78; 19 percentage points higher than the second ranked indicator. A narrow index, mirroring the co-movement of only credit and house prices, does similarly well as the broad index in our early warning exercise comparing the area under the curve (AUC). Still, a broad index performs better considering other criteria, as, e.g., relative usefulness and noise-to-signal ratio.

Second, country financial cycles are distinct in many ways from business cycles. Financial cycles tend to exhibit pronounced booms and busts, with an amplitude of more than twice than that of business cycles. Financial cycles also tend to be long, lasting on average around 15 years in contrast to business cycles of only around 9 years (or 6.7 years excluding Japan). There is significant variation across countries. At one extreme, Germany's financial cycle is found to have the lowest amplitude and shortest length of the G-7 countries, and a close correspondence with business cycles lasting around 9 years. At the other extreme, Japan's financial cycle is long, and closely corresponds to a protracted business cycle (lasting over 20 years). Outside these extremes, most other countries differ in financial and business cycle length. In spite of these differences, our results suggest that country-level financial and business cycles coincide occasionally.

Third, we find that cross-country synchronisation of financial cycles is strong for most of G-7 countries; but not for all. The financial cycles of Germany and Japan seem to be weakly related among G-7 countries; having shown very distinct movements in credit and house prices (Hume and Sentance (2009); André (2010); Knoll, Schularick and Steger (forthcoming)). In contrast, business cycles are homogeneously related across G-7 countries.

These results suggest that macroprudential policies and the surveillance of financial stability need to consider the combined role of indicators for the detection of systemic risk build-up and materialisation. Notably, the composite financial cycle indices perform better in crises prediction than the credit-to-GDP gap that has received a prominent role for setting countercyclical capital buffer rates in the Basel III regulations and the EU Capital Requirements Directive (CRD IV). Moreover, the distinct characteristics of financial cycles relative to business cycles within countries, as well as their divergences across countries, indicate that there is a potential scope for specialised country-level macroprudential policies targeted at the build-up of systemic risk.

This paper relates to an emerging strand of literature analysing the properties of financial cycle variables such as credit, house prices, and equity prices, in contrast to business cycle variables. Studies so far have stressed their increased length, amplitude, and asymmetry. Claessens, Kose and Terrones (2011, 2012) find that financial cycles as separately measured by credit, house prices, and equity prices are longer, more volatile, and more asymmetric than business cycles identified through GDP. Focussing on measures of credit, Aikman, Haldane and Nelson (2015) observe that credit cycles have an important medium term dimension being distinct from business cycles. Drehmann, Borio and Tsatsaronis (2012) and Borio (2014) argue, as well, that medium term variance is especially important for credit cycles but also house price cycles; not so for equity prices. Further, the authors note that the length of financial cycles has increased during the great moderation. Hiebert, Klaus, Peltonen, Schüler and Welz (2014) stress the heterogeneity of financial cycle properties across euro area countries, while also noting differences between financial cycle properties when using spectral approaches or classical turning points analysis; both applied by earlier studies. Following these first studies, subsequent research supported the evidence, especially of distinct credit and house price cycles, applying different methodologies as, e.g., indirect spectral analysis (see Strohsal, Proaño and Wolters (2015a,b)), multivariate unobserved component models (see Rünstler and Vlekke (2016); Galati, Hindrayanto, Koopman and Vlekke (2016)), or wavelet techniques (see Verona (2016)). In contrast to results of previous literature, Verona (2016) does not find an increase in the length of the US financial cycle.

We contribute to this literature on financial cycles in five ways. First, justified by work on leverage cycles or in general by research stressing the importance of borrowing constraints, we argue that the joint fluctuations of credit and asset prices, emphasising expansions and contractions commons to all series, is vital for understanding financial cycles and present an empirical approach for this. Previous literature has tended to analyse properties of single indicators.[2]

Second, we are the first to systematically evaluate the significance of composite financial cycle indices in prediction of systemic banking crises starts and vulnerability periods. This is vital to highlight their potential usefulness, for instance, for policy makers. While previous studies such as Schularick and Taylor (2012) predict systemic banking crises with lagged credit growth, we show that the co-movement of indicators, i.e., a composite financial cycle index is an important predictor of crises. This finding is consistent with Jordà et al. (2015b) researching on the importance of leverage in fostering bubbles. We differ from Jordà et al. (2015b) in that our analysis is purely based on common movements of credit and asset prices both in the frequency and time domain; i.e. we do not identify leveraged asset price bubbles using selected criteria. Our framework allows for a comparison of regularities of financial cycles in

[2]While Drehmann et al. (2012) base their argument on the univariate properties of indicators, they are actually the first to consider joint fluctuations, however, by averaging financial cycle indicators; specifically, cycles of duration of eight to 30 years in credit, credit to GDP, and house prices for the US. The authors use this to illustrate increased duration and amplitude by comparing the latter to short term US GDP cycles. Strohsal et al. (2015b) extract the first principal component from the log levels of credit and house prices for the US and UK. They analyse their interdependence of these two factors in a VAR. Rünstler and Vlekke (2016) and Galati et al. (2016) test for similar medium term cycles in credit and house prices using a multivariate unobserved components framework. Theses studies, however, do not identify a composite financial cycle modelling the joint fluctuations of credit and asset prices.

relation to business cycles, but also across countries; both crucial for policy making.

Third, we contribute by reconciling differences of financial cycle characteristics obtained through the use of two alternative methodologies: frequency decompositions and standard turning points analysis. Longer duration financial cycles have been found in studies using frequency decompositions (see Aikman et al. (2015); Drehmann et al. (2012); Strohsal et al. (2015a); Rünstler and Vlekke (2016); Galati et al. (2016); Verona (2016)), while more similar financial and business cycles arise when using univariate turning point analyses (see, e.g., Claessens et al. (2011, 2012); Drehmann et al. (2012); Hiebert et al. (2014)). Considering joint fluctuations of indicators in the turning point context, financial cycles turn out to be longer than business cycles.

Fourth, we are the first to contrast G-7 financial and business cycle synchronisation.

Fifth, we propose new empirical means of endogenously determining country-specific financial and business cycle frequencies. With this approach, in contrast to seminal work of Drehmann et al. (2012) and Borio (2014), distinct frequencies in financial and business cycles are estimated rather than imposed.

Our study also contributes to research on business cycle measurement and characteristics. Applying our method to business cycle indicators, we find support that longer term business cycles are a phenomenon for the broad set of G-7 countries; thus, supporting results by previous studies, as, e.g., Comin and Gertler (2006) and A'Hearn and Woitek (2001). Notably, for the US, our methodology consistently estimates the business cycle length as derived by the NBER dating committee, while also indicating important fluctuations above 8 years.

The remainder of the paper is organised as follows. Section 2 discusses the indicators that should feed into financial cycle measurement. Section 3 introduces a "power cohesion" methodology to extract common cyclical movements of a set of cycle indicators and presents the characteristics of financial and business cycles across G-7 countries. Section 4 suggests an approach to filter common movements of indicators in the time domain, which are then used to shed light on financial cycle synchronisation versus business cycle synchronisation and the prediction of past systemic banking crises and their preceding vulnerability periods. Section 5 concludes.

2 Financial cycle indicators, transformations, and statistical properties

Much the same way as business cycles relate to recessions, financial cycle indicators should relate to financial recessions, i.e., recessions that occur in tandem with banking crises.[3] In contrast to other recessions, financial recessions occur less frequently, are deeper, and last longer. Further, financial recessions follow credit booms (see Jordà et al. (2013); Boissay, Collard and Smets (2016)).

In this light, credit seems to be a necessary indicator for financial cycles. Boissay et al. (2016) outline several empirical facts about credit, showing that it follows distinct movements, such as higher variance and persistence around financial recessions than other types of recessions. That is, credit has the potential to encapsulate the build-up of imbalances in the financial cycle presaging financial

[3] Financial recessions are defined in this way, for instance, by Jordà, Schularick and Taylor (2013)

recessions and its subsequent unwinding. Indeed, Schularick and Taylor (2012) provide evidence that lagged credit growth predicts financial crises well. Studies actually argue that credit can be a source of instability and not just an amplifier of shocks as described by the financial accelerator approach (see Bernanke (1983), Gertler (1988), Kiyotaki and Moore (1997), Bernanke, Gertler and Gilchrist (1999). Already Minsky (1977) argued that there may be endogenous financial instability through, among other elements, credit, which pushes investors' sentiment into either overoptimism or fear. Bhattacharya, Goodhart, Tsomocos and Vardoulakis (2015) model Minsky's hypothesis formally with the possibility of endogenous default, with support for cycles whereby agents update their expectations during good times and increase their leverage.

While credit may be a necessary element of financial cycles, it is less clear whether it is sufficient. For instance, Mendoza and Terrones (2008) and Gorton and Ordoñez (2016) note that not all credit booms lead to a financial crisis. In this regard, asset prices could complement credit to capture financial cycles arguing via the so-called "balance sheet" channel. That is, one of the implications of credit market frictions is that the state of balance sheets is an important determinant of agents' ability to borrow and lend (e.g., Bernanke and Gertler (1999)). In this view, changes in asset prices alter an agent's net worth and, e.g., through the asset's use as collateral and its associated influence on leverage, thereby affecting the scale of borrowing and lending. The importance of this interaction has been the centre of studies on leverage cycles as, e.g., by Geanakopolos and Fostel (2008) and Geanakopolos (2010), as well as work by Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009) and Adrian and Shin (2010).

Our suggested set of asset price indicators supplementing credit in a financial cycle includes house, equity, and bond prices. The importance of *real estate* is, for instance, noted by Iacoviello (2005), who introduces collateral constraints that are governed by real estate values into a monetary business cycle model as empirics indicate that a large part of borrowing is secured by real estate (see also Campell and Hercowitz (2009); Justiano, Primiceri and Tambalotti (2015)). Jordà, Schularick and Taylor (2015a, 2016) note that risks to financial stability are strongly linked to real estate lending developments. Claessens et al. (2012) and Claessens et al. (2011) provide empirical evidence that recessions marked by *equity* together with *house price* busts tend to be deeper and longer. Jordà et al. (2015b) report that most build-ups of systemic risk involved both equity and house prices past World War 2. Further, corporate *bond prices* have been argued to be an important indicator of the soundness of the financial system, e.g., during the Global Financial Crisis (Gilchrist and Zakrajšek (2012). Gilchrist, Yankov and Zakrajšek (2009) find that an unexpected increase in bond spreads, i.e., corporate yield minus risk free yield, cause large and persistent contractions in economic activity. Further, bond market information is an integral component of financial stress indices. Shocks to these indices have been shown to be highly detrimental for the economic outlook (e.g., Hubrich and Tetlow (2015); Fink and Schüler (2015)).

Building on these studies suggesting that a joint analysis of credit and asset prices may be needed to adequately characterise a notional financial cycle, we opt for a narrow and broad measure of a financial cycle. The narrow measure bringing in credit and house prices is motivated by the close relation of credit and real estate as, e.g., argued by Iacoviello (2005) or as evidenced in Jordà et al. (2015a, 2016). The broad measure also including financial asset markets is motivated by evidence that a larger set of asset prices might be vital to identify emerging risks (e.g., Jordà et al. (2015b)), also on a global scale (see Rey (2015), Miranda-Agrippino and Rey (2015), or Breitung and Eickmeier (2014)). For this we additionally include equity and bond prices.

A standard set of indicators is selected to encapsulate a reference business cycle based on the same approach used for identifying financial cycles. These are output, consumption, investment, and hours worked (see, for instance, Burnside (1998)).

Transformations

We analyse cycles in growth rates, rather than classical cycles or growth cycles (Harding and Pagan (2005)), among others, as the spectral approach taken in this paper requires stationary processes. 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.[4] Further, similar to Comin and Gertler (2006), who research on the importance of medium and long term business cycles, we remove a nonlinear smooth trend from our indicators, i.e., we filter growth rates by removing cycles that are longer than 200 quarters using the Christiano and Fitzgerald (2003) band-pass filter.[5] The removed trend, thus, includes cycles that are larger than 50 years.[6] Further, all variables are in real terms. The exact details on the variables are provided in Appendix A.1.

In sum, total credit, house prices, equity prices, output, consumption, investment, and hours worked are measured in quarterly filtered growth rates excluding cycles of duration longer than 50 years. Corporate bond yields are transformed to reflect filtered growth in bond prices, to be in line with the interpretation of house and equity prices, by exploiting the relation: $p_{b,t} = 1/(1 + y_{b,t})$, where $p_{b,t}$ denotes the price and $y_{b,t}$ the current yield of the respective bond at time t. As we analyse bond indices – given that we require a long history - we do not have all information available for this transformation. Specifically, we assume that all yields have been transformed to zero coupons. Further, given data limitations for the set of countries considered, we resort to a simplifying assumption that indices are derived from a portfolio of bonds with constant average yield to maturity.

[4]Note that cycle characteristics identified by Drehmann et al. (2012), Strohsal et al. (2015a), and Verona (2016) are recovered from annual growth rates – however, this transformation lacks precision for identifying turning points. Schüler, Hiebert and Peltonen (2015) contrast the implications of both year on year (yoy) and quarter-on-quarter (qoq) transformations for the resulting spectral properties. Summarising the results, the authors 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.

[5]An exception to this is the signalling exercise of Section 4.4, for which we construct real time indices based on unfiltered growth rates. This is because the band pass filter suffers from an endpoint bias, leading to a biased real time estimate of the nonlinear smooth trend.

[6]We are aware of the fact such pre-treatment may bias results because of leakage problems and end of sample biases of filters. The latter should be small because of restricting only longer term cycles. In general, however, as all indicators (business versus financial and across countries) are treated equally, biases should be systematic and, thus, leave, relative conclusions valid.

Statistical properties

The nascent literature on credit and financial cycles indicates that the medium term component is more relevant relative to the one in output. In this vein, we compare three summary statistics of financial cycle indicators with those of business cycle indicators dividing each variable's long term cycle (2-200 quarters) into a short (32-2 quarters) and a medium and long (32-200) term frequency component. We consider standard deviation, autocorrelation, and cross-correlation between indicators; similar to Comin and Gertler (2006).[7] For cross-correlation between indicators we use credit as the base variable because of its prominent role as a financial cycle indicator. Output is chosen for business cycle indicators. Comin and Gertler (2006) use such an exercise to provide evidence of a medium/long term business cycle. By simply extending their methodology, we can compare medium and long term components of financial cycle indicators with that of business cycle indicators.

Table 1: US: Descriptive statistics – real growth rates

	Standard deviations			First-order autocorrelations	
Financial cycle	Medium/long-term cycle 2-200	High-frequency component 2-32	Medium/long-frequency component 32-200	Medium/long-term cycle 2-200	High-frequency component 2-32
Credit (Δcr)	0.98	0.67	0.70	**0.76**	**0.50**
House price (Δp_h)	1.70	1.08	1.23	**0.81**	**0.54**
Equity price (Δp_e)	7.96	7.69	1.91	0.05	-0.02
Bond price (Δp_b)	0.89	0.72	0.51	**0.66**	**0.49**
Business cycle					
Output (Δq)	0.82	0.78	0.26	**0.31**	**0.23**
Consumption (Δco)	0.66	0.61	0.26	**0.33**	**0.20**
Investment (Δi)	2.07	1.92	0.76	**0.48**	**0.40**
Hours worked (Δh)	0.37	0.36	0.06	-0.12	**-0.16**

Notes: Bold numbers indicate significance at least at the 10% level. Statistics are derived using HAC standard errors.

In case the medium and long term components of financial cycle indicators were to be more relevant, we would expect three conditions to hold. First, the *variance* of the medium and long frequency component (32-200 quarters) relative to the overall variance would be larger for financial cycle than for business cycle indicators. Second, the *persistence* of financial cycle indicators would be located in the medium and long frequency component more than compared with business cycle indicators. Third, the highest *correlation* of other indicators with credit (as an anchor variable of the financial cycle) can be rather attributed to medium and long frequency components when compared to highest correlation of other indicators with output (as an anchor variable of the business cycle). Results for the US – also the focus of Comin and Gertler (2006) – are reported in Table 1 and Table 2. The tables for the remaining countries are in Appendix A.4.

For the narrow financial cycle measures (credit and house prices) and with respect to the first property above (*variance*), we indeed find evidence in case of all G-7 countries that the variance of the medium/long-frequency component relative to the overall variance is larger for financial cycle than for business cycle indicators. In the case of the US, figures indicate that while for business cycle indicators almost all variation is explained by the high-frequency component, the standard deviation of indicators

[7] Note that Comin and Gertler (2006) analyse growth cycles and not cycles in growth rates.

is even higher for the medium- and long-frequency component. The weakest evidence of this difference is found for Germany, where the overall standard deviation for the medium and long term cycle also is the lowest across all countries. With respect to the second property above (*persistence*), the results indicate that the medium and long term cycle is by far more persistent than considering only a high-frequency component for narrow financial cycle indicators compared to business cycle indicators. In the case of the US, the first order autocorrelation increases from 0.5 to 0.76 in the case of credit and 0.54 to 0.81 for house prices. In contrast, the increase of business cycle indicators is at most from 0.2 to 0.33, for consumption. For house prices in Canada, the increase in persistence is of similar magnitude as for output. For the third property above (*cross correlation*), for the narrow financial cycle indicators, the medium and long term cycle is more strongly correlated than the high-frequency component for both credit and house prices. Again one exception is Germany, where adding the medium- and long-frequency component does not alter the strength of the correlation. When extending this analysis to also consider lead and lag of indicators, we find that for almost all G7 countries maximum correlation is contemporaneous; the exception is France where credit is lagging by one quarter. In contrast to financial cycle indicators, business cycle indicators have strong correlations with output that are largely impervious to adding medium and long term cycles. Similarly, all business cycle indicators share highest co-movement contemporaneously. In the spirit of Comin and Gertler (2006), business cycle indicators, as well, share some important medium- and long-term cycles – in this case with credit, as their cross correlation also increases for the medium/long term cycle. However, a lead-lag relation appears to be present in such a circumstance.

Table 2: US: Maximum absolute correlation with credit and output – leading or lagging up to 4 quarters

	Credit				Output			
Financial cycle	Medium/long-term cycle 2-200		High-frequency component 2-32		Medium/long-term cycle 2-200		High-frequency component 2-32	
Credit (Δcr)	-	(-)	-	(-)	0.41	(2)	0.34	(2)
House price (Δp_h)	0.47	(0)	0.35	(0)	0.40	(-1)	0.37	(-1)
Equity price (Δp_e)	0.19	(-4)	0.18	(-3)	0.34	(-1)	0.31	(-1)
Bond price (Δp_b)	0.40	(0)	0.48	(0)	0.41	(-2)	0.41	(-2)
Business cycle								
Output (Δq)	0.41	(-2)	0.34	(-2)	-	(-)	-	(-)
Consumption (Δco)	0.55	(0)	0.50	(0)	0.66	(0)	0.62	(0)
Investment (Δi)	0.43	(-2)	0.44	(0)	0.77	(0)	0.75	(0)
Hours worked (Δh)	0.16	(-4)	0.19	(-3)	0.43	(0)	0.44	(0)

Notes: Numbers in brackets denote lead (+) or lag (-) of credit or output to respective variable.

These results for narrow financial cycles to some extent carry over when considering a broad financial cycle, i.e., also including both equity and bond prices. For *equity prices*, only a small percentage of *variation* located in the medium- and long-frequency component compared with shorter frequencies. At the same time, this proportion of variance is by far the largest compared to all other indicators – at 1.91 for the US. The characteristics of *persistence* in equity prices is similar to that of business cycle indicators. In the case of the US, this is particularly clear, with no significant first order autocorrelation in either the high-frequency component or the medium- and long-term cycle. The cross-correlation with credit is mostly located in the high-frequency component. Interestingly, however, equity prices, seem to be leading credit by several quarters. In that respect, for France and Italy the highest correlation such a leading property for equity prices appears only relevant for medium- and long-term cycles, not for the high-frequency component. *Bond prices*, in contrast share similar features with credit and house prices. That is, an important share of *variance* is located at the medium- and long-frequency component while cycles in the medium- and long-frequency band are highly *persistent*. Results, however, are rather mixed about the *cross-correlation* with credit. Both the medium term cycle and the high frequency component show highest correlation, which, nonetheless, is in most cases contemporaneous.

In sum, credit and house prices (and also bond prices, to some extent) share characteristics (in their variance, persistence and correlations) which are distinct from business cycle indicators. For these indicators, the highest correlation or cohesion is contemporaneous, similar to the analogous finding for business cycle indicators. Equity prices represent an exception to these regularities among financial cycle indicators. While equity prices are marked by highest variance in the medium- and long-frequency component, this is of relatively low importance in capturing overall variance for this volatile series. At the same time, equity prices appear to lead credit. Business cycle indicators also seem to be related to credit at medium- and long-term frequencies, however, with no systematic lead-lag relation across our set of countries.

In light of these observations, there is evidence that especially the narrow set of financial cycle indicators, i.e., credit and house prices, have important fluctuations at cycle lengths between 8 and 50 years. Cohesion of indicators seems to be strongest contemporaneously, but not exclusively. In the next section, we offer a methodology to arrive at more precise estimates of exact frequencies that are important to explain their coherence, and contrast these results with business cycle indicators.

3 FINANCIAL CYCLE FREQUENCIES

This section deepens the investigation of whether financial cycle indicators share co-movement at different cycle lengths than business cycle indicators. First, a methodology for this purpose is outlined and second, results are reported. Third, a robustness exercise using turning points is presented.

3.1 Methodology: Power Cohesion – discovering important 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 is assumed to contain stationary stochastic processes with well-defined normalised cross spectral densities, which can be written as

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

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.

Proposition 1. PCoh discards phase shifts between variables.

Proposition 2. The support of PCoh is normalised and is between 0 and 1 when integrated from $-\pi$ to π.

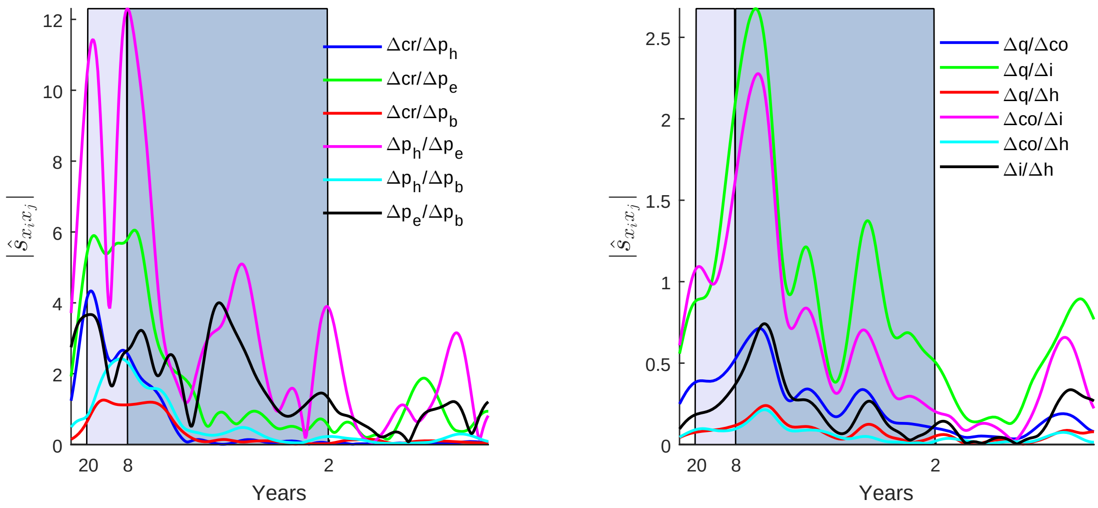
Proposition 3. PCoh indicates the contribution of different cycle lengths to the overall co-variance between indicators and thus differs importantly to the more common measure of squared coherency.

For the relevant proofs and details on empirical issues please refer Appendix A.2. Note that Proposition 1 takes into account lead and lag relations between indicators, as suggested by the estimates presented in the preceding section of this paper.

3.2 *Cross-spectral densities*

Cross-spectral densities, i.e., $s_{x_i x_j}(\omega)$, are one of the building blocks of our measure "Power Cohesion" (PCoh). While the amplitude of PCoh for different sets of indicators cannot be directly related to each other, for cross-spectral densities this is reasonable. In Figure 1, we show the absolute cross-spectral densities of the US financial and business cycle indicators, i.e., measuring covariances in and out of phase (see Appendix A.2 for more details). The other country cases are depicted in Appendix A.5. On the x-axis the graphs indicate the cycle length; from 1.25 years to 50 years. We mark the region of frequencies that are commonly attributed to the business cycle (2-8 years) and the range of frequencies from 8 to 20 years that we find to be important for financial cycles.

In the case of the US, it is evident that financial cycle indicators (Figure 1a) share more important cyclical variance at medium term cycles, indicated by the magnitude of lines, while all most important common cycle for business cycle indicators (Figure 1b (b)) are within the short term region of cycle length. Common cycles of house and equity prices ($\Delta p_h/\Delta p_e$, pink line) are most pronounced just below 20 and 8 years. Common cycles of credit and equity prices ($\Delta cr/\Delta p_e$, green line) are most pronounced for all medium term cycle frequencies with small spikes at the regions of peaks in house and equity prices, while credit and house prices ($\Delta cr/\Delta p_h$, blue line) share most important frequencies towards 20 years. Equity and bond prices ($\Delta p_e/\Delta p_b$, black line), similarly as credit and house prices have important cycles around 20 years, while, however, marginally more important cyclical variance is within the short term region. House and bond prices ($\Delta p_h/\Delta p_b$, turquoise line), have most important cycle above 8 years and credit with bond prices ($\Delta cr/\Delta p_b$, red line) have important both medium as well short term frequencies, however skewed towards the longer business cycles. For business cycles indicators the picture is very clear, all pairs of indicators peak around the same frequency region which is below but close to eight years. Further, business cycle indicators do not have relatively important



(a) Financial cycle indicators

(b) Business cycle indicators

Figure 1: US: Absolute cross-spectra

Notes: This panel shows the absolute cross-spectra of the financial and business cycle indicators. The x-axis measures the frequencies of cycles from 1.25 - 50 years. The blue area depicts business cycle frequencies, i.e., cycles with durations of 2-8 years and the purple area marks frequencies important for financial cycles (8-20 years). Δcr refers to percentage changes in total credit, Δp_h to percentage changes in house prices, Δp_e to percentage changes in equity prices, Δp_b to percent changes in bond prices, Δq to percentage changes in GDP, Δco to percentage changes in consumption, Δi to percentage changes in investment, and Δh percentage changes in hours worked.

cycles located in the medium term region, when compared to financial cycle indicators. While these results seem to hold for most other G-7 countries, there are also exceptional cases. Germany and the UK, in particular, depart from other G-7 countries in that they exhibit more frequency masses of important cycles located below but close to 8 years. The agreement of cycle length across indicator pairs is stronger for Germany, where even common credit and house price cycles are just below 8 years. Further, business cycles for Germany and Canada appear to be atypically long and located in the medium term region.

Concerning the amplitude of cycles in the US, it is evident that financial cycles are more volatile on average relative to business cycles. The peaks of the different financial cycle cross-spectral densities are well above the peaks of the cross-spectral densities of business cycle indicators, except for the cases of house and bond prices as well as credit and bond prices, which are still above most of the cross-spectral densities of business cycle indicators. Looking beyond the US at other G-7 countries, we find that Germany's financial cycle has the lowest amplitude – contrasting with strong amplitude in both Italy and the UK.

3.3 Power Cohesion for G7 countries: Financial cycle frequencies

This section presents our measure PCoh, for the narrow ($\Delta cr, \Delta p_h$) and broad (narrow + $\Delta p_e, \Delta p_b$) financial cycle as well as the business cycle. Figure 2 depicts the case of the US. The remaining country cases are presented in Appendix A.5. Again, graphs indicate on the x-axis the cycle length from 1.25 to 50 years. The region commonly associated with business cycle frequencies is denoted in blue shading, while in the region in purple represents medium term frequencies.

To benchmark PCoh as a new approach to measure important cycles pertinent to a set of indicators, we reference the result for US business cycle indicators to recessions as published by the NBER dating committee, which implicitly demarcates business cycle frequencies. To this end, the peak of PCoh for the US business cycle is located at a cycle length of 5.7 years, identical in length to the reference NBER statistic (average business cycle duration from 1945 to 2009) also at 5.7 years (measuring peak to peak).

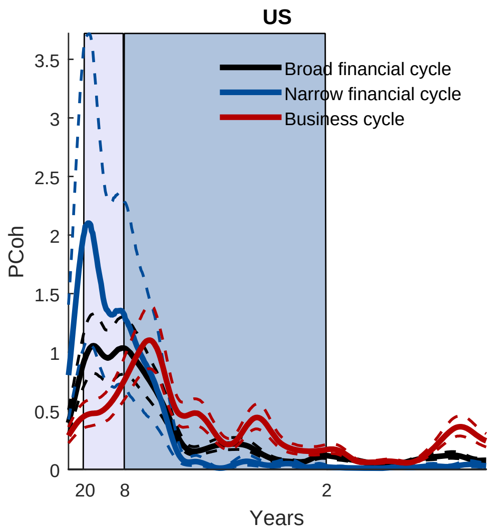


Figure 2: US: Power Cohesion

Notes: This graph shows the measure power cohesion of the narrow (black lines) and broad financial cycle (blue lines) as well as the business cycle (red lines). Broad refers to the inclusion of all indicators, i.e., credit, house, equity, and bond prices, whereas narrow is defined by house prices and credit only. The dashed lines indicate the 68% bootstrapped confidence intervals as discussed in Appendix A.3. The x-axis measures the frequencies of cycles from 1.25 to 50 years. The blue area depicts business cycle frequencies, i.e., cycles with durations of 2-8 years and the purple area (8-20 years) marks frequencies most important for financial cycles.

For the US, both the broad and narrow measure of financial cycles, clearly have most mass located at medium term frequencies, while business cycles just below these cycle lengths – confirming the exercise conducted in the previous section of this paper. While the broad and narrow definition of financial cycles share similar important cycle frequencies, the broad measure envelops relatively more frequency mass amid medium and short term frequencies. That said, most cohesion of financial cycle indicators is located in the frequency range within 20 to 8 years. In this way, financial cycle cohesion is above that of business cycles. While financial cycle indicators do not exhibit strong cohesion for cycles between 2 and 8 years, business cycle indicators have higher cohesion in this range.

Highest density regions across G-7 countries

Across G7 countries, these figures are conveniently summarised by the highest density chart that depicts 25% of most important frequencies between 1.25 and 50 years shown in Figure 3). For the financial cycle, we show the narrow (blue) and broad (black) measure, as well as the narrow plus equity prices (turquoise) on the one and bond prices (purple) on the other hand for robustness. Coloured bars indicate at which cycle lengths 25% of most important cohesion between indicators is located and white dashes indicate the peak of PCoh that is the most important cycle.

Comparing financial cycle frequencies across countries, we find that for the narrow set of indicators

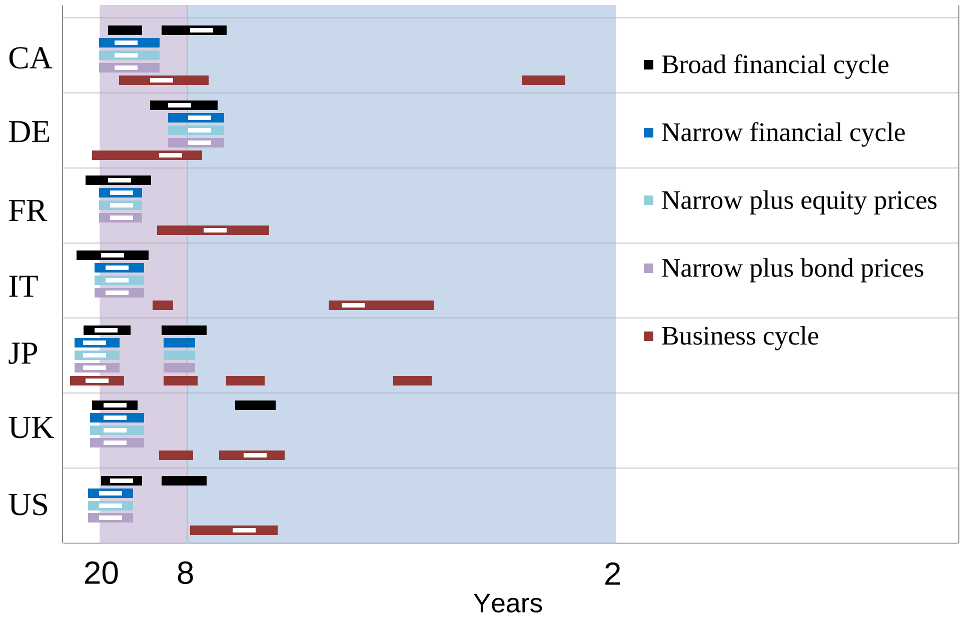


Figure 3: Highest density chart of power cohesion

Notes: This graph depicts the 25% highest density region (see Hyndman (1996)). Broad refers to the inclusion of all indicators, i.e., credit, house, equity, and bond prices, whereas narrow is defined by house prices and credit only. The x-axis measures the frequencies of cycles from 1.25 to 50 years. The blue area depicts business cycle frequencies, i.e., cycles with durations of 2-8 years and the purple area (8-20 years) marks frequencies most important for financial cycles.

almost all G-7 countries have most important cycles close to 20 years. Germany remains a notable exception, while both the UK and Canada exhibit important broad cycles at business cycle frequencies. Further robustness checks suggest that equity and bond prices lower cycle length for these countries in contrast to other G-7 counterparts.

Comparing financial and business cycle within countries the following can be noticed: First, all G-7 countries financial cycles are considerably longer than business cycles with the only exception of Germany. That said, business cycles tend to embed multiple peaks – with a meaningful medium-term component to business cycles for Canada, Germany, and Japan. For Canada and Germany, this may relate to a relative lack of systemic banking crises, while for Japan, a distinct history including a substantial cycle build-up followed by so-called "lost decades" during a lengthy correction phase.

Peak of power cohesion and frequency window across G-7 countries

Table 3 shows the peak of PCoh for the narrow and broad measure of the financial cycle, as well as the business cycle indicators. In addition, we report a frequency window spanned around that peak defined by a maximum and minimum cycle length in years. This frequency window is defined to capture 67% of the densest area around the frequency peak of the function.

Concerning business cycles, the US business cycle length as measured by the peak of PCoh coincides with the one of the NBER committee. Moving to a 67% window, frequencies from 2.6 to 14.5 years are captured for the US, which implies that some more longer cycles should be considered relative to standard findings, i.e., cutting of frequencies above 8 years. The average peak across other G-7 countries is a business cycle of length 8.9 years, which is heavily skewed by the atypical results of Japan – with a

Table 3: Financial and business cycle frequencies

Country	Narrow financial cycle max.	peak	min.	Broad financial cycle max.	peak	min.	Business cycle max.	peak	min.
Canada	50.0	14.1	4.0	50.0	7.3	2.7	13.7	9.8	2.1
Germany	15.4	7.4	2.3	45.6	8.5	3.0	18.8	9.1	2.7
France	36.0	15.0	6.5	50.0	15.4	4.0	50.0	6.7	2.5
Italy	45.6	15.9	3.9	50.0	16.9	3.3	38.7	3.7	2.8
Japan	50.0	23.0	5.2	50.0	18.8	4.0	50.0	22.0	2.3
UK	25.3	16.4	5.0	50.0	16.4	4.4	26.6	5.4	3.1
US	29.7	17.5	7.0	29.7	15.0	4.8	14.5	5.7	2.6
Avg.	*36.0*	*15.6*	*4.8*	*46.5*	*14.0*	*3.7*	*30.3*	*8.9*	*2.6*
CV	*0.37*	*0.30*	*0.33*	*0.16*	*0.31*	*0.20*	*0.52*	*0.69*	*0.12*

Notes: The table shows the peak, maximum (max.), and minimum (min.) cycle length in years. The frequency range, defined by the maximum and minimum, capture 67% of the densest area around the peak. Broad refers to the inclusion of all indicators, i.e., credit, house, equity, and bond prices, whereas narrow is defined by house prices and credit only. *Avg.* denotes the average and *CV* the coefficient of variation that relates the standard deviation to the mean.

minimum window of 2.6 years, and 30.3 as a maximum.

Turning to the narrow financial cycle, it is about 17.5 years long for the US and the actual frequency window is close the one described by Drehmann et al. (2012), i.e., 29.7 to 7 relative to 30 to 8 years. However, across other G-7 countries, the shortest cycles included range around 4.8 years and maximum 36 years. Outliers with respect to cycle length include Germany, which has a very short narrow financial cycle (even shorter than the business cycle), and Japan, which has a very long cycle, exceeding the 20 year range.

With respect to the broad financial cycle, the area around the peak is generally less dense, so that on average the frequency window covers longer as well as shorter cycles on average of 3.7 years. The average cycle length is 14 years, and thus slightly shorter than the narrow financial cycle. While the peaks for the narrow and financial cycle can be argued to be similar for most countries, Canada represents an exception, with the average cycle length reducing from 14.1 (narrow) to 7.3 years.

The coefficient of variation indicates relative variation, so we can compare the spread of the peaks of the different cycles. Results indicate that differences in business cycle length are actually stronger than in financial cycle length; at 0.69 versus 0.3 and 0.31.

3.4 Robustness: Reference cycles through turning points

This robustness exercise aims at using another methodology to validate a comovement in financial indicators yielding longer cycles than that of business cycle indicators. To this end, we apply the methods of turning points as suggested by Harding and Pagan (2002), that extends the methodology Bry and Boschan (1971) to quarterly data and has seen many applications in the business cycle literature. On the one hand, an advantage of the turning points algorithm over the spectral approach is its robustness with respect to non-linearities and structural breaks in the data. On the other hand, a disadvantage lies in its limited mathematical or economic grounding – including notably that censoring rules are chosen arbitrarily. Further, the method is skewed towards shorter term frequencies as it does not decompose time series into individual cyclical components but considers cycles of all lengths jointly.

One means of overcoming the problem of bias toward shorter frequencies is to consider the joint information inherent across a set of indicators. With this aim in mind, we construct reference cycles using the distribution of turning points of individual indicators.[8] We rely on the approaches by Harding and Pagan (2006) and Canova and Schlaepfer (2015).[9]

In more detail, the methodology adds a small additional number of censoring rules to all turning points.[10] It contains the following steps:[11] First, turning points of individual indicators are located via the standard methods established in the literature.[12] Second, from each series of turning points, for every indicator we construct the distance in quarters to the nearest peak and the distance to the nearest trough. Third, the series for distance to peak is aggregated for each period t across every indicator. The series for distance to trough is aggregated similarly. As aggregation method, we choose the median value as recommended by Harding and Pagan (2006). Fourth, local minima are considered in the aggregated series as candidate peaks and troughs for a reference cycle.

Results

The exercise supports the general notion that financial cycles, i.e. common fluctuations in credit and house prices or credit, house, equity, and bond prices, are longer thank business cycles on average across countries, while some country cycles differ in length from the one identified by power cohesion (see Table 4).

Reference cycles as identified with this modified turning points methodology for the narrow set of indicators (credit and house prices) are on average 13 years, not dissimilar to the cycle lasting around 15.6 years on the basis of power cohesion. Highest deviations between the two methodological approaches are found for Italy (reference cycle about 8 years shorter), Canada (6 years shorter), and Germany (4.5 years longer), while the turning points approach constructing reference cycles does not yield results for France as there are ties in the location of the turning points of the reference cycle, i.e., house and credit cycles indicate opposite phases.[13] US, UK, and Japan are all found to be slightly shorter, however still quite close to the length reported in the main exercise.

The broad financial cycle indicators lead to a reference cycle that is on average 9.23 years compared

[8]This is, in many ways, the conceptual analogue of our approach of PCoh based on the frequency comovement of indicators, and in particular also has the potential to allow for phase shifts between variables a local minima are considered and not global.

[9]Next to constructing a reference cycle from indicators, another option is to aggregate information first and then locate turning points, which is more similar to what is done by the NBER and the CEPR Business Cycle Dating Committees as indicated by Canova and Schlaepfer (2015).

[10]The transformation of variables follows the usual one in the literature, i.e., we use indicators in log levels, thereby not taking a stance of trend.

[11]We use the code as kindly provided by Canova and Schlaepfer (2015). For more details, please refer to the indicated paper.

[12]Summarising briefly: Let $x_{i,t}$ be a candidate peak of the stochastic process x_i if $x_{i,t} \in \max\{x_{i,t-2}; x_{i,t-1}; x_{i,t}; x_{i,t+1}; x_{i,t+2}\}$ and a candidate trough if $x_{i,t} \in \min\{x_{i,t-2}; x_{i,t-1}; x_{i,t}; x_{i,t+1}; x_{i,t+2}\}$. A candidate is confirmed in case the following conditions are met: (i) Peaks and troughs must alternate. In case of two subsequent peaks, for instance, the lower one is eliminated. (ii) A peak must be higher than the previous trough and a trough must be lower than the previous peak. (iii) 5 quarters is the minimum length of a cycle, i.e., peak to peak or trough to trough. (iv) 2 quarters is the minimum phases of a cycle. A phase is peak to trough or trough to peak. (v) Turning points at the first or last two quarters are excluded. (vi) Peaks at the beginning or the end are excluded in case of being lower than the initial or last values. Similarly, troughs at the beginning or the end are excluded in case of being higher than the initial or last values.

[13]This is a problem that is more likely to occur using only two indicators and the likelihood of course decreasing the more indicators in use.

Table 4: Reference cycles length through turning points

	Narrow financial cycle	Broad financial cycle	Business cycle
Canada	8.00	10.00	11.92
Germany	11.90	4.93	7.55
France	*n.a.*	8.66	4.73
Italy	7.60	9.00	6.46
Japan	20.00	9.19	3.17
UK	13.83	10.56	6.29
US	16.88	12.25	8.64
Avg.	*13.03*	*9.23*	*6.96*

Notes: Table depict length of reference cycles in years for narrow (credit and house prices) and broad (narrow + equity and bond prices) set of financial cycle indicators as well as for the business cycle indicators (output, consumption, investment, and hours worked). *Avg.* denotes the mean of column and *n.a.* denotes not available, due to missing coincident turning points in the sample.

to 14 years when applying power cohesion. For all countries but CA reference cycles are found to be shorter than the ones found with PCoh, but Canada, for which the reference cycle length is 10 years as opposed to 7.3. Differences are most prominent for Japan (9.19 from 18.8) and Italy (9.19 from 16.9). They are weakest for the US (12.25 from 15) and Canada.

Reference cycle from business cycle indicators are very similar to the one measured by PCoh. Only in the case of Japan the reference cycle indicates an average cycle length of 3.17 years (from 22.0 years), which however is also a highest density region of PCoh but not the most important one. For the US the length is 8.64. The identified set of turning points for the US misses interestingly the recession subsequent to the bursting of the dot-com bubble explaining the longer duration.

In sum, the construction of reference cycle based on a set of turning points of individual indicators leads to a similar picture than our introduced approach. Whereas previous results based only on turning points of individual indicators, e.g. Claessens et al. (2011, 2012) and Hiebert et al. (2014), cannot reconcile evidence on medium term financial cycles, the results suggests that this is possible when considering credit and asset prices *jointly*.

4 Coherent financial cycles across time

In this section, we transfer the concept of co-movement of indicators from the frequency domain to the time domain. In this respect we present a methodology for combining indicators into a composite financial cycle index. Further, we discuss both the use of the identified frequency windows of the previous section as well as a weighted moving average to filter the composite indices. Based on the latter, we analyse financial cycle synchronisation across countries and research whether the common movement can be used both as a coincident as well as an early warning indicator of systemic banking crises.

4.1 Methodology: Time-varying aggregation of standardised indicators and filtering

Time-varying aggregation of standardised indicators

The collation of the filtered growth rates of indicators into a composite financial cycle index requires two steps. First, we standardise variables given different measurement units, but also in light of dissimilar variances and equilibrium growth rates. Second, we aggregate these standardised indicators into composite financial and business cycle series. In keeping with the nomenclature of the previous section, we distinguish between a narrow composite financial cycle (consisting of credit and house prices) and a broad measure (combining credit, house, equity, and bond prices). For these representations, as well as analogous measures for the business cycle, we construct time-varying aggregation weights that exploit changing correlation structures between variables. Our approach is closely related to the methodology followed by Holló, Kremer and Lo Duca (2012) for constructing an indicator of systemic financial stress.[14] Our approach is specifically suited for modelling cyclical fluctuations, while Holló et al. (2012) capture spikes in systemic risk.

More specifically, we transform respective underlying cycle 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]. 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

$$y_{i,t} = F_{i,T}(x_{i,t}) = \begin{cases} \frac{r}{T} & \text{for } x_{i,[r]} \leq x_{i,t} < x_{i,[r+1]}, \quad r = 1, 2, \ldots, T-1 \\ 1 & \text{for } x_{i,t} \geq x_{i,[T]}, \end{cases} \tag{3}$$

where $F_{i,T}$ denotes the empirical cdf.

These standardised indicators are then taken to construct synthetic cycles by linearly combining these using time-varying weights that exploit positive time-varying correlations between indicator pairs. Specifically, let $Y_t = (y_{1,t}, \ldots, y_{M,t})$ and ι be a vector of ones of dimension $M \times 1$. 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 a matrix of time-varying cross-correlations that is based on exponentially-weighted moving average processes, i.e., $\sigma_{ij,t} = \lambda \sigma_{ij,t-1} + (1-\lambda)(y_{i,t} - 0.5)(y_{j,t} - 0.5)$, where $y_{i,t}$ is centered using the median and λ represents the decay factor.[15] Due to the aggregation method $\zeta_t \in (0, 1]$ as well.[16] ζ_t is then called the unfiltered composite indicator.[17]

[14]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.

[15]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.

[16]For expositional purposes, we re-map ζ_t into (0,1] using equation 3. As the case of all four indicators being close to their historical max- or minima is unlikely, the amplitude of the not yet re-mapped indicator ζ_t is dampened towards the median.

[17]Real time updating of ζ_t (as, e.g., done in Section 4.4.1) is done by applying Equation (3) recursively over expanding

While the diagonal elements of C_t are one, the off-diagonal elements, $c_{ij,t}$ with $i \neq j$, are restricted by

$$c_{ij,t} = \begin{cases} \rho_{ij,t} = \sigma_{ij,t}/(\sqrt{\sigma_{ii,t}\sigma_{jj,t}}) & \text{if } \sigma_{ij,t} \geq 0 \\ 0 & \text{if } \sigma_{ij,t} < 0 \end{cases}. \tag{4}$$

That is, our aggregation scheme emphasises positively related or alike movements. While all series enter the final index by construction, it implies that movements of positively related series are emphasised.[18] In capturing cyclical swings to construct a macroprudential notion of the cycle, we 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. This is in line with our aim to capture the build-up of imbalances across different variables.

Filtering

As the signal obtained from the combination of quarterly standardised growth rates is volatile, we filter this composite financial index, in a final step, using our country-specific frequency bands that are based on PCoh (see Table 3). The country-specific frequency bands are employed as an input into the band pass filter proposed by Christiano and Fitzgerald (2003) that allows to specify the exact frequency band of interest.

4.2 Composite cycles

Figure 4 depicts composite financial and business cycle indices for the US in deviations from historical median growth. It is particularly noteworthy that mere aggregation produces a strong cyclical impetus, from which inherent movements can be further emphasised by means of filtering (see Figure 4 (a)). This, in turn, suggests that high frequency noise surrounding certain financial asset prices, such as equity prices, are effectively dampened as part of the aggregation process. The right panel complements this information, showing both the narrow and broad composite financial cycle as well the business cycle.

It is important to keep in mind that we construct cycles in growth rates. However, there is a close correspondence to growth cycles or gap measures given our quarter-on-quarter differencing. That is, a peak is reached when the composite indices pass from above 0.5 to below; a through when from below 0.5 to above.

A divergence of US financial and business cycles during upswing phases (growth rates above 0.5), seems to precede systemic banking cries. Specifically, Laeven and Valencia (2012) define two US systemic banking crises for our sample period, i.e., the savings and loans crises in 1988 (borderline

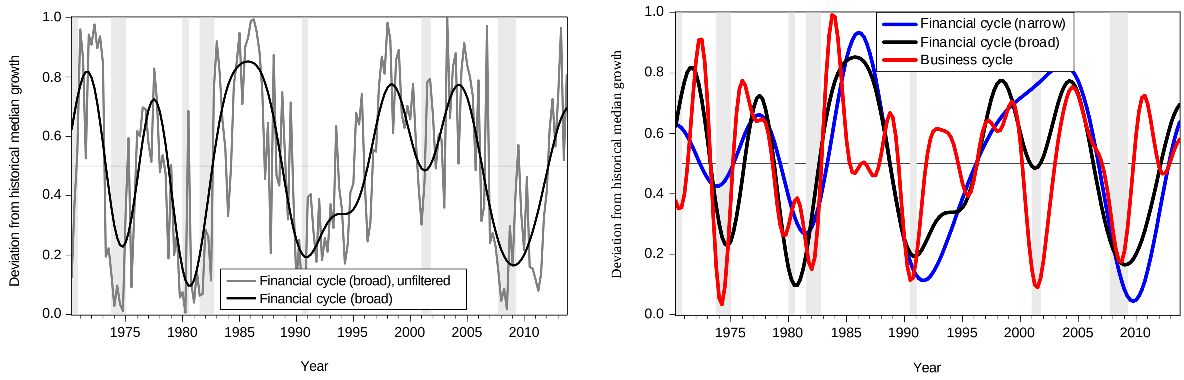
samples, i.e., "old" observations are fixed and new ones are added to the existing distribution.

[18]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.

case) and the global financial crises in 2007. Before both crises a divergence of financial (both broad and narrow) and business cycle is visible. Or put differently, the upswing phases of the financial cycles preceding crises are especially long.

Further, recovery periods are longer for both financial cycles than for the business cycle.

Nonetheless, there is an apparent co-movement between the two cycles, which is both in line with our analysis of statistical properties as well with the literature emphasising a medium term link between financial and business cycles (see Rünstler and Vlekke (2016)) or the importance of financial cycle indicators' downturns in shaping recessionary phases (see Claessens et al. (2012)). These results are broadly consistent with the findings for the remaining country composite cycles (see Appendix A.6). Interestingly the composite financial cycles of Germany and Japan follow very distinct movements around the last global financial crises. Further, for UK is seems that financial and business cycles have been very similar until a peak located around 1990.



(a) Filtered and unfiltered financial cycle, broad

(b) Filtered composite cycle indices

Figure 4: US' composite cycles

Notes: This panel shows the US composite financial and business cycles in standardised growth rates, where 0.5 denotes the historical median after removing a nonlinear trend; 0 is the smallest and 1 the largest growth rate observed in a country's history. A crossing of 0.5 from above can be interpreted as locating the peak of a hypothetical gap measure, while from below as reflecting the trough. Left graph depicts the broad composite financial cycle (filtered and unfiltered) combining information from credit, house prices, equity prices and bond prices. Right graph shows the filtered financial (narrow and broad) and business cycles. Filtering is done using the Christiano and Fitzgerald (2003) band-pass filter employing country specific frequency windows as described in Table 3. Aggregation of standardised indicators is done using linear averaging in case of the narrow financial cycle and using time-varying weights that emphasise directional movements between indicators for the broad financial cycle. See Section 4.1 for further details. Grey area indicates NBER recession dates.

4.3 Synchronisation of financial and business cycles

Next we consider how G-7 financial (broad and narrow) and business cycles relate to the respective country cycles. We construct G-7 cycles as the first principal component of the respective country cycles (see Figure 5 (a)). In case of the financial cycles (broad) a first principal component summarises 54.2% of the common contemporaneous variation; in case of the financial cycle (narrow) 46.3% and in case of the business cycle 52.6%.[19] The broad and narrow G-7 financial cycle seem to be strongly correlated, while the G-7 business cycle less. The broad and the narrow measure are correlated with a coefficient of 0.74. The business cycle is correlated with a coefficient of 0.68 with the broad and 0.47 with the narrow financial cycle. In this context, Breitung and Eickmeier (2014) find evidence of a global factor affecting

[19]The second principal components only capture 18.4%, 16.8%, and 16.47% respectively.

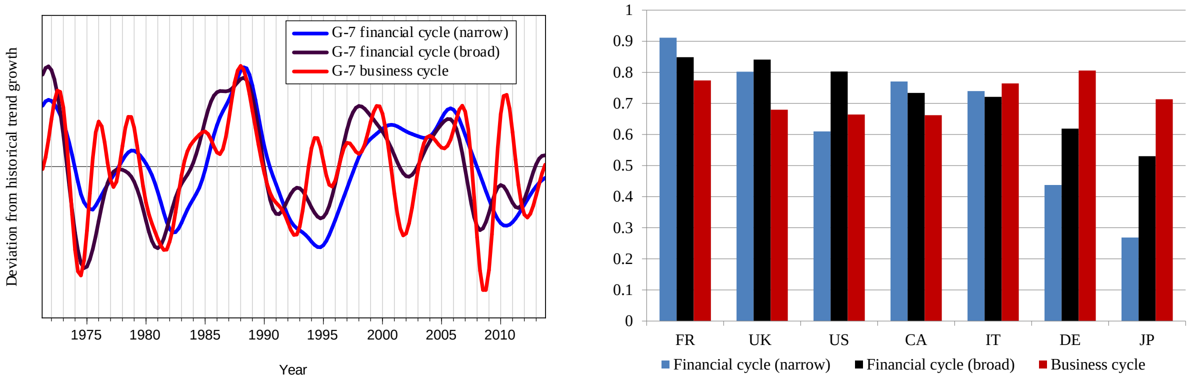
both business and financial cycles, while there is still an important financial factor independent from the macro factors affecting financial variables. Note that similar to the US financial cycle, we observe phases of coupling and de-coupling of financial and business cycles. Specifically, there is one phase during which financial cycles in their upswing phase (above 0.5) decouple from business cycles. This is the period that leads into the global financial crisis that had severe effects on all G-7 countries, but Canada.

In the right panel of Figure 5 we relate the G-7 cycles to their respective country cycles, that is for instance, G-7 financial cycle (broad) with the financial cycle (broad) of France. At least three results are worth emphasising. *First*, while financial cycles (broad and narrow) seem to strongly relate to a group of countries and not so strongly to another, business cycles are rather homogeneously related across G-7 countries. Specifically, the broad measure of financial cycles is closely related to France (0.85), UK (0.84), and the US (0.80), but also Canada (0.73) and Italy (0.72). It is less related to Germany and Japan (0.62 and 0.53). Results are even more heterogeneous when considering the narrow measure. Related are France (0.91), UK (0.80), Canada (0.77), and Italy (0.74). Less related are US (0.61), Germany (0.43), and Japan (0.27). The weak relation of Germany and Japan to a common component might be partly related to their distinct development both in the housing and credit market in recent years. These are the only countries where house prices have been declining alongside stagnated or declining residential investment at least until 2009 (see André (2010); Knoll et al. (forthcoming)). In light with our argument that joint movements in credit in asset prices matter, it is also Germany and Japan that do not undergo a credit boom (see Hume and Sentance (2009)). In contrast to heterogeneous financial cycles linkages, business cycles relate homogeneously between a correlation of 0.81 and 0.66. The strongest link to the common component shares Germany while the weakest Canada and the US (both 0.66), which however is still elevated compared to the results of financial cycles. *Second*, financial assets (equity and bond prices) are an important link for financial cycles across countries. In general, total interlinkage is stronger among the G-7 countries when considering a broader class of assets in line with the studies of Rey (2015) and Breitung and Eickmeier (2014). Explanations entail for example that credit and house prices are rather a domestic component. For instance, houses are not tradable and underly strong country-specific regulations, also with respect to financing. *Third*, while Germany and Japan have the weakest links with the G-7 financial cycles, i.e., broad and narrow, their business cycles rank among the most linked.

In sum, we find that business cycle relations are strong and homogeneous across G-7 countries, while financial cycle synchronisation is rather heterogeneous. Germany and Japan are the least linked. In line with previous studies, we find that financial asset prices account for strong international linkages.

4.4 Coincident and early warning indicator of systemic banking crises

To validate the coherent financial cycles, we conduct a signalling exercise testing their performance both as coincident as well as early warning indicators of systemic banking crises. We compare their performance to the indicators and the credit-to-GDP gap. In the following we lay out the methodology for conducting our signalling exercise and present the results subsequently.



(a) G-7 financial (narrow and broad) and business cycles

(b) Correlation of respective G-7 with respective country cycles

Figure 5: G-7 cycles and correlation with country cycles

Notes: The left panel depicts the first principal component of the countries' financial and business cycles. The right panel shows the correlation of country financial (narrow and broad) and business cycles with the respective first principal components. Countries are ordered by highest correlation of financial cycles (broad) with the G-7 financial cycle (broad) principal component.

4.4.1 *Methodology: Pooled logit and real time composite cycles*

The signalling approach is based on the predicted probabilities of a logit model estimated on a pooled data set to explain the start as well as a one to four quarters ahead vulnerability horizon prior to systemic banking crises as defined by Laeven and Valencia (2012). Specifically, we use the quarterly starting dates of systemic banking. To this end we code two dummy variables ($\tilde{y}_{lt}$ for $l \in \{1, 2\}$), each taking a value of one at the pre-specified event and zero otherwise.[20]

We assess the signalling properties of indicator(s) ($\tilde{X}_t$) using both a pseudo-out-of- and an in-sample setup, whereas we put more emphasis on the former analysis as it mirrors more closely the decisions faced by policy makers in real time.

The *pseudo-out-of-sample exercise* predicts the one quarter ahead probabilities using the lagged relation

$$\tilde{y}_{lt} = \phi_0 + \sum_{k=1}^{5} \phi_k \tilde{X}'_{t-k} + \varepsilon_t, \tag{5}$$

where ϕ_0 is the intercept, ϕ_k a vector of coefficients, and ε_t the error term. We use five lags in accordance with the study by Schularick and Taylor (2012). Such setup accounts on the one hand for a publication lag of one quarter of economic aggregates and on the other hand for the persistence of indicators. We estimate the model on data from 1980Q1 until 1999Q4 – using the period prior 1980Q1 to initialise the standardisation of indicators (see Equation (3)) – and conduct the pseudo-out-of-sample exercise on an expanding sample for the period thereafter. For each sample $(1, \ldots, t)$ we determine the optimal signalling threshold using the predicted probabilities up to period t. Following, we evaluate whether the one quarter ahead out-of-sample prediction, i.e., for $t+1$, breaches the optimal threshold that has been derived for information up to time period t. The threshold value is optimally determined by minimising a loss function that gives equal importance to avoiding Type I (missing

[20]We include the US 1988 crisis which is described as a borderline case by Laeven and Valencia (2012) and use Q1 as its starting date.

crisis or vulnerability period) and II (false alarms) errors, i.e., $L = \frac{\text{Quarters no signal}}{\text{Quarters crisis}} + \frac{\text{Quarters signal}}{\text{Quarters no crisis}}$. In this manner, we collect the true positive (TP), false positive (FP), true negative (TN), and false negative (FN) rates for the entire out-of-sample period. Using these we derive the Type I (TI) and II (TII) errors, the relative usefulness (U^r), the noise-to-signal ratio (NtS), and the area under the curve (AUC). Relative usefulness is defined as $(0.5 - L)/0.5$ and measures the relative gain to discarding the indicator(s) (see Alessi and Detken (2011)). The noise-to-signal ratio is captured by T$II/(1-$T$I)$, relating two ratios: the ratio of bad signals to all quarters without crisis (noise) to the ratio of good signals to all quarters with crisis (signal) (see Kaminsky, Lizondo and Reinhart (1998)). Finally, the AUC is reported for the collection of all out-of-sample predicted probabilities. Note an indicator based on a coin toss would lead in large samples to an AUC of 0.5. A perfect indicator, on the other hand, would completely discriminate between crisis and non-crisis, leading to an AUC of 1.

For the *in-sample* exercise we discard the publication lag as all data is assumed to be available. Still we use the lagged values of indicators, i.e., $\tilde{X}'_{t-k}$ for $k \in \{0, 1, 2, 3, 4\}$. The in-sample predicted probabilities are then evaluated against the crisis starting dates (and the vulnerability periods) using all thresholds values; summarised by the AUC.

For both exercises we employ real time estimates of our filtered financial cycles.[21] To construct such measures we smooth our unfiltered financial cycle estimates using a weighted moving average of six quarters instead of applying the Christiano and Fitzgerald (2003)' band pass filter, as the latter is known to suffer from endpoint biases. We employ declining weights that are based on an one sided Bartlett window that gives highest weight to the last observation at time t. Weights are 1 (ζ_t), 5/6 (ζ_{t-1}), 4/6 (ζ_{t-2}), 3/6 (ζ_{t-3}), 2/6 (ζ_{t-4}), and 1/6 (ζ_{t-5}) scaled by their sum to keep the scale (0,1]. The real time cycles of the US are depicted in Figure 6. The one of the remaining countries are shown in Appendix A.7. Note that while these are more volatile than the Christiano and Fitzgerald (2003)'s band pass filtered cycles, the changes in cyclical phases are still clearly visible.

We compare the signalling performance of our real time composite cycles 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).[22] Further, studies have suggested that the latter variable ranks among the ones with the best early warning properties for banking crises (see, e.g., Behn, Detken, Peltonen and Schudel (forthcoming)). Note that the credit-to-GDP gap is a level concept, but our composite indices are built from growth rates. This means that the credit-to-GDP gap indicates a build up of imbalances explicitly, i.e. through the deviation from an assumed trend. Our measure emphasises expansions and contractions common to credit and asset prices and is, thus, related to the build-up and corrective phases of leverage cycles. Three advantages of our measure compared to the credit-to-GDP gap are worth stressing: First, the application of the HP filter on the credit-to-GDP ratio for extracting medium term fluctuations has been shown to induce spurious medium term cycles by amplifying specific medium term movements and dampening shorter term ones

[21] As indicated in Section 2, for the real time estimates we use the unfiltered, i.e., standard, growth rates of indicators.

[22] The credit-to-GDP gap is derived on an expanding window and using the HP-filter with a smoothing parameter of $\lambda = 400,000$. 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".

(see Schüler (forthcoming)). Besides possibly not reflecting the country-specific cycle of interest, the so-called credit gap is necessarily a bad coincident indicator of crises, as abrupt changes (short term cycles) are dampened. Our measure allows for abrupt changes. Second and in a similar vein, a decline in growth rates always precedes peaks of a gap measure. Thus, considering growth rates can possibly signal vulnerability periods better than a gap measure. Third, the credit gap mixes two indicators for which we find very different cyclical patterns. These different patterns can be argued to originate from differing propagation mechanisms of financial and technology shocks (see Jaccard (forthcoming)). This implies that movements in the overall credit gap measure can be caused by either of the shocks, which, however, have different implications for systemic banking crises. On the contrary, our measures combine indicators with similar statistical properties that are also linked through the concept of leverage cycles.

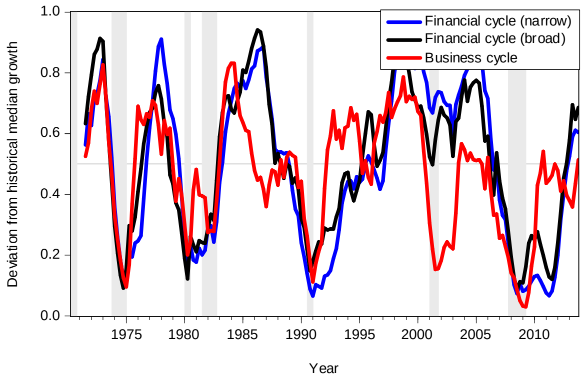


Figure 6: US real time composite financial and business cycles

Notes: The real time US composite financial and business cycles are measured in standardised growth rates, where 0.5 denotes the historical median; 0 is the smallest and 1 the largest growth rate observed in a country's history. A crossing of 0.5 from above can be interpreted as locating the peak of a hypothetical gap measure, while from below as reflecting the trough. Smoothing is done using a 6 quarter one-sided moving average based on the weights of a Bartlett window. See Section 4.1 and 4.4.1 for further details. Grey area indicates NBER recession dates.

4.4.2 Results

The signalling results reinforce the case for aggregation, suggesting that combining information helps to improve the capacity of financial variables to predict the start and vulnerability periods prior to systemic banking crises.

Panel A of Table 5 offers the results for the signalling of start of crisis. The left part of the table, "One quarter out-of-sample", suggests that – by far – the broad financial cycle index is the best coincident indicator, while the narrow financial cycle ranks second. The broad measure allows to detect 3 (TP) out of 5 (TP+FN) crisis starting dates correctly. Its relative usefulness is highest (0.47) and noise to signal ratio lowest (0.22). The AUC is found to be 0.78, while it is 0.59 for the narrow financial cycle, the second ranked specification. On the contrary, the credit-to-GDP gap does not indicate any start of crisis correctly. In-sample, the broad financial cycle measure receives the highest AUC (0.90), however the differences are marginal when compared to the specification employing the entire set of indicators (0.87). The narrow financial cycle does not rank second for the in-sample exercise. Overall,

Table 5: Signalling exercise: Coincident and early warning

	One quarter out-of-sample										*In-sample*	
	Observ.	TP	FP	TN	FN	TI	TII	U^r	NtS	AUC	Observ.	AUC
Panel A: At start of crisis												
Financial cycle (narrow)	392	2	77	310	3	0.60	0.20	0.20	0.50	0.59	924	0.76
Financial cycle (broad)	392	3	50	337	2	0.40	0.13	0.47	0.22	0.78	924	0.90
Business cycle	392	1	142	245	4	0.80	0.37	-0.17	1.83	0.40	924	0.82
Δcr	392	2	121	266	3	0.60	0.31	0.09	0.78	0.47	924	0.65
Δcr & Δp_h	392	2	116	271	3	0.60	0.30	0.10	0.75	0.41	924	0.75
Δcr, Δp_h, Δp_e, & Δp_b	392	0	51	336	5	1.00	0.13	-0.13	-	0.26	924	0.87
Credit-to-GDP gap	392	0	131	256	5	1.00	0.34	-0.34	-	0.37	924	0.74
Panel B: 1-4 quarters before crisis												
Financial cycle (narrow)	392	14	170	202	6	0.30	0.46	0.24	0.65	0.70	924	0.73
Financial cycle (broad)	392	15	136	236	5	0.25	0.37	0.38	0.49	0.72	924	0.85
Business cycle	392	9	174	198	11	0.55	0.47	-0.02	1.04	0.57	924	0.65
Δcr	392	10	88	284	10	0.50	0.24	0.26	0.47	0.64	924	0.70
Δcr & Δp_h	392	9	99	273	11	0.55	0.27	0.18	0.59	0.56	924	0.71
Δcr, Δp_h, Δp_e, & Δp_b	392	8	83	289	12	0.60	0.22	0.18	0.56	0.58	924	0.80
Credit-to-GDP gap	392	11	98	274	9	0.45	0.26	0.29	0.48	0.50	924	0.59

Notes: Table shows results of the out-of- and in-sample exercise as described in Section 4.4.1. "Observ." refers to observations, "TP" to true positive, "FP" to false positive, "TN" to true negative, "FN" to false negative, "TI" to Type I error, "TII" to Type II error, "U^r" to relative usefulness, "NtS" to noise-to-signal ratio, and "AUC" to area under the curve. "-" indicates that the statistic is not defined.

this points to the benefits of combining information for a real time exercise. Idiosyncratic movements in individual indicators are damped and, thus, the signalling performance increases over considering individual indicators.

Panel B of the same table shows the results of the early warning exercise. In the context of the out-of-sample exercise, similarly to before, the broad financial cycle indicator ranks first when considering the AUC (0.72). On this dimension the narrow financial cycle measure does, however, equivalently well (0.70). Thus, additionally considering a larger fraction of asset markets does not necessarily increase the early warning performance of the composite indicator.[23] Nonetheless, the broad measure performs better considering relative usefulness or noise-to-signal ratio. Within the early warning exercise, credit and the credit-to-GDP gap do not perform as bad as in the previous analysis. Their noise-to-signal ratios are even marginally below the one of the broad financial cycle (0.47 and 0.48 compared to 0.49). In-sample, the broad financial cycle measure does again slightly better than considering the single indicators (0.85 to 0.8). The narrow financial cycle ranks third with an AUC of 0.73. The credit-to-GDP gap reaches only to 0.59 and ranks last. Again the relatively stronger performance of our indicators in the out-of- but not in-sample exercise stresses the benefits of combining information.

5 Conclusions

Attenuating financial cycles, i.e., preventing the build-up of systemic risk, is one of the main goals of macroprudential policy. Indeed, recent experience of the global financial crisis and its aftermath has vividly illustrated systemic risk inherent in the build-up and correction phases of ebullient financial cycles. Despite the prominence of this goal in macroprudential policy our knowledge with respect to

[23] Of course, the negative shock of the global financial crises, which is the only crisis contained in the out-of-sample signalling exercise, was related to imbalances in the housing markets.

financial cycles is still limited.

Our results suggest that the joint fluctuations of credit and asset prices, i.e., emphasising expansions and contractions common to all series, are important for the early detection of a systemic risk build-up. This joint modelling is both in line with theoretical research on leverage cycles as well as empirical studies on the detrimental effects of leveraged asset price bubbles. Additionally, it reconciles differences of financial cycle characteristics obtained through two alternative methodologies: frequency decompositions and classical turning point analysis.

Empirical regularities of indicators suggest that credit and asset prices exhibit fluctuations distinct from indicators commonly associated with business cycles – notably higher amplitude and persistence; especially at medium and long term frequencies. Employing a novel spectral methodology, we show that financial cycle frequencies tend to differ from those of business cycles; around 15 years on average in contrast to only 9 years or 6.7 years when excluding Japan. In the time domain, we find that domestic financial cycles are heterogeneously synchronised across countries. Most financial cycles of G-7 countries are closely related while the ones of Germany and Japan are not. In comparison, business cycles are closely linked within this set of countries.

Two main policy conclusions can be drawn. First, differences between financial and business cycles such as increased length and amplitude, but also the high predictive power of financial cycles, support a case for macroprudential policy addressing the build-up of systemic risk at the national level that might differ both from policies aimed at business cycle stabilisation, as well as policies across countries. This case is especially strong for the subset of euro area countries considered: while we find that business cycles are closely linked across our selected euro area countries, there are differences in financial cycle synchronisation. Even abstracting from different properties of financial and business cycles, still it seems unlikely that one instrument can suffice to curb heterogeneously related financial cycles. Second, macroprudential policy and financial stability surveillance may gain considering the common movement of indicators jointly describing the health of balance sheets as we find that the combined role of indicators is important for the detection of systemic risk build-up; also when compared to the Basel III credit-to-GDP gap. While macroprudential tools, such as loan-to-value ratio or countercyclical capital buffer are specific instruments, one may gain from a coordination of policies. But of course, the underlying drivers of the financial cycle need to be understood in order to efficiently address the building up of vulnerabilities with macroprudential instruments.

Paths for future research are ample. Possibilities for extensions range from deepening the understanding of financial cycles across countries – such as the exact lead-lag relation – and their interaction with macroeconomic policies. Just as important, theoretical work is clearly needed to complement these empirical estimates, and explain diverging financial and business cycle phases also to inform the best use of policies.

References

Adrian, T. and Shin, H.: 2010, Liquidity and leverage, *Journal of Financial Intermediation* **19**, 418–437.

A'Hearn, B. and Woitek, U.: 2001, More international evidence on the historical properties of business cycles, *Journal of Monetary Economics* **47**, 321–346.

Aikman, D., Haldane, A. and Nelson, B.: 2015, Curbing the credit cycle, *The Economic Journal* **125**, 1072–1109.

Alessi, L. and Detken, C.: 2011, Quasi real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity, *European Journal of Political Economy* **27**, 520–533.

André, C.: 2010, A bird's eye view of the OECD housing market, *OECD Economics Department Working Paper 746*.

Behn, M., Detken, C., Peltonen, T. and Schudel, W.: forthcoming, Setting countercyclical capital buffers based on early warning models: Would it work?, *International Journal of Central Banking*.

Berkowitz, J. and Diebold, F.: 1998, Bootstrapping multivariate spectra, *The Review of Economics and Statistics* **80**, 664–666.

Bernanke, B.: 1983, Non-monetary effects of the financial crisis in propagation of the great depression, *American Economic Review* **73**, 257–276.

Bernanke, B. and Gertler, M.: 1999, Monetary policy and asset price volatility, *Economic Review, Federal Reserve Bank of Kansas City, Q4*.

Bernanke, B., Gertler, M. and Gilchrist, S.: 1999, The financial accelerator in a quantitative business cycle framework, *in* J. Taylor and M. Woodford (eds), *Handbook of Macroeconomics*, Vol. 1C, Elsevier-Science, North-Holland, New York.

Bhattacharya, S., Goodhart, C., Tsomocos, D. and Vardoulakis, A.: 2015, A reconsideration of Minsky's financial instability hypothesis, *Journal of Money, Credit and Banking* **47**, 931–973.

Boissay, F., Collard, F. and Smets, F.: 2016, Booms and banking crises, *Journal of Political Economy* **124**, 489–538.

Borio, C.: 2014, The financial cycle and macroeconomics: What have we learnt?, *Journal of Banking and Finance* **45**, 182–198.

Breitung, J. and Eickmeier, S.: 2014, Analyzing business and financial cycles using multi-level factor models, *Discussion Paper 11/2014, Deutsche Bundesbank, Research Centre*.

Brunnermeier, M. and Pedersen, L.: 2009, Market liquidity and funding liquidity, *The Review of Financial Studies* **22**, 2201–2238.

Bry, G. and Boschan, C.: 1971, Cyclical analysis of time series: Selected procedures and computer programs, *NBER, New York*.

Burnside, C.: 1998, Detrending and business cylce facts: A comment, *Journal of Monetary Economics* **41**, 512–532.

Campell, J. and Hercowitz, Z.: 2009, Welfare implications of the transition to high household debt, *Journal of Monetary Economics* **56**, 1–16.

Canova, F. and Schlaepfer, A.: 2015, Has the euro-mediterranean partnership affected mediterranean business cycles?, *Journal of Applied Econometrics* **30**, 241–261.

Christiano, L. and Fitzgerald, T.: 2003, The band pass filter, *International Economic Review* **44**, 435–465.

Claessens, S., Kose, M. and Terrones, M.: 2011, Financial cycles: What? How? When?, *IMF Working Paper WP/11/76*.

Claessens, S., Kose, M. and Terrones, M.: 2012, How do business and financial cycles interact?, *Journal of International Economics* **87**, 178–190.

Comin, D. and Gertler, M.: 2006, Medium-term business cycles, *American Economic Review* **96**, 523–551.

Croux, C., Forni, M. and Reichlin, L.: 2001, A measure of comovement for economic variables: Theory and empirics, *The Review of Economics and Statistics* **83**, 232–241.

Drehmann, M., Borio, C. and Tsatsaronis, K.: 2012, Characterising the financial cycle: Don't lose sight of the medium term!, *BIS Working Paper 380*.

Fink, F. and Schüler, Y.: 2015, The transmission of US systemic financial stress: Evidence for emerging market economies, *Journal of International Money and Finance* **55**, 6–26.

Franke, J. and Härdle, W.: 1992, On bootstrapping kernel spectral estimates, *The Annals of Statistics* **20**, 121–145.

Frankel, J. and Rose, A.: 1996, Currency crashes in emerging markets: An empirical treatment, *Journal of International Economics* **41**, 351–366.

Galati, G., Hindrayanto, I., Koopman, S. and Vlekke, M.: 2016, Measuring financial cycles with a model-based filter: Empirical evidence for the United States and the euro area, *Economics Letters* **145**, 83–87.

Geanakopolos, J.: 2010, The leverage cycle, *in* D. Acemoglu, K. Rogoff and M. Woodford (eds), *NBER Macroeconomics Annual 2009, Volume 24*, University of Chicago Press, Chicago, chapter 1, pp. 1–65.

Geanakopolos, J. and Fostel, A.: 2008, Leverage cycle and the anxious economy, *American Economic Review* **98**, 1211–1244.

Gertler, M.: 1988, Financial structure and aggregate economic activity: An overview, *Journal of Money, Credit, and Banking* **20**, 559–588.

Gilchrist, S., Yankov, V. and Zakrajšek, E.: 2009, Credit market shocks and economic fluctutations: Evidence from corporate bond and stock markets, *Journal of Monetary Economics* **56**, 471–493.

Gilchrist, S. and Zakrajšek, E.: 2012, Credit spreads and business cycle fluctuations, *American Economic Review* **102**, 1692–1720.

Gorton, G. and Ordoñez, G.: 2016, Good booms, bad booms, *NBER Working Paper 22008*.

Gromb, D. and Vayanos, D.: 2002, Equilibrium and welfare in markets with financially constrained arbitrageurs, *Journal of Financial Economics* **66**, 361–407.

Hamilton, J.: 1994, *Time Series Analysis*, Princeton University Press, Princeton.

Harding, D. and Pagan, A.: 2002, Dissecting the cycle: A methodological investigation, *Journal of Monetary Economics* **49**, 365–381.

Harding, D. and Pagan, A.: 2005, A suggested framework for classifying the modes of cycle research, *Journal of Applied Econometrics* **20**, 151–159.

Harding, D. and Pagan, A.: 2006, Synchronization of cycles, *Journal of Econometrics* **132**, 59–79.

Hiebert, P., Klaus, B., Peltonen, T., Schüler, Y. and Welz, P.: 2014, Capturing the financial cycle in the euro area, *Financial Stability Review: Special Feature B*.

Holló, D., Kremer, M. and Lo Duca, M.: 2012, CISS - A composite indicator of systemic stress in the financial system, *ECB Working Paper 1426*.

Hubrich, K. and Tetlow, R.: 2015, Financial stress and economic dynamics: The transmission of crises, *Journal of Monetary Economics* **70**, 100–115.

Hume, M. and Sentance, A.: 2009, The global credit boom: Challenges for macroeconomics and policy, *Journal of International Money and Finance* **28**, 1426–1461.

Hyndman, R.: 1996, Computing and graphing highest density regions, *The American Statistician* **50**, 120–126.

Iacoviello, M.: 2005, House prices, borrowing constraints, and monetary policy in the business cycle, *American Economic Review* **95**, 739–764.

Jaccard, I.: forthcoming, Asset pricing and the propagation of macroeconomic shocks, *Journal of the European Economic Association*.

Jermann, U. and Quadrini, V.: 2012, Macroeconomic Effects of Financial Shocks, *American Economic Review* **102**, 238–271.

Jordà, O., Schularick, M. and Taylor, A. M.: 2013, When credit bites back, *Journal of Money, Credit and Banking* **45**, 3–28.

Jordà, O., Schularick, M. and Taylor, A. M.: 2015a, Betting the house, *Journal of International Economics* **96**, S2–S18.

Jordà, O., Schularick, M. and Taylor, A. M.: 2015b, Leveraged bubbles, *Journal of Monetary Economics* **76**, S1–S20.

Jordà, O., Schularick, M. and Taylor, A. M.: 2016, The great mortgaging: housing finance, crises and business cycles, *Economic Policy* **31**, 107–152.

Justiano, A., Primiceri, G. and Tambalotti, A.: 2015, Credit supply and the housing boom, *mimeo*.

Kaminsky, G., Lizondo, S. and Reinhart, C.: 1998, Leading indicators of currency crises, *IMF Staff Papers, Palgrave Macmillian Journal* **45**.

Kaminsky, G. and Reinhart, C.: 1999, The twin crises: The causes of banking and balance of payments problems, *American Economic Review* **89**, 473–500.

Kindleberger, C.: 1978, *Manias, panics, and crashes: A history of financial crises*, Basic Books, New York.

Kiyotaki, M. and Moore, J.: 1997, Credit cycles, *Journal of Political Economy* **105**, 211–248.

Knoll, K., Schularick, T. and Steger, T.: forthcoming, No price like home: Global house prices, 1870-2012, *American Economic Review*.

Laeven, L. and Valencia, F.: 2012, Systemic banking crises database: An update, *IMF Working Paper WP/12/163*.

Mendoza, E. and Terrones, M.: 2008, An anatomoy of credit booms: Evidence from macro aggregates and micro data, *NBER Working Paper 14049*.

Minsky, H.: 1977, The financial instability hypothesis: An interpretation of Keynes and an alternative to “standard” theory, *Nebraska Journal of Economics and Business* **16**, 5–16.

Miranda-Agrippino, S. and Rey, H.: 2015, World asset markets and the global financial cycle, *NBER Working Paper 21722*.

Ohanian, L. and Raffo, A.: 2012, Aggregate hours woked in OECD countries: New measurement and implications for business cycles, *Journal of Monetary Economics* **59**, 40–56.

Reinhart, C. and Rogoff, K.: 2009, *This Time is Different: Eight Centuries of Financial Folly*, Princeton University Press.

Rey, H.: 2015, Dilemma not trilemma: The global financial cycle and monetary policy independence, *NBER Working Paper 21162*.

Rünstler, G. and Vlekke, M.: 2016, Business, housing and credit cycles, *ECB Working Paper 1915*.

Sargent, T.: 1987, *Macroeconomic Theory*, 2nd edn, Academic Press, San Diego.

Schularick, M. and Taylor, A.: 2012, Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008, *American Economic Review* **102**, 1029–1061.

Schüler, Y.: forthcoming, Detrending and financial cycle facts across G-7 countries: Mind a spurious medium term!, *ECB Working Paper*.

Schüler, Y., Hiebert, P. and Peltonen, T.: 2015, Characterising the financial cycle: A multivariate and time-varying approach, *ECB Working Paper 1846*.

Strohsal, T., Proaño, C. and Wolters, J.: 2015a, Characterizing the financial cycle: Evidence from a frequency domain analysis, *Deutsche Bundesbank Discussion Paper 22/2015*.

Strohsal, T., Proaño, C. and Wolters, J.: 2015b, How do financial cycles intereact? Evidence for the US and the UK, *SFB 649 Discussion Paper 2015-024*.

Verona, F.: 2016, Time-frequency characterization of the U.S. financial cycle, *Economics Letters* **144**, 75–79.

A Appendix

A.1 Data

The financial cycle data are from the Bank of International Settlements (BIS), Datastream (DS), Global Financial Data (GFD), Haver Analytics (HA), or the OECD. The business cycle data set is taken from Ohanian and Raffo (2012).[24] All series are measured in real terms and deflated with the respective country consumer price index (CPI). Seasonal adjustment is carried out using X-12.

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) adjusted for breaks.

House prices: This measure reflects real residential property prices from the BIS. Italy's house price series starts in 1970Q3.

Equity prices: We employ the index from OECD main economic indicators, except in the case of the US. In the case of the US we choose for the S&P500 index instead of the OECD main indicator, as this one is more standard in academic research. Datastream code is S&PCOMP.

Corporate bond yields: Corporate bond yields are downloaded from GFD. For Canada, the long term corporate bond yields are employed until Q1 2006 (Source: Bank of Canada), whereas for periods

[24]An updated dataset can be found on Andrea Raffo's homepage (http://www.andrearaffo.net/araffo/Research.html, last accessed 19/07/16)

after Q1 2006 we use the Bank of America Merril Lynch Canada Corporate Effective Yield from HA. For Germany, we use yields on debt securities outstanding issued by residents from the Bundesbank. For France, we take the first class private bonds average yields provided by the Banque de France. For Italy, the average corporate bond yield is provided by Banca d'Italia. For Japan, data are from The Economist. From November 2011, the yield on Nomura Securities bonds is used. For the UK, data are taken from an index of corporate bond yields as calculated by the Financial Times. From November 2011, the EIB 2028 bond is used. For the US, we use Moody's Corporate BAA yield. Moody's tries to include bonds with remaining maturities as close as possible to 30 years. Moody's drops bonds if the remaining life falls below 20 years, if the bond is susceptible to redemption, or if the rating changes.

Inflation: CPI is taken from the OECD main economic indicators database.

Business cycle indicators: The data by Ohanian and Raffo (2012) provides real GDP, real private consumption, real gross fixed capital formation from the OECD Economic Outlook database. The study derives their own dataset on hours worked which is consistently measured across countries.

A.2 Power Cohesion

Proof of Proposition 1. 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 $s_{x_ix_j}(\omega) = c_{x_ix_j}(\omega) - \mathrm{i}q_{x_ix_j}(\omega)$, where the real part is captured by the co-spectrum $c_{x_ix_j}(\omega)$ and the imaginary part by the quadrature spectrum $q_{x_ix_j}(\omega)$. The real part describes the covariance in phase, whereas the imaginary part the one out of phase.[25] Using the modulus operation in Equation (1), we can see that

$$|f_{x_ix_j}(\omega)| = \frac{|s_{x_ix_j}(\omega)|}{\sigma_{x_i}\sigma_{x_j}} = \frac{\sqrt{c^2_{x_ix_j}(\omega) + q^2_{x_ix_j}(\omega)}}{\sigma_{x_i}\sigma_{x_j}}. \tag{6}$$

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

Proof of Proposition 2. 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)),

$$\int_{-\pi}^{\pi} s_{x_ix_j}(\omega)d\omega = \mathrm{Cov}[x_{i,t}, x_{j,t}]. \tag{7}$$

From this it follows that

$$-1 \leq \int_{-\pi}^{\pi} f_{x_ix_j}(\omega)d\omega \leq 1. \tag{8}$$

[25] 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.

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

$$0 \leq \int_{-\pi}^{\pi} |f_{x_ix_j}(\omega)| d\omega \leq 1. \tag{9}$$

The upper bound of 1 in Equation (9) holds as the covariance in phase and out of phase cannot exceed the product of the standard deviations of both variables. □

Proof of Proposition 3. 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.[26] Let squared coherency cohesion be denoted by SCoh. It is defined as

$$\text{SCoh}_X(\omega) = \frac{1}{(M-1)M} \sum_{i \neq j} \frac{|s_{x_ix_j}(\omega)|^2}{s_{x_ix_i}(\omega) s_{x_jx_j}(\omega)}. \tag{10}$$

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, $s_{x_ix_j}$, to the respective auto-spectra, $s_{x_ix_i}(\omega)$ and $s_{x_jx_j}(\omega)$, 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):

$$x_{i,t} = \psi_{i,t} + \varepsilon_{i,t}, \tag{11}$$

which is characterised by a cyclical component

$$\psi_{i,t} = \alpha_{i,t} \cos(\lambda t). \tag{12}$$

$\alpha_{i,t}$ denotes a random amplitude, which may follow a stationary autoregressive process of order one, λ is the cycle frequency.[27] The idiosyncratic component, $\varepsilon_{i,t}$, is white noise with possible contemporaneous covariance.

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

[27] 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

$$X_t = \gamma \psi_t + \varepsilon_t. \tag{13}$$

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.,

$$s_X(\omega) = \gamma s_\psi(\omega)\gamma' + s_\varepsilon(\omega). \tag{14}$$

For this DGP SCoh can be written as

$$\begin{aligned} \text{SCoh}_X(\omega) &= \frac{1}{(M-1)M} \sum_{i \neq j} \frac{|s_{x_i x_j}(\omega)|^2}{s_{x_i x_i}(\omega) s_{x_j x_j}(\omega)} && (15) \\ &= \frac{1}{(M-1)M} \sum_{i \neq j} \frac{(\gamma_i \gamma_j s_\psi(\omega) + s_{\varepsilon_i \varepsilon_j}(\omega))^2}{(\gamma_i^2 s_\psi(\omega) + s_{\varepsilon_i \varepsilon_i}(\omega))(\gamma_j^2 s_\psi(\omega) + s_{\varepsilon_j \varepsilon_j}(\omega))} && (16) \end{aligned}$$

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:

$$\text{SCoh}_X(\omega) = \frac{1}{(M-1)M} \sum_{i \neq j} \frac{\gamma_i^2 \gamma_j^2 s_\psi^2(\omega)}{\gamma_i^2 \gamma_j^2 s_\psi^2(\omega)} = 1 \tag{17}$$

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

$$\text{SCoh}_X(\omega) = \frac{1}{(M-1)M} \sum_{i \neq j} \frac{(\gamma_i \gamma_j s_\psi(\omega) + s_\varepsilon(\omega))^2}{(\gamma_i^2 s_\psi(\omega) + s_\varepsilon(\omega))(\gamma_j^2 s_\psi(\omega) + s_\varepsilon(\omega))} \tag{18}$$

$$\lim_{s_\psi(\omega \neq \lambda) \to 0} \text{SCoh}_X(\omega \neq \lambda) = 1 \tag{19}$$

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. □

A.3 *Empirical issues*

We estimate the (cross-)spectral densities through cross-correlations. Further, a Parzen window with a bandwidth of $\sqrt{T}\cdot 8$ is used, which compared to the bandwidth used in Aikman et al. (2015) is larger and emphasises our aim to have rather unbiased spectral density estimates; at the cost of a higher variance. As is common, we only regard 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, e.g., Figure 2). 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.[28]

We calibrate the frequency window around the peak of power cohesion using available knowledge on business cycles. We restrict the possible cycles to be within 5 and 200 quarters. Five quarters as a minimum is standard in the literature on turning points. 50 years as the maximum length of cycles can be derived from the phenomenon of Kondratiev waves. Further, we require to capture 67% of total co-movements across indicators that leads to frequency windows for business cycle indicators for which the minimum cycle length is around 2.5 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 ($\omega_2, \omega_1 \in [2\pi/200, 2\pi/5] \wedge \omega_2 \geq \omega_1$) through

$$\min_{\omega_2 - \omega_1} \frac{\int_{\omega_1}^{\omega_2} \text{PCoh}_X(\omega)d\omega}{\int_{2\pi/5}^{2\pi/200} \text{PCoh}_X(\omega)d\omega} \geq p. \tag{20}$$

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 and above 50 years.[29] In our setup we assume $p = 0.67$. 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; i.e., densest area of PCoh around the peak.

[28]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.

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

A.4 Statistical properties of financial and business cycle indicators

Table 6: Descriptive statistics – real growth rates

Country	Variables	Standard deviations: Med./long-term cycle 2-200	Standard deviations: High-frequency component 2-32	Standard deviations: Med./long-frequency component 32-200	First-order autocorrelations: Med./long-term cycle 2-200	First-order autocorrelations: High-frequency component 2-32
Canada	*Financial cycle:*					
	Credit (Δcr)	1.02	0.81	0.61	**0.54**	**0.27**
	House price (Δp_h)	2.49	2.29	0.95	**0.39**	**0.28**
	Equity price (Δp_e)	7.46	7.28	1.55	**0.27**	**0.23**
	Bond price (Δp_b)	0.84	0.64	0.50	**0.64**	**0.40**
	Business cycle:					
	Output (Δq)	0.82	0.76	0.31	**0.38**	**0.27**
	Consumption (Δco)	0.79	0.71	0.33	0.08	-0.12
	Investment (Δi)	2.26	2.14	0.66	**0.34**	**0.26**
	Hours worked (Δh)	0.41	0.40	0.08	-0.08	-0.14
Germany	*Financial cycle:*					
	Credit (Δcr)	0.75	0.64	0.37	**0.35**	0.12
	House price (Δp_h)	0.81	0.69	0.34	**0.43**	0.22
	Equity price (Δp_e)	8.26	7.92	2.15	**0.36**	**0.31**
	Bond price (Δp_b)	0.66	0.53	0.36	**0.49**	**0.23**
	Business cycle:					
	Output (Δq)	0.56	0.49	0.24	**0.51**	**0.38**
	Consumption (Δco)	0.61	0.56	0.24	0.05	-0.14
	Investment (Δi)	1.20	0.97	0.66	**0.63**	**0.44**
	Hours worked (Δh)	0.36	0.33	0.13	**0.79**	**0.76**
France	*Financial cycle:*					
	Credit (Δcr)	0.98	0.80	0.53	**0.50**	**0.25**
	House price (Δp_h)	1.30	0.80	1.02	**0.81**	**0.51**
	Equity price (Δp_e)	9.03	8.67	2.39	**0.33**	**0.28**
	Bond price (Δp_b)	0.90	0.63	0.62	**0.71**	**0.42**
	Business cycle:					
	Output (Δq)	0.99	0.96	0.21	0.12	0.07
	Consumption (Δco)	0.95	0.92	0.23	**-0.23**	**-0.33**
	Investment (Δi)	2.67	2.58	0.60	-0.14	**-0.21**
	Hours worked (Δh)	0.64	0.63	0.06	-0.27	-0.28
Italy	*Financial cycle:*					
	Credit (Δcr)	1.45	1.11	0.90	**0.45**	0.08
	House price (Δp_h)	1.93	1.53	1.12	**0.82**	**0.71**
	Equity price (Δp_e)	10.69	10.06	3.43	**0.39**	**0.31**
	Bond price (Δp_b)	1.32	0.99	0.83	**0.70**	**0.46**
	Business cycle:					
	Output (Δq)	0.82	0.78	0.24	**0.48**	**0.42**
	Consumption (Δco)	0.72	0.65	0.30	**0.34**	**0.19**
	Investment (Δi)	1.70	1.55	0.68	**0.28**	0.13
	Hours worked (Δh)	0.57	0.56	0.10	**-0.29**	**-0.34**
Japan	*Financial cycle:*					
	Credit (Δcr)	1.22	0.93	0.73	**0.58**	**0.28**
	House price (Δp_h)	1.62	1.16	0.99	**0.78**	**0.60**
	Equity price (Δp_e)	8.58	8.01	2.77	**0.37**	**0.28**
	Bond price (Δp_b)	1.06	0.82	0.62	**0.59**	**0.32**
	Business cycle:					
	Output (Δq)	1.07	1.03	0.28	0.12	0.04
	Consumption (Δco)	1.11	1.08	0.23	**-0.21**	**-0.28**
	Investment (Δi)	2.04	1.86	0.75	**0.15**	-0.02
	Hours worked (Δh)	0.80	0.79	0.14	**-0.28**	**-0.33**
UK	*Financial cycle:*					
	Credit (Δcr)	2.04	1.68	1.13	**0.40**	0.12
	House price (Δp_h)	2.75	2.23	1.48	**0.78**	**0.67**
	Equity price (Δp_e)	8.17	7.90	2.03	**0.27**	**0.22**
	Bond price (Δp_b)	1.21	0.95	0.72	**0.59**	**0.34**
	Business cycle:					
	Output (Δq)	0.96	0.89	0.32	0.20	0.08
	Consumption (Δco)	1.07	0.97	0.44	0.13	-0.07
	Investment (Δi)	2.94	2.82	0.72	0.03	-0.04
	Hours worked (Δh)	0.39	0.37	0.10	-0.17	**-0.25**

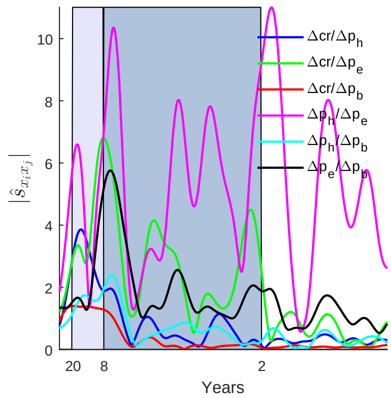
Notes: Bold numbers indicate significance at the 10% level. Statistics are derived using HAC standard errors. Med. refers to medium.

Table 7: Maximum absolute correlation with domestic credit and output – leading or lagging up to 4 quarters

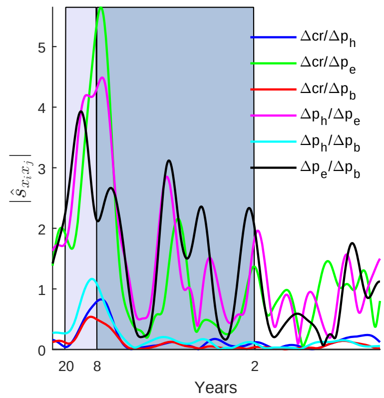
Country	Variable	Domestic credit: Med./long-term cycle 2-200		Domestic credit: High-frequency component 2-32		Domestic output: Med./long-term cycle 2-200		Domestic output: High-frequency component 2-32	
Canada	*Financial cycle:*								
	Credit (Δcr)	-	(-)	-	(-)	0.35	(2)	0.29	(2)
	House price (Δp_h)	0.31	(0)	0.22	(0)	0.29	(-1)	0.26	(-1)
	Equity price (Δp_e)	0.21	(-4)	0.24	(-4)	0.38	(-1)	0.40	(-1)
	Bond price (Δp_b)	-0.31	(4)	-0.26	(4)	0.33	(-3)	0.31	(-3)
	Business cycle:								
	Output (Δq)	0.35	(-2)	0.29	(-2)	-	(-)	-	(-)
	Consumption (Δco)	0.40	(-3)	0.26	(-3)	0.53	(0)	0.46	(0)
	Investment (Δi)	0.32	(-3)	0.25	(-3)	0.50	(0)	0.46	(0)
	Hours worked (Δh)	0.19	(-3)	0.20	(-3)	0.26	(0)	0.25	(0)
Germany	*Financial cycle:*								
	Credit (Δcr)	-	(-)	-	(-)	0.18	(0)	0.05	(-3)
	House price (Δp_h)	0.24	(0)	0.24	(0)	0.23	(2)	0.20	(2)
	Equity price (Δp_e)	-0.13	(4)	-0.11	(4)	0.21	(-1)	0.25	(-1)
	Bond price (Δp_b)	-0.28	(4)	-0.23	(4)	0.27	(-4)	0.27	(-4)
	Business cycle:								
	Output (Δq)	0.18	(0)	0.05	(3)	-	(-)	-	(-)
	Consumption (Δco)	0.18	(-4)	0.14	(-4)	0.55	(0)	0.46	(0)
	Investment (Δi)	0.17	(1)	0.07	(1)	0.77	(0)	0.72	(0)
	Hours worked (Δh)	-0.11	(-3)	-0.12	(-3)	-0.23	(4)	-0.24	(4)
France	*Financial cycle:*								
	Credit (Δcr)	-	(-)	-	(-)	0.25	(2)	0.19	(2)
	House price (Δp_h)	0.27	(-1)	0.11	(0)	0.25	(0)	0.29	(0)
	Equity price (Δp_e)	0.15	(-4)	0.17	(1)	0.27	(-1)	0.27	(-1)
	Bond price (Δp_b)	0.35	(0)	0.44	(0)	0.24	(-3)	0.26	(-3)
	Business cycle:								
	Output (Δq)	0.25	(-2)	0.19	(-2)	-	(-)	-	(-)
	Consumption (Δco)	0.26	(-2)	0.22	(-2)	0.49	(0)	0.46	(0)
	Investment (Δi)	0.24	(-2)	0.20	(-2)	0.73	(0)	0.72	(0)
	Hours worked (Δh)	-0.13	(1)	0.13	(-3)	0.35	(0)	0.38	(0)
Italy	*Financial cycle:*								
	Credit (Δcr)	-	(-)	-	(-)	0.17	(2)	0.13	(2)
	House price (Δp_h)	0.27	(0)	0.07	(0)	0.28	(2)	0.25	(2)
	Equity price (Δp_e)	-0.09	(3)	0.15	(2)	0.29	(-1)	0.29	(-1)
	Bond price (Δp_b)	0.37	(0)	0.30	(0)	0.28	(-3)	0.35	(-3)
	Business cycle:								
	Output (Δq)	0.17	(-2)	0.13	(-2)	-	(-)	-	(-)
	Consumption (Δco)	0.23	(-3)	0.12	(-3)	0.50	(0)	0.44	(0)
	Investment (Δi)	0.29	(-2)	0.17	(-2)	0.59	(0)	0.56	(0)
	Hours worked (Δh)	-0.10	(1)	0.07	(4)	0.21	(0)	0.23	(0)
Japan	*Financial cycle:*								
	Credit (Δcr)	-	(-)	-	(-)	0.35	(0)	0.28	(0)
	House price (Δp_h)	0.67	(0)	0.55	(0)	0.38	(0)	0.37	(0)
	Equity price (Δp_e)	0.27	(0)	0.23	(0)	0.28	(-1)	0.23	(-1)
	Bond price (Δp_b)	0.52	(0)	0.72	(0)	0.24	(0)	0.32	(0)
	Business cycle:								
	Output (Δq)	0.35	(0)	0.28	(0)	-	(-)	-	(-)
	Consumption (Δco)	0.44	(0)	0.43	(0)	0.72	(0)	0.71	(0)
	Investment (Δi)	0.40	(0)	0.28	(0)	0.65	(0)	0.62	(0)
	Hours worked (Δh)	0.16	(-1)	0.20	(-1)	0.22	(-1)	0.21	(-1)
UK	*Financial cycle:*								
	Credit (Δcr)	-	(-)	-	(-)	0.28	(0)	0.23	(0)
	House price (Δp_h)	0.47	(0)	0.31	(0)	0.50	(0)	0.43	(0)
	Equity price (Δp_e)	0.34	(-3)	0.34	(-3)	0.35	(-3)	0.35	(-3)
	Bond price (Δp_b)	0.40	(0)	0.39	(0)	0.38	(0)	0.35	(0)
	Business cycle:								
	Output (Δq)	0.28	(0)	0.23	(0)	-	(-)	-	(-)
	Consumption (Δco)	0.35	(0)	0.24	(0)	0.68	(0)	0.63	(0)
	Investment (Δi)	0.25	(-4)	0.16	(-4)	0.39	(0)	0.34	(0)
	Hours worked (Δh)	0.17	(-3)	0.16	(-3)	0.23	(0)	0.19	(0)

Notes: Number in brackets denotes lead (+) or lag (-) of credit or output to respective variable. Med. refers to medium.

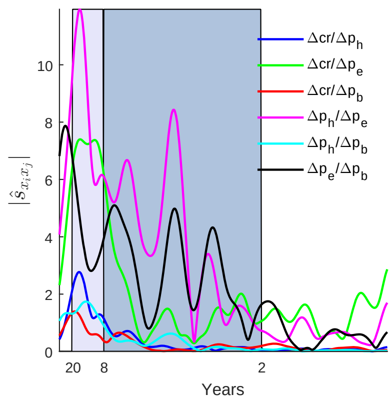
A.5 Cross spectral densities and Power Cohesion



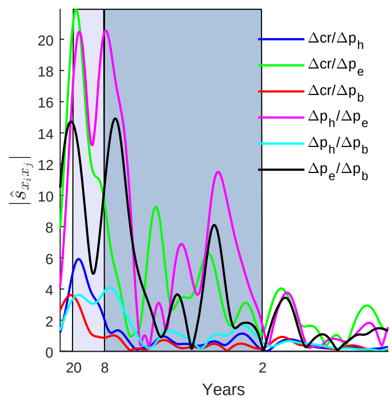
(a) Canada



(b) Germany



(c) France



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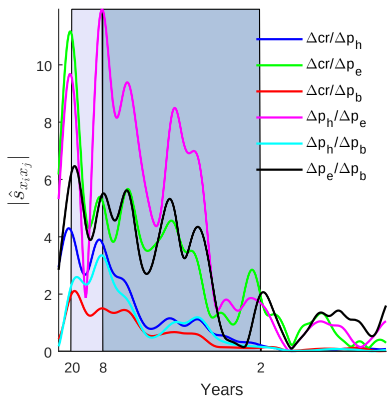
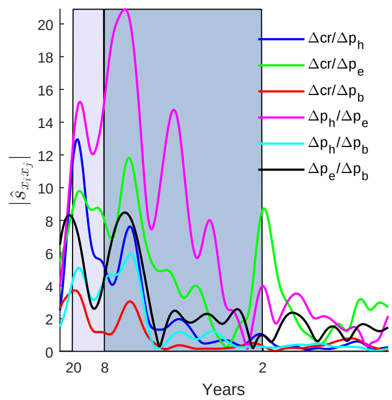


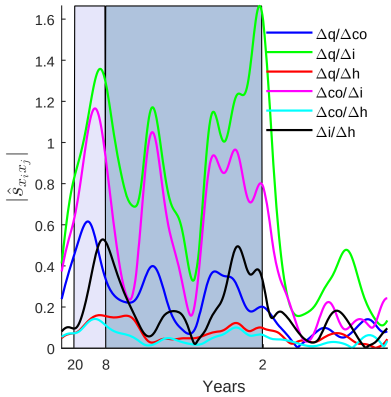
(e) Japan



(f) UK

Figure 7: Absolute cross-spectra for financial cycle indicators

Notes: This panel shows the absolute cross-spectra of the financial indicators. The x-axis measures the frequencies of cycles from 1.25 - 60 years. 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). Δcr refers to percentage changes in total credit, Δp_h to percentage changes in house prices, Δp_e to percentage changes in equity prices, Δp_b to percent changes in bond prices.



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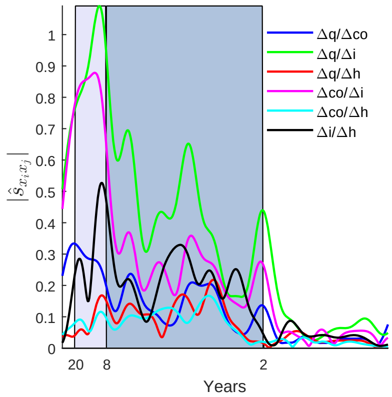

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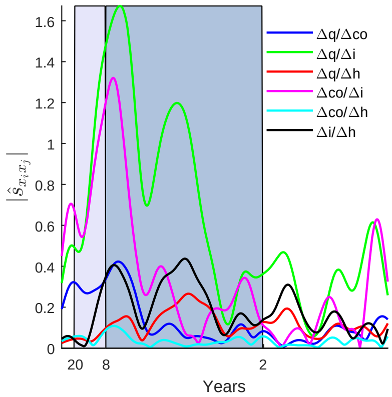
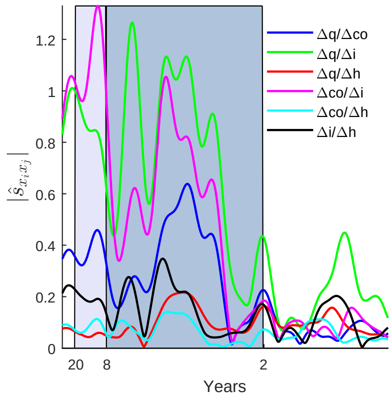


(c) France



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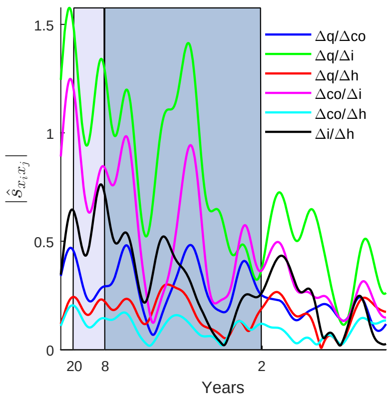
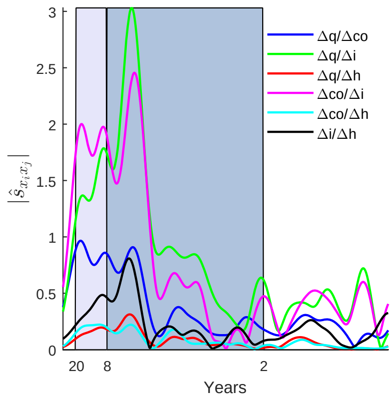


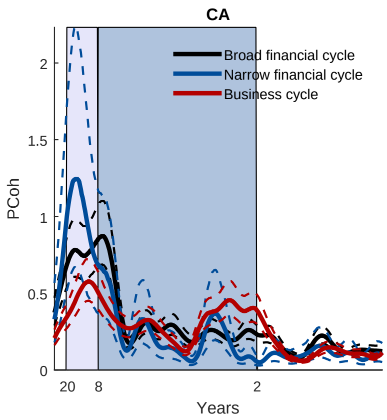
(e) Japan



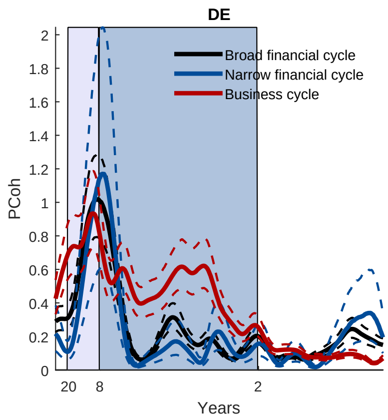
(f) UK

Figure 8: Absolute cross-spectra of business cycle indicators

Notes: This panel shows the absolute cross-spectra of the business cycle indicators. The x-axis measures the frequencies of cycles from 1.25 - 50 years. 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). Δq refers to percentage changes in GDP, Δco to percentage changes in consumption, Δi to percentage changes in investment, and Δh percentage changes in hours worked.



(a) Canada



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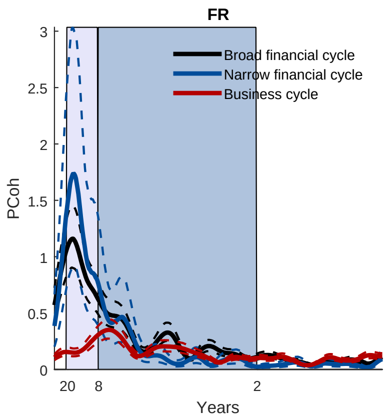
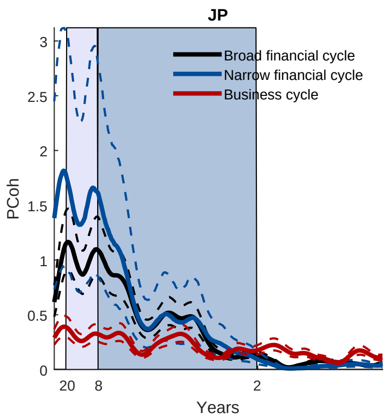


(c) France

(d) Italy



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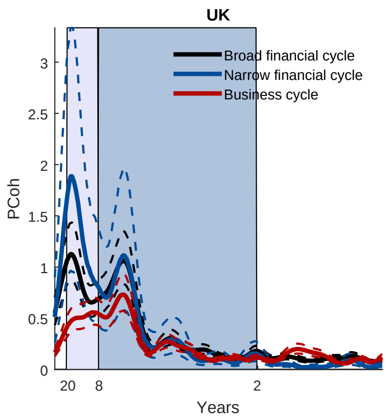
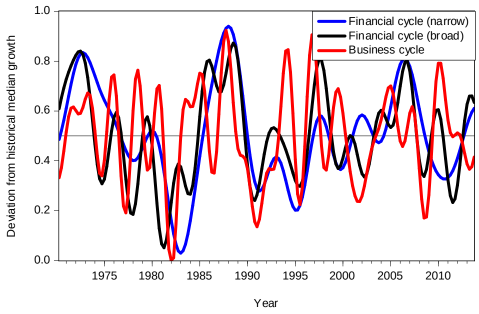


(f) UK

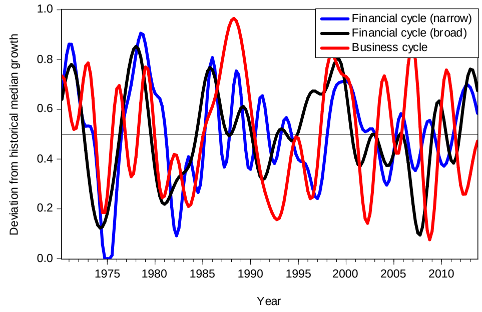
Figure 9: Power cohesion of G7 countries

Notes: This graph shows the measure power cohesion of the narrow (black lines) and broad financial cycle (blue lines) as well as the business cycle (red lines). Broad refers to the inclusion of all indicators, i.e., credit, house, equity, and bond prices, whereas narrow is defined by house prices and credit only. The dashed lines indicate the 68% bootstrapped confidence intervals as discussed in Appendix A.3. The x-axis measures the frequencies of cycles from 1.25 to 50 years. The blue area depicts business cycle frequencies, i.e., cycles with durations of 2-8 years and the purple area (8-20 years) marks frequencies most important for financial cycles.

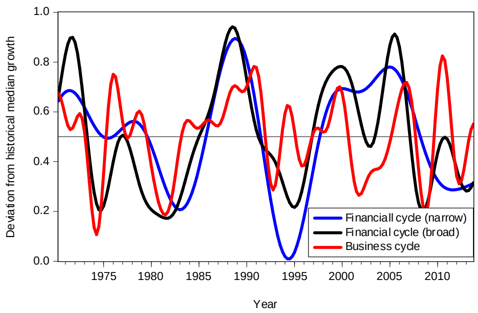
A.6 Composite financial and business cycles



(a) Canada



(b) Germany



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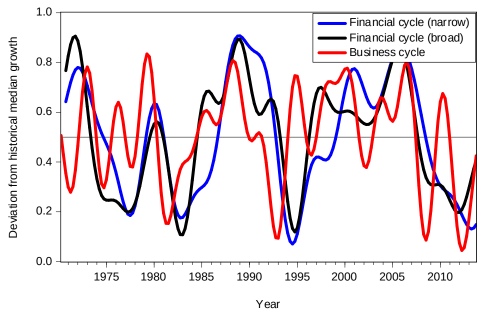

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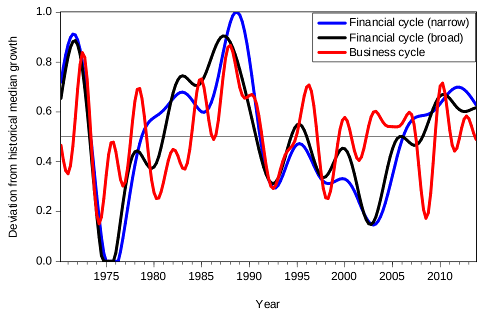

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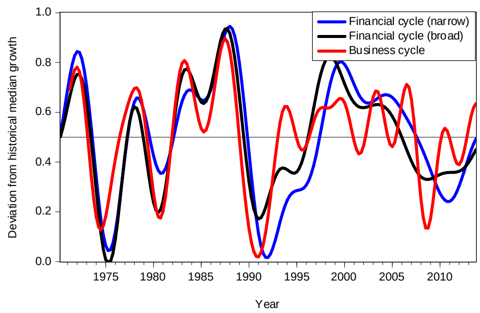
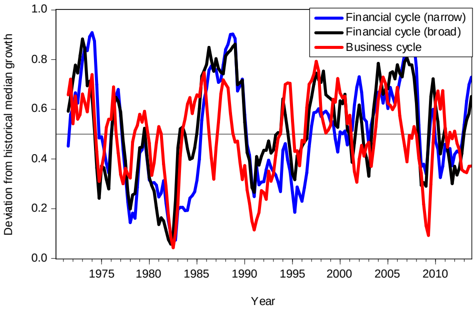


(f) UK

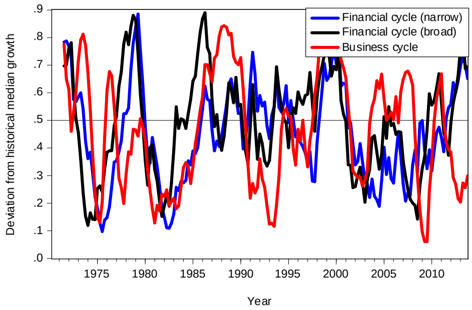
Figure 10: Composite cycles

Notes: This panel shows composite financial and business cycles in standardised growth rates, where 0.5 denotes the historical median after removing a nonlinear trend; 0 is the smallest and 1 the largest growth rate observed in a country's history. A crossing of 0.5 from above can be interpreted as locating the peak of a hypothetical gap measure, while from below as reflecting the trough. Specifically, it depicts the filtered financial (narrow and broad) and business cycles. Filtering is done using the Christiano and Fitzgerald (2003) band-pass filter employing country specific frequency windows as described in Table 3. Aggregation of standardised indicators is done using linear averaging in case of the narrow financial cycle and using time-varying weights that emphasise directional movements between indicators for the broad financial cycle. See Section 4.1 for further details.

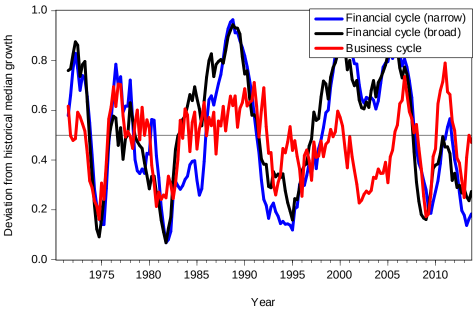
A.7 Real time composite financial and business cycles



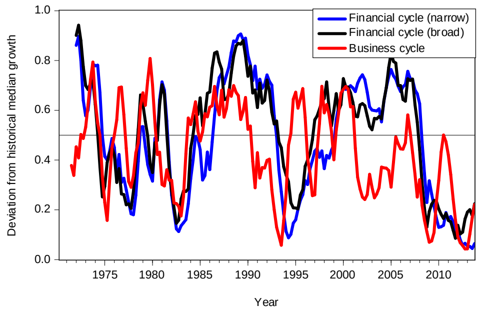
(a) Canada



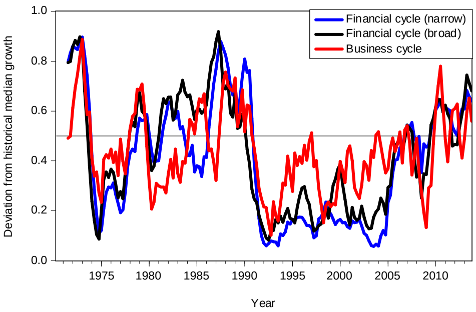
(b) Germany



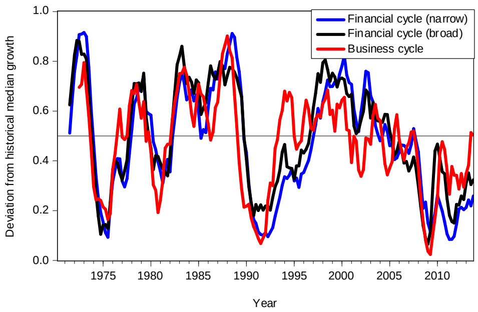
(c) France



(d) Italy



(e) Japan



(f) UK

Figure 11: Real time composite cycles

Notes: The real time composite financial and business cycles are measured in standardised growth rates, where 0.5 denotes the historical median; 0 is the smallest and 1 the largest growth rate observed in a country's history. A crossing of 0.5 from above can be interpreted as locating the peak of a hypothetical gap measure, while from below as reflecting the trough. Smoothing is done using a 6 quarter one-sided moving average based on the weights of a Bartlett window. See Section 4.1 and 4.4.1 for further details.

Imprint and acknowlegements

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