

■ Financial cycles in the euro area

In the aftermath of the financial and economic crisis, researchers and those involved in economic policy-making have increasingly been turning their attention to cyclical fluctuations in the financial system. In these discussions, the term “financial cycles” is usually used to describe joint upward and downward movements of credit aggregates and asset prices over the medium run, which extend beyond the length of business cycles. The academic literature often presents financial cycles as the result of mutually reinforcing interactions between asset valuation and risk perception in the financial system, which can then generate pronounced fluctuations in financial market variables and thus make for a more vulnerable economy.

When it comes to discussing financial cycles, there is no single generally accepted theoretical basis, nor a dominant method for measuring them. In this article, we apply methods from the field of frequency domain analysis to investigate properties of financial cycles in selected euro area countries. This is done using time series for credit aggregates and house prices, the dynamics of which are often regarded as being representative of financial cycles. The focus lies on cross-country synchronisation of financial cycles in the euro area, looking primarily at whether credit and house prices in euro area countries follow cross-country cycles. The flexible empirical approach employed has the benefit of allowing the analysis of changes in these relationships over time and according to periodicity.

As a first step, a cohesion analysis is carried out. It reveals that cross-country financial cycles in the euro area play a less significant role in determining credit and house price dynamics in the individual countries than the overall euro area business cycle does for the dynamics of gross domestic product (GDP). This result suggests that it makes sense to be guided by developments in the individual member countries when setting macroprudential policy in the euro area.

Following on from this, the second step involves a detailed analysis of country-specific cycles and their cross-country synchronisation. It shows that fluctuations in the growth of loans to households in Germany are more weakly synchronised with the average of the other euro area members included in the study than is the case for the other countries. Furthermore, house price growth in Germany exhibits significantly smaller fluctuations than in other countries.

The analysis of the relationship between real economic cycles and financial cycles reveals that credit growth, house price inflation and real GDP growth in the individual countries are subject to common cycles. Hence, financial cycles and real economic cycles should be viewed not as independent phenomena but as being interrelated. It is therefore likely that macroeconomic policy measures also affect the real economy. In this case, there is also the potential for interactions between macroprudential policy and monetary policy to arise.

■ Introduction

Cyclical build-up of risks in the financial system increases vulnerability

In the aftermath of the financial and economic crisis, researchers and those involved in economic policy-making have increasingly been turning their attention to cyclical fluctuations in the financial system. The financial crisis was a reminder that pronounced financial upswings may see market participants tend towards taking on too much risk and underestimating the riskiness of investments. By driving up asset prices even further, this behaviour can also lead households and firms to run up excessive debt. In an extreme case, asset prices and credit growth may decouple from the underlying fundamentals to a large extent. If this happens, even small disturbances in the financial system or real economy have the potential to provoke a significant and abrupt rise in risk aversion and burst the asset price bubble. Financial institutions that had been financing the credit-driven climb of asset prices will find themselves forced to shrink their strongly expanded balance sheets – an exercise which generally entails a tightening of credit for firms and households and a drop in asset prices driven by “fire sales”, bringing significant costs for the real economy.¹

Empirical link between financial cycles and financial crises

Patterns of joint upward and downward movements of credit aggregates and asset prices, such as house prices, are commonly referred to as “financial cycles”.² These tend to be longer than business cycles.³ Furthermore, the results of numerous empirical investigations have shown that synchronisation of credit and asset price cycles across countries has increased over time.⁴ While it is true that asset price booms driven by excessive credit growth, as happened in the lead-up to the financial crisis of 2008-09, occur only rarely, this kind of excessive manifestation of the financial cycle generally culminates in a financial crisis.⁵ In addition, recessions associated with financial crises generally tend to be more severe.⁶ This means that information on the financial cycle offers important insights for assessing risks to financial stability.

The concept of the financial cycle is not uniformly defined, however. Nor is there a generally accepted method for measuring financial cycles. For the most part, the literature describes financial cycles as the result of mutually reinforcing interaction between asset valuation and risk perception in the financial system that can lead to pronounced credit and asset price fluctuations.⁷ These can be explained by various imperfections and distortions in the financial markets, such as information asymmetries, liquidity and financing constraints, or distorted

Financial cycles interpreted as the result of self-reinforcing processes

¹ See, for example, M. K. Brunnermeier (2009), Deciphering the Liquidity and Credit Crunch 2007-2008, *Journal of Economic Perspectives*, 23, pp. 77-100.

² See M. Drehmann, C. Borio and K. Tsatsaronis (2012), Characterising the Financial Cycle: Don't Lose Sight of the Medium Term, BIS Working Papers 380; D. Aikman, A. Haldane and B. Nelson (2013), Curbing the Credit Cycle, *The Economic Journal*, 125, pp. 1072-1109; and Y. Schüler, P. Hiebert and T. Peltonen (2017), Coherent Financial Cycles for G-7 Countries: Why Extending Credit Can Be an Asset, ESRB Working Paper 43.

³ See Drehmann et al. (2012), op. cit.; S. Claessens, M. Kose and M. Terrones (2011), Financial Cycles: What? How? When?, NBER International Seminar on Macroeconomics, 7, University of Chicago Press, pp. 303-344; and Aikman et al. (2013), op. cit.

⁴ See, for example, Aikman et al. (2013), op. cit.; Claessens et al. (2011), op. cit.; B. Meller and N. Metiu (2017), The Synchronization of Credit Cycles, *The Journal of Banking & Finance*, 82, pp. 98-111; and T. Strohsal, C. Proaño and J. Wolters (2015a), How Do Financial Cycles Interact? Evidence From the US and the UK, SFB 649 Discussion Paper 2015-024, Humboldt University Berlin.

⁵ See, for example, C. Reinhart and K. Rogoff (2009), *This Time is Different: Eight Centuries of Financial Folly*, Princeton University Press; P. Gourinchas and M. Obstfeld (2012), Stories of the Twentieth Century for the Twenty-First, *American Economic Journal: Macroeconomics*, 4, pp. 226-265; and M. Schularick and A. Taylor (2012), Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008, *American Economic Review*, 102, pp. 1029-1061. For a critique of Schularick and Taylor (2012) see S. Baker, D. López-Salido and E. Nelson (2018), The Money View Versus the Credit View, *International Finance and Economics Discussion Paper 2018-042*, Board of Governors of the Federal Reserve System.

⁶ See, for example, M. Hutchinson and I. Noy (2005), How Bad Are Twins? Output Costs of Currency and Banking Crises, *Journal of Money, Credit and Banking*, 37, pp. 725-752; S. Claessens, A. Kose und M. Terrones (2012), How Do Business and Financial Cycles Interact?, *Journal of International Economics*, 87, pp. 178-190; and Ó. Jordà, M. Schularick and A. Taylor (2015), Leveraged Bubbles, *Journal of Monetary Economics*, 76, pp. 51-520.

⁷ See T. Adrian and H. Shin (2010), Liquidity and Leverage, *Journal of Financial Intermediation*, 19, pp. 418-437; C. Borio (2014), The Financial Cycle and Macroeconomics: What Have We Learnt?, *Journal of Banking and Finance*, 45, pp. 182-198; and T. Adrian and H. Shin (2014), Pro-cyclical Leverage and Value-at-Risk, *Review of Financial Studies*, 27, pp. 373-403.

expectations.⁸ If such financial market imperfections are relevant, a downturn in the financial cycle may be accompanied by – or even amplify – an economic contraction. In an extreme case, this can result in a financial crisis.

ket variables and asset prices within one particular economy but also across countries.

By comparison with business cycles, when it comes to choosing a set of variables which adequately captures the financial cycle, opinions are divided to a greater degree. At one end of the spectrum are those who boil the financial cycle down to fluctuations in credit aggregates.¹² At the other end lies the use of a broad range of financial data and asset prices, including (but by no means limited to) interest rates, equity prices and house prices.¹³ The majority of studies position themselves somewhere between these two extremes and use a small set of variables that can adequately capture the

Analyses focus on credit aggregates and house prices

Macprudential policy as a policy area in its own right

It was once widely believed that microprudential oversight monitoring the stability of individual institutions was sufficient to maintain the stability of the financial system. The global financial crisis of 2008-09 changed all of this. The old view prevented recognition of risks that pose a threat for the stability of the financial system as a whole. Influenced by experiences gathered during the crisis, macroprudential policy was developed as a policy field in its own right. Its purpose is to bolster the financial system's resilience to systemic risk and prevent market participants collectively from taking on excessive risk.⁹

This article addresses the question of whether selected euro area countries share a common financial cycle and how pronounced it is. Further, we examine the relationship between financial and real economic cycles.

⁸ See, for example, N. Kiyotaki and J. Moore (1997), *Credit Cycles*, *Journal of Political Economy*, 105, pp. 211-248; B. Bernanke, M. Gertler and S. Gilchrist (1999), *The Financial Accelerator in a Quantitative Business Cycle Framework*, *Handbook of Macroeconomics*; Aikman et al. (2013), op. cit.; and K. Adam, J. Beutel and A. Marcet (2017), *Stock Price Booms and Expected Capital Gains*, *American Economic Review*, 107, pp. 2352-2408.

⁹ See C. Buch, J. Reich and B. Weigert (2016), *Makroprudenzielle Politik*, *Wirtschaftsdienst*, 96, pp. 557-562.

¹⁰ See the standard definition of business cycles as contained in A. Burns and W. Mitchell (1946), *Measuring Business Cycles*, National Bureau of Economic Research, New York.

¹¹ For more on international business cycles, see, for example, M. Kose, C. Otrok and C. Whiteman (2003), *International Business Cycles: World, Region and Country-Specific Factors*, *American Economic Review*, 93, pp. 216-239.

¹² See, for example, Aikman et al. (2013), op. cit.; L. Kurowski and K. Rogowicz (2018), *Are Business and Credit Cycles Synchronised Internally or Externally?*, *Economic Modelling*, 74, pp. 124-141; and B. Meller and N. Metiu (2017), op. cit.

¹³ Credit, house prices and equity prices are used, for example, in European Commission (2018), *Financial Cycle in Euro Area*, *Quarterly Report on the Euro Area*, 17(2), pp. 17-30; Drehmann et al. (2012), op. cit.; T. Strohsal, C. Proaño and J. Wolters (2015b), *Characterising the Financial Cycle: Evidence from a Frequency Domain Analysis*, *Deutsche Bundesbank Discussion Paper No 22/2015*; and F. Verona (2016), *Time-Frequency Characterization of the U.S. Financial Cycle*, *Economics Letters*, 144, pp. 75-79. Papers that employ a relatively broad range of variables include D. Kunovac, M. Mandler and M. Scharnagl (2018), *Financial Cycles in Euro Area Economies: A Cross-Country Perspective*, *Deutsche Bundesbank Discussion Paper No 04/2018*; M. Mandler and M. Scharnagl (2018), *Financial Cycles Across G7 Economies: A View from Wavelet Analysis*, mimeo; G. Rünstler et al. (2018), *Real and Financial Cycles in EU Countries: Stylised Facts and Modelling Implications*, *Occasional Paper Series*, No 205, *European Central Bank*; Y. Schüler, P. Hiebert and T. Peltonen (2015), *Characterising the Financial Cycle: A Multivariate and Time-Varying Approach*, *ECB Working Paper 1846*; and Schüler et al. (2017), op. cit.

Financial cycles cannot be adequately captured by single variables alone

Conventional methods from business cycle analysis generally serve as the starting point for empirical measurement of financial cycles. In business cycle analysis, the notion of a cycle is generally understood to denote more or less regularly occurring fluctuations along a long-term growth trend for GDP. Financial cycles cannot be characterised by reference to just one economic variable, though. Just as the business cycle is to be understood as the comovement of multiple variables (for example, economic activity, income and employment, affecting more than one sector of the economy),¹⁰ the financial cycle, too, is a multivariate phenomenon. As such, it encompasses coinciding fluctuations of different financial market variables and asset prices. Similarly to the business cycle, the financial cycle also has within-country and cross-country dimensions,¹¹ i.e. it can consist of common cycles in financial mar-

interactions between credit aggregates and asset prices. The selection of reference variables can have a significant bearing on the characteristics of any financial cycle identified from the data.¹⁴ In the literature, common fluctuations in loans to the non-financial private sector and in house prices are often regarded as being informative indicators for the financial cycle. This is because, in particular, credit-fuelled real estate price bubbles can result in risks to financial stability.¹⁵ The empirical application presented in this article is therefore based on data on credit aggregates and house prices.¹⁶

Overview of approaches for estimating financial cycles

In addition to the choice of reference variables, there is another decision to be made: a suitable detrending method needs to be selected so that the time series of financial variables can be decomposed into trend and cyclical components. There are a wealth of different detrending procedures available. They vary in terms of the number of underlying variables, the degree of theoretical foundation and the assumptions they make about the characteristics of the trend and its relationship to the cyclical components (linear or non-linear, for instance).¹⁷ Arguably the most commonly used approaches for measuring the financial cycle are based on univariate turning point analyses or techniques for filtering data developed in order to identify business cycles.¹⁸ These methods are mostly assumption-driven and do not allow us to test the existing hypotheses in respect of the financial cycle's characteristics.¹⁹ When applying filters, the relevant frequency for the financial cycle has to be specified a priori, for example. This article therefore centres on a far more flexible, multivariate approach (wavelet analysis), which makes it possible to identify common cycles in different variables and determine the relevant frequency ranges for those cycles from the data.

Empirical analyses yield stylised facts

Applying this flexible econometric approach, it is thus possible to systematise the characteristics of the financial cycle in the form of robust "stylised facts". These refer to different traits of

the cycles, such as average cycle length and amplitude, the interaction between the financial cycle and real economic cycles, and the interplay between financial cycles across countries. The analyses can only provide us with descriptive results and trace correlations between variables; they do not enable any direct statements as to causality. Causal relationships can only be derived by employing structural models which contain restrictions rooted in theory and which go beyond pure description. However, stylised facts derived from descriptive analyses can serve as the basis for more in-depth analysis and inform the development of such models.

¹⁴ See, for example, European Commission (2018), op. cit.

¹⁵ See, for example, Jordà et al., op. cit.

¹⁶ See, for example, C. Borio (2014), op. cit.; or Drehmann et al. (2012), op. cit. Other analyses using credit aggregates and house prices include Claessens et al. (2011), op. cit.; G. Galati, I. Hindrayanto, S. Koopman and M. Vlekke (2016), Measuring Financial Cycles in a Model-Based Analysis: Empirical Evidence for the United States and the Euro Area, *Economics Letters*, 145, pp. 83-87; G. Rünstler and M. Vlekke (2018), Business, Housing, and Credit Cycles, *Journal of Applied Econometrics*, 33, pp. 212-226; Strohsal et al. (2015a), op. cit.; and V. Voutilainen (2017), Wavelet Decomposition of the Financial Cycle: An Early Warning System for Financial Tsunamis, Bank of Finland, Research Discussion Paper 11-2017.

¹⁷ See F. Canova (2007), *Methods for Applied Macroeconomic Research*, Princeton University Press, Chapter 3.

¹⁸ See R. Hodrick and E. Prescott (1997), Postwar U.S. Business Cycles: An Empirical Investigation, *Journal of Money, Credit and Banking*, 29, pp. 1-16; M. Baxter and R. King (1999), Measuring Business Cycles: Approximate Band-Pass Filters for Economic Time Series, *The Review of Economics and Statistics*, 81, pp. 575-593; D. Harding and A. Pagan (2002), Dissecting the Cycle: A Methodological Investigation, *Journal of Monetary Economics*, 49, pp. 365-381; and L. Christiano and T. Fitzgerald (2003), The Band Pass Filter, *International Economic Review*, 44, pp. 435-465.

¹⁹ Other statistical detrending procedures available include, in particular, the Beveridge-Nelson decomposition, the unobserved components model and (Markov) regime-switching models. See S. Beveridge and C. Nelson (1981), A New Approach to Decomposition of Economic Time Series into Permanent and Transitory Components with Particular Attention to Measurement of the "Business Cycle", *Journal of Monetary Economics*, 7, pp. 151-174; J. Valle e Azevedo, S. Koopman and A. Rua (2006), Tracking the Business Cycle of the Euro Area: A Multivariate Model-Based Bandpass Filter, *Journal of Business and Economic Statistics*, 24, pp. 278-290; and J. Hamilton (1989), A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle, *Econometrica*, 57, pp. 357-384.

How are financial cycles measured?

Financial cycles not directly observable and have to be estimated

Financial cycles cannot be observed directly and must therefore be estimated. Generally speaking, any time series can be expressed as the sum of a variety of cycles oscillating at different frequencies (see the box on pp. 56 ff.). One stylised fact drawn from the empirical literature dealing with credit and house price cycles is that the length of their quantitatively most significant cyclical components exceeds those of business cycles; business cycles are generally assumed to last up to eight years.²⁰

Each time series represents the aggregate of all of the cycles contained within. This means that the components associated with the financial cycle need to be isolated. To be able to infer that these components are the result of financial cycles, it is also necessary to check whether there are common cycles across countries or different variables. If there are no such dynamics in common, then the cycles are idiosyncratic, i.e. they are variable-specific and country-specific – credit cycles or house price cycles, for instance.

Much of the literature adopts a two-stage procedure for this analysis. First, univariate filters are applied to extract the cycles with selected lengths from the variables under investigation. Second, the time series components extracted in this way are scrutinised with a view to identifying their characteristics and relationships to one another.

Statistical filtering to extract cycles requires pre-determination of cycle length

The filter procedures applied in the first step extract components with pre-determined cycle lengths – in other words, cycles at a given frequency interval (see p. 58).²¹ They are purely statistical procedures and, as such, do not involve any assumptions with respect to economic structural relationships. A key decision to be taken when applying filters for measuring financial cycles is what frequency range will be pre-defined as relevant, i.e. the assumption as to the duration of oscillations.

Setting too narrow a frequency range can result in potentially relevant common cycles in different variables being overlooked. Another issue is that the cycle lengths relevant for the financial cycle in the data can change over time and may, for example, over-run the pre-defined range. This would give the impression that the financial cycle has weakened or disappeared, when in actual fact its cycle length has simply changed. If a very wide band is set for cycle length, a broad range of cycles in the variables is captured. This makes it harder to identify common cycles if these only cover a fraction of the observed frequencies.

In many studies, the frequency band for the statistical filtering is set on an ad hoc basis. Cycle lengths of eight to 20 years or eight to 30 years are among the commonly selected options.²² The chart on p. 59 illustrates one example of this. It shows the cycles lasting be-

²⁰ See, for example, C. Borio (2014), op. cit. For more on the length of business cycles, see, for example, M. Baxter and R. King (1996), op. cit.

²¹ Other commonly used approaches are turning point analysis and trend-cycle decompositions with structural time series models. Turning point analysis plays an important role in the dating of economic cycles. See G. Bry and C. Boschan (1971), *Cyclical Analysis of Time Series: Selected Procedures and Computer Programs*, National Bureau of Economic Research, New York; and D. Harding and A. Pagan (2002), *Synchronization of Cycles*, *Journal of Econometrics*, 132, pp. 59-79. For examples of how this approach is applied to financial cycles, see Claessens et al. (2011), op. cit., and Drehmann et al. (2012), op. cit. For more on trend-cycle decompositions with structural time series models, see A. Harvey and S. Koopman, *Multivariate Structural Time Series Models*, in C. Heij et al. (eds., 1997), *System Dynamics in Economic and Financial Models*, Wiley, New York. These models can also be interpreted as filter approaches, but with trend and cycles parametrically specified. Galati et al. (2016), op. cit., apply the approach to the United States, Germany, France, Italy, Spain and the Netherlands. For each country, they extract common cycles in house prices and credit or the credit-to-GDP ratio. G. Rünstler and M. Vlekke (2018), op. cit., extend this analysis to common cycles in house prices, credit and real GDP. For more information on this, see Section 3 of Rünstler et al. (2018), *ibid*.

²² Examples of analyses on the basis of cycle lengths in the eight to 20-year range include Aikman et al. (2013), op. cit. ("medium-term" cycles), and B. Meller and N. Metiu (2017), op. cit. Cycle lengths of eight to 30 years are assumed in Drehmann et al. (2012), op. cit. In other analyses the frequency band is extended to include shorter oscillations, of the kind used in business cycle analysis. See, for example, Aikman et al. (2013), op. cit.; Kunovac et al. (2018), op. cit.; and Rünstler et al. (2018), op. cit.

Frequency analysis and bandpass filters

Wavelet analysis, the method used in the present article, is a refinement of frequency analysis or spectral analysis. Time series analysis in the frequency domain is an alternative perspective to the more common time domain analysis.¹

Both perspectives are mutually complementary and emphasise different aspects of time series. In the time domain, a time series is interpreted as the sum of current and past random innovations (independently and identically distributed (i.i.d.) disturbances).² In the frequency domain, a time series is decomposed into periodic functions, i.e. functions that exhibit recurring cycles. This decomposition makes it possible to analyse the significance of cycles for the time series.

The chart on p. 57 illustrates the concept of cycles with different frequencies. With y_1 and y_2 it shows two sine functions $y_t = \sin(\omega t)$ with different frequencies (ω). By definition, there is an inverse relationship $\omega = 2\pi/T$ between frequency and cycle length (T): the length of the first cycle is four periods (for quarterly data, one year), corresponding to a frequency of $2\pi/4 = 1.57$; that of the second is 12 observations (for quarterly data, three years), resulting in a frequency of $2\pi/12 = 0.52$. The shortest possible cycle (not shown) has a length of two observations, implying a frequency of $2\pi/2 = \pi$.

Cycles can differ not only in terms of frequency but also in terms of amplitudes or phases. The example in the chart on p. 57 shows two further cycles of the general form $y_t = A \cdot \sin(\omega t + \varphi)$. A denotes the amplitude, i.e. the size of the oscillations,

and φ the phase, i.e. the horizontal shift of y_t relative to a standard sine function.

y_3 is a sine oscillation having the same frequency as y_1 but an amplitude of $A = 1/2$. Its oscillations are only half the size of y_1 . y_4 has the same frequency and amplitude as y_1 but, compared to y_1 , displays a phase shift of $\pi/2$, i.e. it leads by one period.³

The idea behind frequency analysis is that a time series can always be written as the sum of a large number of cycles with different lengths. This is given by the spectral representation of a covariance stationary time series Y_t :

$$Y_t = \mu + \int_0^\pi [\alpha(\omega) \cos(\omega t) + \delta(\omega) \sin(\omega t)] d\omega$$

μ is the mean of Y_t and ω is, as before, the frequency (within the interval between 0 and π). $\alpha(\omega)$ and $\delta(\omega)$ are frequency-dependent weights which determine the importance of a cycle at a given frequency for the pattern of the time series relative to cycles at other frequencies.

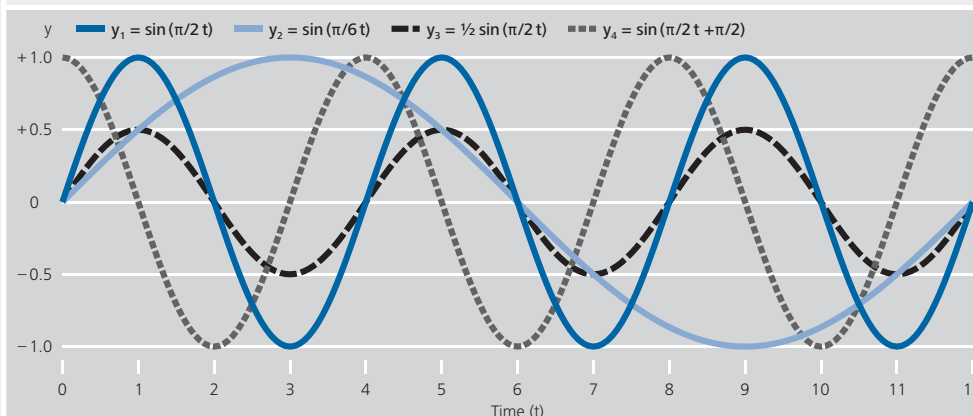
An important instrument of frequency analysis is the (power) spectrum. It is a tool for identifying the frequencies of those cycles which are particularly important to the dynamics of a time series. The power

¹ For an introduction to spectral analysis, see, for example, J. Hamilton (1994), *Time Series Analysis*, Princeton University Press, Princeton, chap. 6.

² See, for example, J. Hamilton (1994), *op. cit.*, chap. 4. The discussion below will refer to covariance stationary time series.

³ A phase shift of φ implies a shift by φ/ω observations compared with a sine oscillation of the same frequency, since $\sin(\omega t + \varphi) = \sin\left(\omega\left(t + \frac{\varphi}{\omega}\right)\right)$.

Sine waves of various amplitudes, frequencies and phases



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spectrum of time series y_t is a function of the frequency ω :

$$f_y(\omega) = \frac{1}{2\pi} \left[\gamma_0 + 2 \sum_{j=1}^{\infty} \gamma_j \cos(\omega j) \right] \geq 0.$$

Here, γ_0 is the variance of y_t and γ_j the autocovariance of order j .⁴ Cycles with frequencies for which the power spectrum assumes large values are more important for the dynamics of the time series than those with small values. The share of the area between two frequencies $0 \leq \underline{\omega} < \bar{\omega} \leq \pi$ below the power spectrum in the total area represents the share of the variance of the time series Y_t caused by cycles from the selected frequency interval.⁵ As is shown by the equation, the power spectrum is not time-varying, i.e. the analysis assumes that there is no change in the relative importance of the various cycles for the time series over time (covariance stationarity).⁶

As an example, the chart on p. 58 shows the power spectra of an artificially generated time series containing stochastic cycles having a length of 16 and 48 observations (for quarterly data, four and 12 years).⁷ The time series Y_t and the two stochastic cyclical components contained therein are

shown in the lower half of the chart. The spectrum peaks at frequencies of $\pi/8$ and $\pi/24$; these correspond to the cycle lengths contained in the time series.⁸

⁴ $\gamma_j = E(Y_t - \mu)(Y_{t-j} - \mu)$

⁵ The power spectrum can be estimated for a time series by, for instance, estimating the variance and the autocovariances of the time series and inserting the estimated values for γ_0 and γ_j into the above equation or by estimating an ARMA(p,q) process for the time series and calculating the spectrum from the estimated ARMA coefficients. See J. Hamilton (1994), op. cit., pp. 163 ff.

⁶ A simple way to allow for time variability is by using a rolling window to estimate the power spectrum and other frequency analysis statistics. This approach, however, is inefficient compared with the elaborated time-varying approach of wavelet analysis. See, for instance, the annex to this article and also A. Rua (2012), Wavelets in Economics, Economic Bulletin, Summer, Banco de Portugal, pp. 71-79.

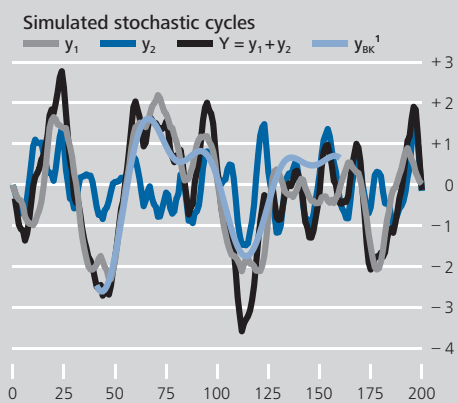
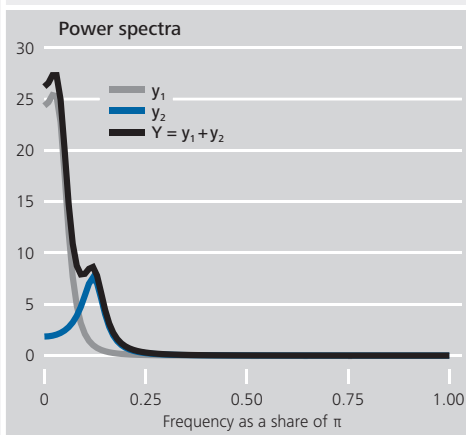
⁷ For more on stochastic cycles, see A. Harvey and T. Trimbur (2003), General Model-Based Filters for Extracting Cycles and Trends in Economic Time Series, The Review of Economics and Statistics, 85, pp. 244-255.

⁸ The power spectrum in the chart can be calculated via the AR coefficients of the time series. For an AR(2) process with coefficients ϕ_1 and ϕ_2 ,

$$f_y(\omega) = \frac{\sigma^2}{2\pi(1 + \phi_1^2 + 2\phi_2 + \phi_2^2 + 2(\phi_1\phi_2 - \phi_1)\cos\omega - 4\phi_2\cos^2\omega)}$$

An AR(2) process taking on the general form $y_t = 2\rho \cos(\omega)y_{t-1} - \rho^2 y_{t-2} + \varepsilon_t$ generates stochastic cycles having the frequency ω . For the two cyclical components of the time series $Y_t = y_{1,t} + y_{2,t}$ in the chart, it is assumed that $\rho = 0.9$; $\omega_1 = \frac{2\pi}{48}$ and $\omega_2 = \frac{2\pi}{16}$. This yields the AR(2) processes, $y_{1,t} = 1.79y_{1,t-1} - 0.81y_{1,t-2} + \varepsilon_{1,t}$ and $y_{2,t} = 1.66y_{2,t-1} - 0.81y_{2,t-2} + \varepsilon_{2,t}$. $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are i.i.d. disturbances with a standard deviation of, respectively, 0.1 and 0.16.

Power spectra and simulated stochastic cycles



The upper section shows the power spectrum of the simulated time series displayed in the lower section as a function of the frequency (horizontal axis). For more on the simulated time series, see footnote 8. **1** Component of time series Y extracted using the Baxter-King filter, with cycles lasting from 8 to 30 years.

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Bandpass filters extract the cycles falling within a pre-defined frequency range out of a time series which potentially contains multiple cycles of varying frequencies.⁹ For instance, the lower half of the chart shows the component extracted from the time series Y_t using such a procedure (the Baxter-King filter) with fluctuations lasting between 32 and 120 observations (for quarterly data, eight and 30 years).¹⁰ The above chart shows that the filtered time series corresponds largely to the longer cycle component.

⁹ Standard filters used in practice include the Baxter-King, Christiano-Fitzgerald and Hodrick-Prescott filters. See M. Baxter and R. King (1999), *Measuring Business Cycles: Approximate Band-Pass Filters for Economic Time Series*, *The Review of Economics and Statistics*, 81, pp. 575-593; L. Christiano and T. Fitzgerald (2003), *The Band Pass Filter*, *International Economic Review*, 44, pp. 435-465; and R. Hodrick and E. Prescott (1981), *Postwar U.S. Business Cycles: An Empirical Investigation*, Discussion Paper 451, Northwestern University. Y. Schüler (2018), *Detrending and Financial Cycle Facts Across G7 Countries: Mind a Spurious Medium-Term*, ECB Working Paper 2138, shows one of the problems associated with using bandpass filters to analyse financial cycles: the filter can induce “spurious cycles” at the frequencies generally associated with financial cycles or amplify weak cycles in this range.

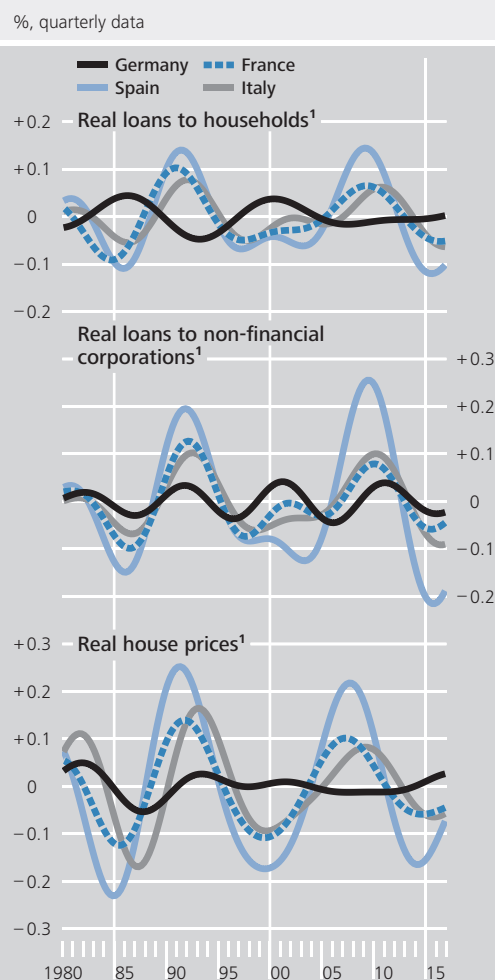
¹⁰ This corresponds to a frequency interval between $\pi/60$ and $\pi/16$.

tween eight and 20 years extracted using the popular Christiano-Fitzgerald filter for real loans by monetary financial institutions (MFIs) to households and non-financial corporations, as well as real house prices in Germany, France, Italy and Spain.²³ The chart provides initial indications of cross-country synchronisation of cycles, in particular when it comes to loans to corporations.

Wavelet approach does not require pre-defined cycle lengths and allows for variation over time

Some other approaches to empirical modelling of the financial cycle do not involve pre-setting relevant cycle lengths and instead determine them on the basis of the data. Given that research on the characteristics of financial cycles is still lagging behind the body of work done on business cycles, it seems prudent to avoid making assumptions about the relevant frequencies as far as possible and to allow the data to “speak for themselves”.²⁴ In this article, methods from wavelet analysis are employed with a view to pinpointing the frequency ranges relevant for financial cycles. This approach does not require pre-specification of cycle length.²⁵ Instead, the empirical analysis serves to reveal which cycle lengths are respon-

Financial cycle components extracted using the bandpass filter*



Sources: BIS, ECB, Eurostat, IMF, OECD and Bundesbank calculations. * Cycle length: 33 to 80 quarters. Log time series filtered by applying an asymmetric Christiano-Fitzgerald filter with drift adjustment assuming an I(1) process. ¹ MFI loans and house prices deflated using the GDP deflator.
 Deutsche Bundesbank

23 MFI loans to households and non-profit institutions serving households, MFI loans to non-financial corporations and house prices. The time series have been deflated using the GDP deflator. The dataset builds on an updated version of the dataset from K. Hubrich et al. (2013), Financial Shocks and the Macroeconomy: Heterogeneities and Non-linearities, Occasional Paper Series, No 143, European Central Bank. For information on the data sources, see Kunovac et al. (2018), op. cit. The credit series constitute actual stocks and not the notional stocks usually used in monetary analysis from which non-transaction-driven changes are removed. It would only be possible to construct notional stocks for the period from 1997 onwards because data on the adjusted changes needed to do so are only available from that point on.

24 See Schüler et al. (2015), op. cit. There is, for instance, empirical evidence to suggest that financial cycles in East Asian economies are much shorter in length than is usually assumed in analyses of financial cycles. See V. Pontines (2017), The Financial Cycles in Four East Asian Economies, Economic Modelling, 65, pp. 51-66.

25 Schüler et al. (2015, 2017), op. cit., take a similar approach. To construct their financial cycle indicator, they select the frequency range in which co-movements in the variables they have chosen are particularly pronounced and develop a new measure for this – power cohesion. Strohsal et al. (2015b), op. cit., use the power spectrum of the time series they analyse to set the frequency range.

26 For analyses of a similar dataset using other empirical approaches see European Commission (2018), op. cit., and Rünstler et al. (2018), op. cit.

sible for the largest share of the variation in a given time series and for which periodicities there are common cycles with other variables. Moreover, wavelet analysis is a time-varying approach, meaning that it allows for changes in the relevant frequencies over time and does not assume that the characteristics of the financial cycle remain constant over time. The annex beginning on p. 71 provides an overview of the wavelet analysis used here.²⁶

Estimation results for the euro area

Analysis for credit and house prices in selected euro area countries

We begin by presenting below an analysis of the cross-country dimension of the euro area financial cycle using data on credit and house prices for selected euro area economies. The investigation is intended to reveal whether, and for which cycle lengths, common – i.e. cross-country – fluctuations can be discovered and whether and how the strength of their synchronicity and their duration have changed over time. The discovery of pronounced synchronised cycles would support the case for centralising or coordinating macroprudential policy. Following on from this, we explore whether there is a relationship between credit or house price cycles and cycles of real economic activity. To what extent are financial cycles to be interpreted as a phenomenon detached from real economic cycles?²⁷

The analysis covers the economies of six euro area countries: Belgium, France, Germany, Italy, the Netherlands and Spain.²⁸ For these countries, relevant data are available as of 1980. However, for reasons of clarity, the results presented are often just those of the four large countries.²⁹ The examined variables are real loans to non-financial corporations and households, real house prices, and, as a benchmark, real GDP. The nominal time series were deflated using the GDP deflator, i.e. converted into real values, and transformed and standardised into annual growth rates for the wavelet analysis.³⁰

Application 1: Are there cross-country financial cycles in loans and house prices in the euro area?

Analysis of cross-country cycles using wavelet cohesion

Indications of the importance of cross-country cycles in lending and house prices are provided by the “wavelet cohesion” of the variables across countries (see the chart on p. 64).³¹ This can be understood in simplified terms as a measure of the average pairwise synchronicity of the respective variables across countries, with the weighting of the pairwise results

based on the countries’ real GDP. More detailed information on the calculation is provided in the Annex. The chart shows the wavelet cohesion for all variables as a function of time (horizontal axis) and cycle length (vertical axis).³² Cohesion can take on values of between minus one (black) and plus one (full synchronisation, white), i.e. cohesion increases from darker to lighter colours. The black curved lines on the sides mark the area of interpretable results. Cohesion values outside this area should not be interpreted as they are subject to start point and end point problems (see p. 72). The light areas surrounded by black lines in the charts show the time frequency combinations where cohesion is statistically significantly different from zero (at the 10% level).

Loans to households show cohesion of close to zero, i.e. a relatively weak synchronisation across countries, up to the beginning of the 1990s. Subsequently, the synchronisation of cycles of about four to over six years is significantly more pronounced and cohesion rises to

Cross-country synchronisation of loans to households intensifying over time

²⁷ The estimates were produced with a modified version of the ASToolbox for Matlab: <https://sites.google.com/site/aguiaconraria/joanasoares-wavelets/> See L. Aguiar-Conraria and M. Soares (2014), The Continuous Wavelet Transform: Moving Beyond Uni- and Bivariate Analysis, *Journal of Economic Surveys*, 28, pp. 344-375.

²⁸ This is the country selection in Kunovac et al. (2018), op. cit., on which parts of this article draw. The length of the dataset limits the maximum length of the cycles that can be assessed by means of wavelet analysis. For this reason, the analysis only covers euro area countries for which data are available as of at least 1980 for all of the variables examined in the reference paper.

²⁹ Further results can be found in Kunovac et al. (2018), op. cit. For results of a broader selection of EU countries see European Commission (2018), op. cit. and Rünstler et al. (2018), op. cit.

³⁰ See footnote 23 on p. 59.

³¹ L. Kurowski and K. Rogowicz (2018), op. cit., perform a wavelet analysis in order to examine the international cohesion of output and credit cycles and find indications of an increase in the synchronisation of credit cycles over time.

³² In fact, the vertical axis shows the angular frequency of the cycles, which is standardised between π , the shortest cycle with two observations – i.e. a length of half a year for quarterly data – and zero, the longest cycle of infinite length. However, as maximum cycle lengths are limited by the length of the time series available for the fitting of the wavelet functions, the minimum angular frequency here is limited above zero. The inverse relationship between the angular frequency and the cycle length implies a non-linear scaling of the vertical axis after conversion to the oscillation period.

Analysing the wavelet power spectra of credit aggregates, house prices and real gross domestic product in Germany

This box outlines how the wavelet power spectrum is used to analyse the cyclical characteristics of time series on credit, house prices and real gross domestic product (GDP), as featured in the main text.

In the same way as the power spectrum described in the box on p. 57, the wavelet power spectrum shows the relative importance of various cycle lengths for the variance of a time series. By contrast, however, the level of importance can change over time, making the wavelet power spectrum time-varying.¹ This means that the cycle lengths of the most important time series components can be determined for more in-depth analysis on the basis of the wavelet power spectrum. In addition, it is possible to examine whether and how the length of the cycles of key importance to the time series changes over time. Moreover, the power spectra allow cross-checks to be carried out to determine whether common cross-country cycles derived using different methods are of any major importance to the development of a given time series in a single country.

The chart on p. 62 illustrates the power spectra estimated using the wavelet approach regarding the annual growth rates of loans to households and to non-financial corporations, of house prices and of real GDP for Germany.² The value of the power spectrum is colour coded for each combination of cycle length (vertical axis) and time (horizontal axis). Its value increases from black (zero) to white. The black and roughly horizontal lines link the wavelet power spectrum's maxima over time. The black dashed and curved lines denote what is known as the cone of influence. Only results for combinations of time and cycle

length between the two lines can be interpreted. The reason for this is that the estimate of the wavelet representation of the time series at each point in time includes both prior as well as future observations. As explained in the Annex on pp. 71ff., the length of this "window" is contingent on the frequency under review and widens as the length of the cycle increases.³ A sufficient number of observations in both time directions is available only for the estimates of the power spectrum between the two curved lines. As the cycle length increases, the "width of the window" expands and the period for which estimates can be made becomes continuously shorter as a consequence. The results for the combinations of time and cycle length within the cone of influence, i.e. those between the right (left) curved line and the right (left) border of the chart, suffer from start or end point problems and should not be interpreted.⁴

The wavelet power spectra for the variables exhibit considerable differences. Although credit and house prices each contain three dominant cycles, they have differing levels of stability and operate at different cycle

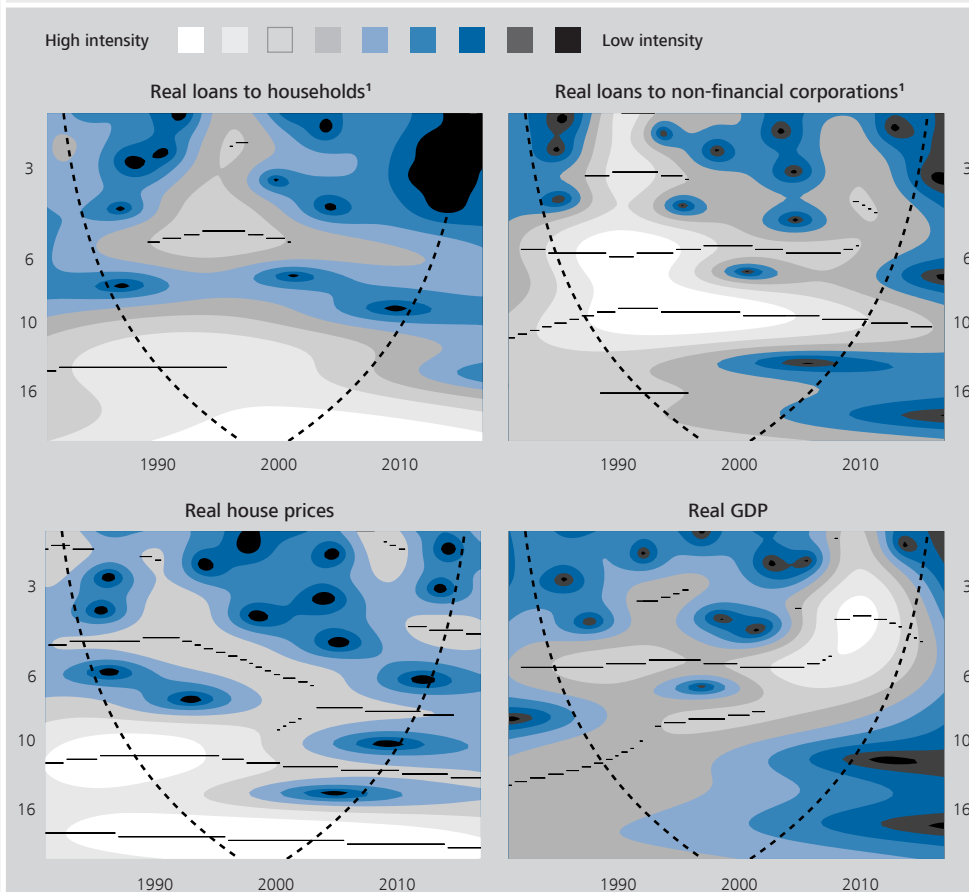
¹ See the text in the Annex starting on p. 71.

² For the data sources, see footnote 23 on p. 59. For a comparison with the wavelet power spectra of the variables in the three other large euro area countries, see M. Scharnagl and M. Mandler (2018), *Real and Financial Cycles in Euro Area Economies: Results from Wavelet Analysis*, mimeo. For results for the United States, see F. Verona (2016), *Time-Frequency Characterization of the U.S. Financial Cycle*, *Economics Letters*, Vol. 144, pp. 75-79. The estimates were produced with a modified version of the ASToolbox for Matlab: <https://sites.google.com/site/aguiaconraria/joanasaes-wavelets/> See L. Aguiar-Conraria and M. Soares (2014), *The Continuous Wavelet Transform: Moving Beyond Uni- and Bivariate Analysis*, *Journal of Economic Surveys*, Vol. 28, pp. 344-375.

³ This represents the dilation (scaling) of the wavelet.

⁴ Technically, the power spectrum in these border areas is estimated by reflecting the time series at its start or end points.

Wavelet power spectra for credit, house prices and real GDP in Germany*



Sources: BIS, ECB, Eurostat, IMF, OECD and Bundesbank calculations. * Wavelet power spectra calculated from annual growth rates. The horizontal axis shows the time, while the vertical axis shows the oscillation period (in years). The values indicate the relative contribution made by cycles to the variance of the time series for each combination of cycle length and point in time. See the text on p. 72. The thin black lines mark the power spectrum's local maxima over time. The values in the peripheral areas marked by the curved lines suffer from start and end point problems. ¹ Deflated using the GDP deflator.

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lengths. In the case of loans to households and house prices, the values for the power spectrum are stable and large in the lowest frequency range, while the values for loans to non-financial corporations are stable and large for cycles with a length of around ten years. For loans to households and house prices, local maxima of the spectrum can also be identified for cycles of between ten and 16 years; however, their importance diminishes over time. The situation is similar for cycle lengths of around five years for loans to non-financial corporations. While the power spectrum for the third and shorter cycle for house prices is relatively stable in terms of value, the cycle length in-

creases over the course of the estimation period. The shorter cycles of loans to households and loans to non-financial corporations (with a duration of five or three years) are only of temporary importance.

In a comparison with credit and house prices, the lower right-hand section of the chart depicts the power spectrum of real GDP, which exhibits two dominant cycles. The first cycle has a length of around six years while the second, longer cycle, which initially has a length of just over ten years, converges towards the first cycle over time.

values that are close to one. A similar development is also apparent for cycles of about ten years in length, albeit with a lag. Overall, the synchronisation between the growth rates of MFI loans to households across the countries under review has increased over time.

Stable cross-border synchronisation of cycles of loans to non-financial corporations over time

For loans to non-financial corporations, the estimation shows stable cohesion of close to one throughout the entire period, both for cycles with a length of between eight and ten years and for those with a length of around 16 years. In the course of the 2000s, the synchronisation intensifies for shorter cycles. This could be due to the likewise increasingly strong synchronisation of real economic cycles (in the lower right-hand section of the chart) in these frequency bands.

Cross-country synchronisation of house price cycles only in a very narrow frequency range

Between the house price cycles of six to 16 years there is a strong synchronisation across countries at the beginning of the estimation period. However, the cycle lengths with relatively high cohesion narrow over time to about 12-14 years in the late 1990s. In this narrower frequency band, cohesion is also statistically significant. Therefore, the results do not point to increasing synchronisation across countries over time for house prices.

Avoidance of a priori specification of frequency ranges beneficial for empirical work

The results for the three variables already show how important it is to avoid an a priori focus on a single frequency range for all variables. For example, the frequencies in which common, cross-country cycles occur differ between variables, and limiting cycle length to eight or more years would, for instance, ignore an important part of the common oscillations in loans to households. The narrowing of the band of cycle lengths with high cohesion in the case of house prices and the increase in cohesion of cycles of loans to households illustrates the advantageousness of wavelet analysis, which can detect this time variability. Indicators based on estimates derived from fixed frequency bands are therefore potentially problematic. This is particularly true if they are used for policy purposes.

For the purpose of comparison, the last part of the chart on p. 64 presents the results of the cohesion analysis for real GDP. Here there is tight synchronisation between the cycles of the individual countries over a wide range of frequencies. A relatively stable synchronisation is seen for cycles of around ten and around 16 years. Moreover, from around 1990 onwards, there is also significant cohesion for shorter cycles, which are usually associated with business cycles. This can be interpreted as evidence of increasing synchronisation between the business cycles of the observed countries over time.

Comparing the results for real GDP with those for the other variables, it is clear that common cycles of real GDP across countries cover a much wider frequency range than common cycles of the other variables. This is particularly true in comparison with house prices, for which common cross-country cycles cover only a narrow band. According to these results, cross-country cycles in the euro area for loans to households and house prices play a smaller role than for real GDP. Across countries, the financial cycle in the euro area for loans to households and house prices is thus less pronounced than the business cycle, meaning that the rationale for a single European macroprudential policy appears less obvious than for a single European monetary policy.

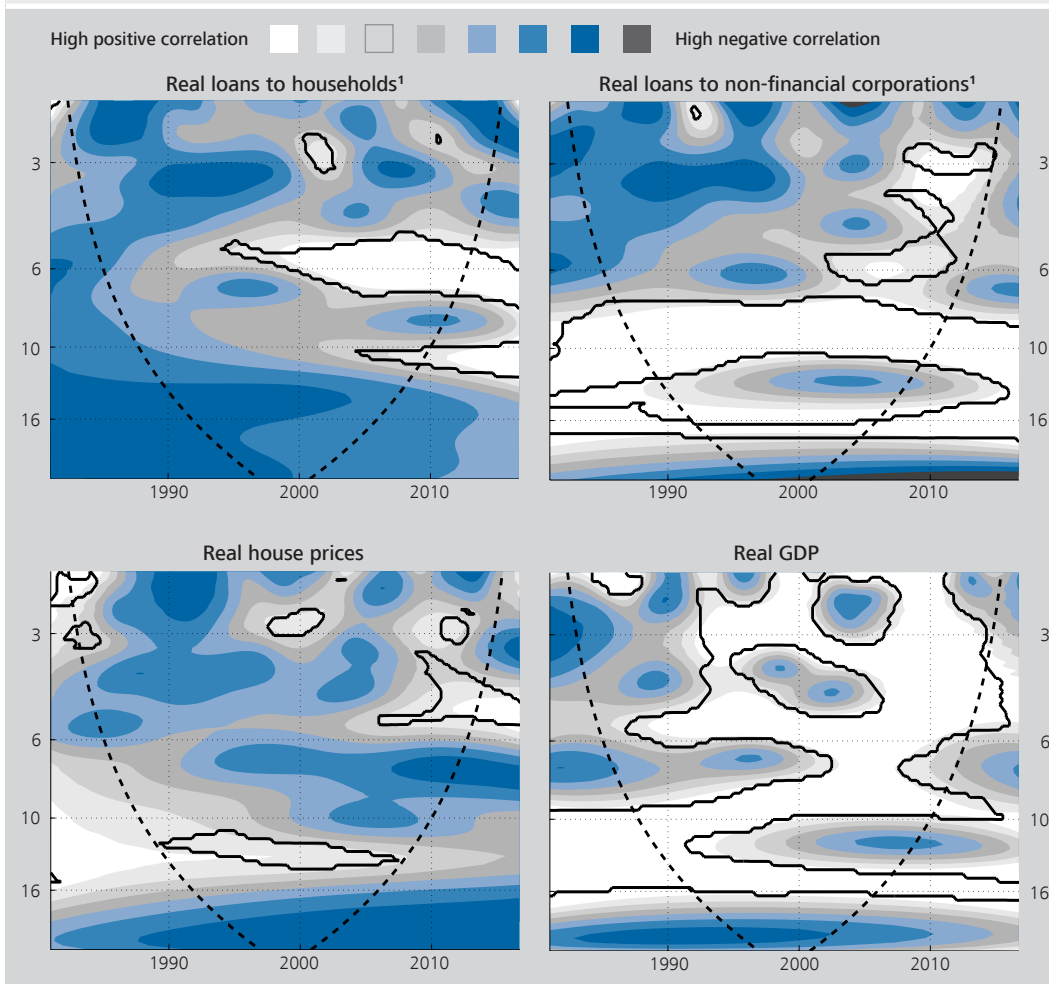
The cohesion analysis indicates that the cross-country synchronisation of all the variables considered increased over time, with the exception of house prices. One reason for this could be the start of European monetary union in the middle of the estimation period.

The above analysis relates to the average cross-country synchronisation of the variables' cycles, measured by wavelet cohesion (see p. 74). The analysis focuses on the question of whether the cycles of the variables are synchronised or whether there is a lag between them, i.e. whether there is what is known as a phase shift. Given that Germany has the largest GDP

Common cycles of real GDP cover wider frequency ranges than those of loans and house prices

Increase in synchronisation in the second half of the estimation period, except for house prices

Wavelet cohesion*



Sources: BIS, ECB, Eurostat, IMF, OECD and Bundesbank calculations. * Wavelet cohesion is a measure of the cross-country synchronisation of cycles. See p. 74. Countries: BE, DE, ES, FR, IT, NL. The horizontal axis shows time, while the vertical axis shows the oscillation period (in years). The black lines delineate areas with cohesion significantly different from zero at the 10% level. The values in the peripheral areas marked by the curved lines are subject to start and end point problems. ¹ Deflated using the GDP deflator.

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weight in the sample, the degree of synchronisation of the cycles in Germany with those of the other countries has a particularly strong impact on the results of the cohesion analysis as the paired results are weighted according to the real GDP of the two respective countries.

The chart on p. 65 provides an impression of the relative positions of the cycles in the annual growth rates of the two credit aggregates and house prices in each country.³³ A distinction is made here between cycles of six to ten years in length and cycles of between ten and 16 years. These frequencies cover the lengths of the most important cycles for each variable.³⁴ In

the chart, each cyclical component is displayed only over periods that are not affected by start and end point problems. For the longer cycles (ten to 16 years), the period for which esti-

Inversion of the wavelet representation provides filtered time series

³³ For selected variables and frequency ranges, the cycles were calculated by inverting the estimated wavelet representation of the time series for certain frequency ranges. In addition, the standardisation of data is reversed. The inversion can be interpreted as a (two-sided) statistical filter which extracts components with the selected cycle lengths from the time series.

³⁴ For Germany, see the results on p. 61f. For the other countries, see M. Scharnagl and M. Mandler (2018), Real and Financial Cycles in Euro Area Economies: Results from Wavelet Analysis, mimeo. For real house prices, cycles with a length of between six and ten years are not shown, as the cohesion analysis did not provide any indication of synchronisation.

mates are available is therefore shorter.³⁵ In addition to the estimated cycles for the four large countries, the chart also shows the cycles of the aggregate of all six countries, including Belgium and the Netherlands.³⁶

As regards loans to households, it is apparent that the cycles of between ten and 16 years in Germany are substantially out of sync with those of other countries over most of the observation period, which, taken in isolation, reduces cohesion for this variable as shown in the chart on p. 64. While the shorter cycles of six to ten years in Germany are also initially out of sync with those of other countries, over time they increasingly converge towards the cycle of the aggregate, which contributes to the increase in cohesion in this frequency band, as shown in the chart on p. 64.

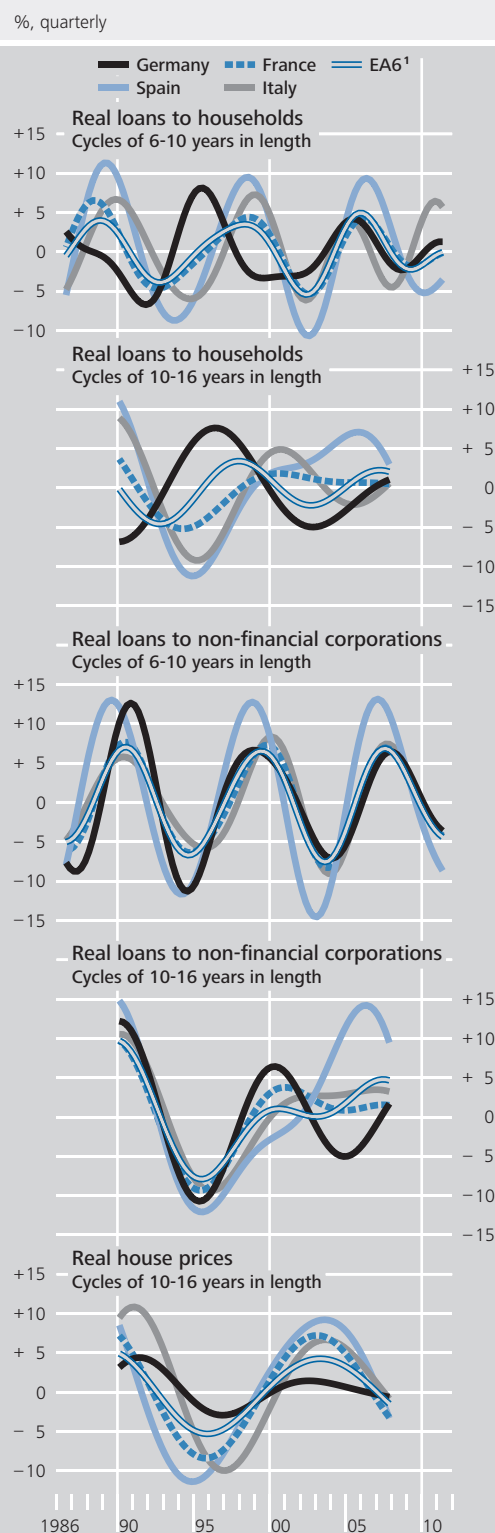
The chart also shows that, for loans to non-financial corporations, the cycles with a length of six to ten years are relatively strongly synchronised across countries, which is in line with the stable cohesion in this range shown in the chart on p. 64. Cycles in Germany have converged over time towards the average cycle, while the amplitude in Spain has slightly increased. For the longer cycles (ten to 16 years), a high level of synchronisation is apparent at the beginning of the period. However, the cycles later diverge somewhat, especially towards the mid-2000s – with the credit boom in Spain, for example, being clearly visible. That said, at the end of the estimation period, the cyclical components converge once more.

House prices exhibit a relatively high degree of phase synchronisation for oscillations of ten to 16 years, which is reflected in the significant

³⁵ As the length of time with interpretable results shrinks as cycle lengths increase, extending the analysis to cover even longer cycles makes little sense, given the length of the time series at hand. It would reduce the period of time for which interpretable results can be estimated and make it virtually impossible for conclusions to be drawn on the time variability of these relations.

³⁶ For house prices, the growth rate of the aggregate is calculated as the mean growth rate of the individual countries weighted by real GDP of the given country.

Filtered annual growth rates from wavelet analysis*



Sources: BIS, ECB, Eurostat, IMF, OECD and Bundesbank calculations. * MFI loans and house prices deflated using the GDP deflator. Selected cyclical components of annual growth rates, calculated through inversion of the estimated wavelet representation. Average values over the given range of cycle lengths. ¹ Results for EA6 relate to the sum of real loans in BE, DE, ES, FR, IT and NL or to the real-GDP-weighted average of annual growth rates in real house prices.

Standard deviations of the cyclical components*

Item	Time period	Germany	Spain	France	Italy
Real loans to households	6 to 10 years	3.52	6.64	3.33	4.29
	10 to 16 years	4.43	6.20	2.41	4.72
Real loans to non-financial corporations	6 to 10 years	6.28	8.81	4.98	4.91
	10 to 16 years	6.12	8.78	4.83	5.43
Real house prices	6 to 10 years	1.79	8.28	5.17	3.61
	10 to 16 years	2.06	6.99	5.26	6.40
Relative to the standard deviation of GDP					
Real loans to households	6 to 10 years	1.48	2.74	2.10	1.88
	10 to 16 years	2.52	3.94	1.71	3.42
Real loans to non-financial corporations	6 to 10 years	2.64	3.64	3.14	2.15
	10 to 16 years	3.47	5.58	3.43	3.94
Real house prices	6 to 10 years	0.75	3.42	3.26	1.58
	10 to 16 years	1.17	4.44	3.73	4.64

Sources: BIS, ECB, Eurostat, IMF, OECD and Bundesbank calculations. * Standard deviations of the cyclical components in the chart on p. 65. The lower part of the table shows the standard deviation relative to the standard deviation of real GDP.

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cohesion in the chart on p. 64. The amplitude of house price cycles is noticeably smaller in Germany than in the other countries.³⁷

Amplitude of house price cycles smaller in Germany than in the other countries

The above table shows the standard deviations of the filtered time series for all variables and thus provides information on the average amplitude of the cycles. The amplitude of house price cycles is noticeably smaller in Germany than in the other countries. This also applies to the standard deviation of house price cycles relative to the standard deviation of GDP cycles (lower part of the table). The amplitudes of the cycles of loans to non-financial corporations are greater than those of loans to households in all of the countries. In general, both credit cycles and house price cycles exhibit a larger standard deviation than the GDP cycles:³⁸ with the exception of house price cycles in Germany, the values in the lower part of the table are all greater than one.

Analysis of the cycles' phase synchronisation across countries supports the results of the cohesion analysis

A more precise assessment of cycles' phase synchronisation across countries is made possible by the chart on p. 67. It shows the average time difference, i.e. the lead or lag in a country's cycle compared to the GDP-weighted average of the cycles of the other countries, for the variables and frequency bands in the chart on p. 65. Positive time differences (vertical axis)

represent a lead and negative differences represent a lag.

Consistent with the results of the cohesion analysis, the time differences among cycles of loans to households with a length of between 6 and 10 years are decreasing over time, i.e. the cycles are becoming more synchronised. For the longer cycles of between ten and 16 years, the three other large countries are converging towards the average cycle; Germany, however, has a cycle that is four to five years out of sync over the entire period. Due to Germany's large weight in the calculation of cohesion, this presumably leads to cohesion remaining relatively low, despite the increasing synchronisation of the other countries. The time differences between the cycles of loans to non-financial corporations are for the most part less than one year, corroborating the finding of strong cross-country synchronisation in the cohesion analysis.

³⁷ On the clear deviations of the cycles in Germany from those of the other countries, see Kunovac et al. (2018), op. cit.

³⁸ For similar results, see C. Borio (2014), op. cit., G. Rünstler and M. Vlekke (2018), op. cit., and Rünstler et al. (2018), op. cit. Rünstler et al (2018) document a positive correlation for EU countries between the volatility of credit and house price cycles and the home ownership rate, and a negative correlation with the current account balance.

Clear phase shift of house price cycle in Germany

The estimated time differences for house price cycles point to some convergence over time. However, the time difference of cycles in Germany to the average of the other countries is relatively large until the beginning of the 2000s. The subsequent major change in the phase shift in house price cycles in Germany goes hand in hand with a declining importance of these cycles (see p. 62). This implies rising estimation uncertainty with regard to the time difference, which means that the change in the time difference should be interpreted with caution.

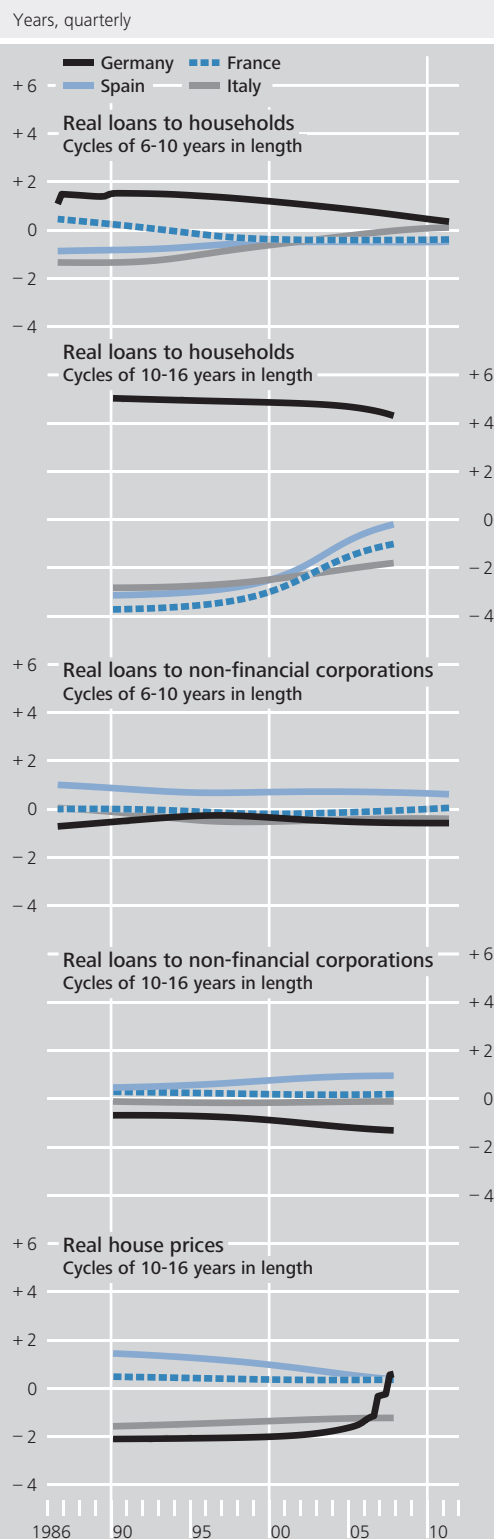
Overall, the analysis of the time differences supports the conclusions based on the measures of cohesion. Cycles of loans to non-financial corporations exhibit relatively stable and tight synchronisation across countries, while the synchronisation of loans to households has increased over time, especially for cycles of between six and ten years in length. As regards the longer cycles of loans to households, the discernible special role of Germany implies that the aggregate measure of cohesion does not sufficiently reflect the link between the cycles of other countries.³⁹ The time differences of house price cycles point to a slight convergence between countries.

Application 2: Relationship between financial cycles and real economic cycles

What is the relationship between financial cycles and cycles of real economic activity?

The cohesion analysis has shown that the frequency ranges in which there are cross-country cycles of real GDP also encompass frequency ranges in which there are common cycles of credit and house price growth. This also applies internally within countries, as real GDP growth also includes cyclical components of lengths similar to those found in the growth rates of credit and house prices.⁴⁰ The chart on p. 68 examines the correlation between real eco-

Time difference to the aggregated cycle of the other countries for selected cycle lengths*

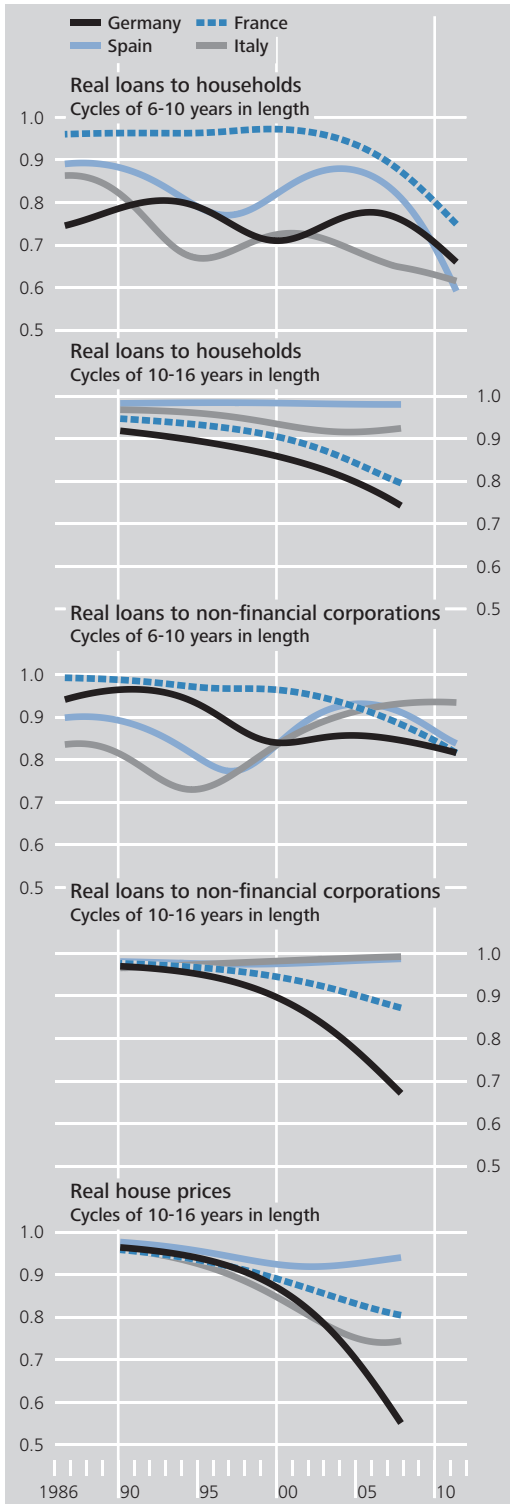


Sources: BIS, ECB, Eurostat, IMF, OECD and Bundesbank calculations. * MFI loans and house prices deflated using the GDP deflator. Average time differences, calculated for selected ranges of cycle lengths, between the cycle of the variable of the observed country and the GDP-weighted average of the other countries.

³⁹ Evidence that the German financial cycle is less strongly synchronised with the cycle of the rest of the euro area is also documented in European Commission (2018), op. cit.
⁴⁰ On these findings, see also M. Scharnagl and M. Mandler (2018), op. cit.

Wavelet coherence between credit aggregates/house prices and real GDP for selected cycle lengths*

% , quarterly



Sources: BIS, ECB, Eurostat, IMF, OECD and Bundesbank calculations. * MFI loans and house prices deflated using the GDP deflator. Wavelet coherence is a measure of the strength of the variables' correlation with real GDP, depending on the point in time and the cycle length. See p. 74. Average values over the given range of cycle lengths.

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economic cycles and cycles of loans and house prices. It shows the wavelet coherence between the growth rates of the two credit aggregates and house prices, on the one hand, and those of real GDP, on the other. This is a measure of the strength of the local correlation between two time series, depending on time and the cycle lengths considered, and can take values of between zero (no coherence) and one (perfect coherence).⁴¹

According to the estimates, the cycles of loans to households and loans to non-financial corporations exhibit strong commonality with real GDP cycles. In the case of longer cycles, this is likely to reflect, in particular, the economy's growing demand for funding as activity increases. For Germany, the coherence of the cycles of between ten and 16 years for corporate loans is decreasing over time. However, this result is not very meaningful, as the cycles with the specified duration play only a minor role in the growth rate of corporate loans (see the chart and the text on p. 62).

Commonalities between credit and house price cycles and cycles of real GDP

The coherence between real GDP growth and growth in house prices is stable in Spain and close to one. By contrast, in Italy, but above all in Germany, there is a noticeable decline in coherence. In Germany, the result could reflect, inter alia, the weak growth in real house prices over the 2000s accompanied by a simultaneous acceleration of GDP growth as of 2003.⁴²

Further analysis shows that within France, Italy and Spain, the two credit aggregates and house prices are strongly synchronised for cycle lengths of ten years or more. There is therefore another dimension to the financial cycle in these countries, namely common cycles of different variables within a country. As the variables in these frequency ranges are also closely

Within-country dimension of the financial cycle

⁴¹ In highly simplified terms, coherence can be compared to the positive root of the R^2 of a regression.

⁴² See also the cyclical component in the chart on p. 65. In the charts on p. 62, this is reflected in the much higher reduction in the power spectrum of real GDP in the given frequency range compared to house prices.

correlated with real GDP cycles, it can be concluded that cycles in real economic activity and financial cycles are potentially interdependent phenomena. In Germany, however, there is no similar synchronisation of cycles of loans and house prices, which means that from the point of view of this analysis, there is no pronounced evidence of a financial cycle in Germany in terms of a synchronisation of loans and house prices.

■ Assessment and outlook

Descriptive analytical results should not be interpreted as causal relationships

The empirical results for the euro area presented above show correlations between variables within individual countries and across countries, but do not allow any direct conclusions to be drawn with regard to the causalities. Structural models are needed to infer causal relationships, for example between real economic cycles and financial cycles, to identify the causes of such cycles and to derive policy recommendations. The stylised facts obtained from this analysis and other empirical studies thus serve as a reference point for structural model analyses, which means that structural models should be able to reproduce the key characteristics of financial cycles in the data and their interaction with real economic cycles.⁴³

Cross-country cycles less important for loans and house prices than for economic activity

The main empirical findings of the analysis presented are as follows:

- There are indications of cross-country cycles in the growth of credit aggregates and house prices.
- However, common cross-country cycles of these variables are less pronounced than those of real economic activity. This suggests that country-specific cycles are of considerable importance for credit growth, particularly for loans to households, and for house price dynamics. Indeed, there are significant fluctuations in the variables at country level

that are not covered by the cycle lengths of the identified common cycles.

- In comparison, coverage for cycles of real GDP is much greater, i.e. the common euro area business cycle is more important for GDP growth in the Member States than the common financial cycle is for growth in loans and house prices.
- The cycles of loans to households and of house prices in Germany differ significantly from those in the other countries.⁴⁴ Furthermore, additional analyses do not provide strong evidence of common cycles for loans or property prices in Germany.

These results have implications for the proper orientation of macroprudential policy. In the euro area, responsibility for the use of macroprudential policy measures, such as the countercyclical capital buffer, is generally assigned at the national level. At the same time, macroprudential policy is embedded in an international framework of rules. An understanding of the synchronisation between national financial cycles is therefore essential for successful coordination at the European and global level. The orientation of macroprudential policy in the euro area to country-specific developments is supported by the empirical findings presented above.

Another important finding is that credit growth, house price inflation and real GDP growth in the countries under review exhibit common medium-term fluctuations. It can therefore be concluded that financial cycles and real eco-

Financial cycles and real economic cycles as interrelated phenomena

⁴³ With dynamic general equilibrium models (DSGE models), which are often used for policy analysis, this is currently possible only to a limited extent; see Rünstler et al. (2018), op. cit.

⁴⁴ See also B. Meller and N. Metiu (2017), op. cit., Schüller et al. (2017), op. cit., and Kunovac et al. (2018), op. cit. The empirical methodology, however, does not yield results concerning the causes of these deviations. G. Rünstler and M. Vlekke (2018), op. cit., and Rünstler et al. (2018), op. cit., draw a connection between the lower amplitude of credit and property price cycles in Germany compared to other countries and a lower share of home ownership.

economic cycles should not be regarded as independent phenomena. However, the results do not allow any conclusions to be drawn on the direction of causality, i.e. whether these common cycles are caused predominantly by real economic or financial factors, or both. It is therefore likely that measures that aim to increase the resilience of the financial system to systemic risks are also likely to have a real economic impact.⁴⁵ In this case, there can also be interactions between macroprudential policy and monetary policy.⁴⁶ In the long term, macroprudential policies reinforce the framework conditions for a stability-oriented monetary policy by setting the right incentives and ensuring sufficient resilience in the financial sector. Macroprudential policy should therefore be consistently focused on financial stability and should not be reinterpreted as a tool for demand-side management at the national level.⁴⁷

Problem of estimating the financial cycle in real time

Macroprudential policy has a number of instruments to counteract systemic risks from excessive credit and asset price booms. The use of these instruments requires indicators which allow for a timely assessment of the risk situation and which should therefore be available with as little delay as possible. These indicators, such as the credit-to-GDP gap or the early warning indicator for systemic financial crises used at the Bundesbank,⁴⁸ build on the results of empirical studies on financial cycles.⁴⁹ However, it should also be noted that, because they are estimated metrics, financial cycle indicators are inherently uncertain, especially if they are identified in real time in order to support policy decisions and are intended to provide an estimate that is as up to date as possible.⁵⁰ Studies show that uncertainty in real-time estimates of financial cycles is of a comparable order of magnitude, in relation to cycle amplitude, to that in estimates of the business cycle or the output gap.⁵¹ The design of appropriate indica-

tors therefore presents a similar challenge to estimating the macroeconomic output gap.

⁴⁵ See S. Eickmeier, B. Kolb and E. Prieto (2018), Tighter bank capital requirements do not reduce lending long term, Deutsche Bundesbank Research Brief No 22, November 2018.

⁴⁶ While price and financial stability are interdependent in the long term, there can be short to medium-term trade-offs between the two. For example, macroprudential instruments to mitigate risks in the financial system can counteract monetary policy objectives in the short to medium term, and monetary policy measures, such as via the risk-taking channel, can temporarily put a strain on financial stability. For a detailed analysis of the relationship between macroprudential policy and monetary policy, see Deutsche Bundesbank, The importance of macroprudential policy for monetary policy, Monthly Report, March 2015, pp. 39-71.

⁴⁷ See C. Buch (2014), Alter Wein in neuen Schläuchen? Die Ziele makroprudenzieller Regulierung, speech at the Banken- und Unternehmensabend event which took place at the Bundesbank's Regional Office in Bavaria, and Deutsche Bundesbank (2015) op. cit.

⁴⁸ See Deutsche Bundesbank, Financial Stability Review 2018.

⁴⁹ For example, M. Drehmann and K. Tsatsaronis (2014), The Credit-to-GDP Gap and Countercyclical Capital Buffers: Questions and Answers, BIS Quarterly Review, March, pp. 55-73.

⁵⁰ The uncertainty regarding real time estimates of financial cycles has multiple components. The first is the general estimation or parameter uncertainty associated with any econometric estimation. Where filtering techniques are used, another component is filter uncertainty resulting from the absence of future observations at or near the current end of the data. In the wavelet estimates, this problem is reflected in the non-interpretability of the border regions. This problem can be partially circumvented by using a one-sided filter or by extending the data with forecasts. However, both of these approaches lead to increased uncertainty of the estimation results at the current end. Furthermore, data revisions may mean that estimates of the financial cycle turn out to be incorrect ex post. The uncertainty of real-time estimates has been discussed in the past mainly for estimates of the output gap, i.e. deviation of actual real GDP from equilibrium or potential output, or for estimates of the unemployment gap, i.e. the deviation of the unemployment rate from the natural rate of unemployment. See, for example, A. Orphanides and S. van Norden (2003), The Unreliability of Output Gap Estimates in Real Time, The Review of Economics and Statistics, 85, pp. 569-583; and A. Basistha and R. Startz (2007), Measuring the NAIRU with Reduced Uncertainty: A Multiple-Indicator-Common-Cycle Approach, The Review of Economics and Statistics, 90, pp. 805-811.

⁵¹ For more information see G. Rünstler and M. Vlekke (2018), op. cit., and Rünstler et al. (2018), op. cit. These studies take into account parameter and filter uncertainty, but not data revisions. The results suggest that multivariate structural time series models are associated with lower uncertainty for real time estimates than univariate filtering approaches.

■ Annex

An introduction to wavelet analysis

Wavelet analysis is a tool for analysing time series within the frequency domain.⁵² It represents a refinement of spectral analysis to cover non-stationary time series, which are common in economic applications. While the conventional spectral analysis, which is based on the Fourier transform, works on the assumption that the importance for the variance of the time series of certain cycle lengths remains constant over time, the spectrum of the time series being constant, wavelet analysis allows for the spectrum to change over time. Accordingly, the same applies to multivariate analyses. Wavelet analysis is therefore also suitable for studying changes in the relationship between multiple time series over time. Typically, variables containing trends are transformed into annual growth rates before applying the wavelet analysis.

Unlike Fourier analysis, which is based on cycles with infinite support, wavelet analysis uses local base functions with finite support. The maximum length of cycles which can be examined is limited by the number of observations, i.e. the length of the underlying time series. A distinction is made between the discrete wavelet transform (DWT) and the continuous wavelet transform (CWT). The discussion below will be confined to the CWT.⁵³ A wavelet (mother wavelet) $\psi_{\tau,s}$ is characterised as a small wave as opposed to a sine function, which is a large wave

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{|s|}} \psi\left(\frac{t-\tau}{s}\right),$$

where s is the scale and τ the localisation in time. A wavelet, in other words a wave function, must be different from zero within a certain range, i.e. it must exhibit both positive and negative elements (wave-like behaviour); at the same time, it must tend towards zero outside this range, otherwise it would not have finite support. The mother wavelet ψ can be compressed or stretched and shifted across the time axis in order to capture waves of different cycle lengths and at different points in time. In order to analyse longer cycles, the wavelet is stretched, whereas it is compressed to analyse shorter cycles. The larger the scaling parameter s , the more ψ is stretched and vice versa. As a consequence, wavelet analysis works with frequency-dependent window lengths, which means that more data points are in-

cluded in estimations for longer cycles than for shorter ones.⁵⁴

In the context of the CWT, a specific wavelet function, known as the Morlet wavelet,⁵⁵ which possesses certain desirable characteristics, is used very frequently. The Morlet wavelet is defined as:

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

The second term in brackets is negligible for $\omega_0 > 5$ and is disregarded in the following, implying that:

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

The first term is a normalisation factor, the second term a complex sine curve, and the last term the Gaussian bell curve. An optimal time-frequency localisation for the decomposition of a time series is obtained for $\omega_0 = 6$. In addition, this value implies a direct relationship between scale and frequency ($\omega \approx 1/s$).

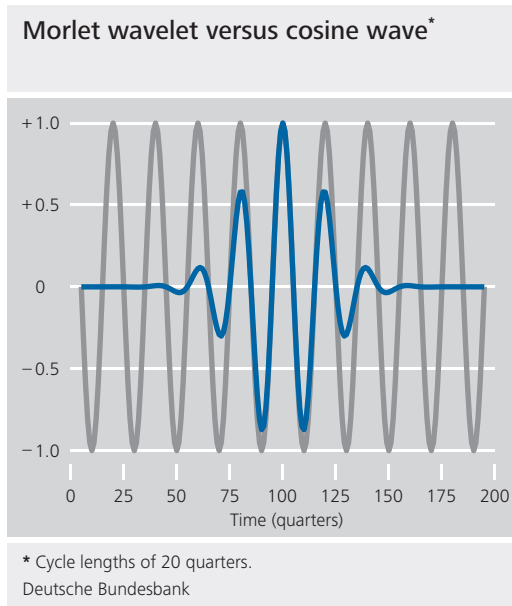
The Morlet wavelet, with $\omega_0 = 6$, is shown in the chart on p. 72. It can be described as a complex sine wave modulated by a Gaussian function, which means that the wavelet is, at the centre, equivalent to a complex sine wave. Closer to the borders, there is a steady decrease in oscillation, ultimately converging towards the value of zero. The chart depicts the

⁵² For information on the frequency representation of time series, see the box on pp. 56 ff. For an introduction to wavelet analysis, see, for example, A. Rua (2012), Wavelets in Economics, Economic Bulletin, Banco de Portugal, Summer, pp. 71-79; or L. Aguiar-Conraria and M. Soares (2014), The Continuous Wavelet Transform: Moving Beyond Uni- and Bivariate Analysis, Journal of Economic Surveys, Vol. 28, pp. 344-375.

⁵³ Unlike the CWT, the DWT only stretches or shifts wavelets by discrete numerical values. In the extreme case of the dyadic approach, a factor of two is applied in the stretching process.

⁵⁴ In conventional spectral analysis, time variation can be taken into account through what is referred to as a windowed Fourier transform. The calculation of the spectrum does not include the entire time series, but instead only observations within a window of fixed length, which is shifted along the time axis. Adjusting the window length in the wavelet analysis in accordance with the frequency leads, by comparison, to a higher resolution for low frequencies in the frequency dimension, and for short cycles in the time dimension; see A. Rua (2012), op. cit.

⁵⁵ Morlet wavelets were first introduced in P. Goupillaud, A. Grossman and J. Morlet (1984), Cycle-Octave and Related Transforms in Seismic Signal Analysis, Geoprospection, Vol. 23, pp. 85-102.



comparison of the real part of the Morlet wavelet, with $\omega_0 = 6$, with a cosine wave spanning a cycle length of twenty quarters.⁵⁶

The upper chart on p. 73 shows how, once the Morlet wavelet is substituted in the first equation, the wavelet function can be stretched or – as in the example – compressed by changing s and shifted across time by changing τ . The left side of the chart illustrates how the Morlet wavelet is scaled to adjust to higher frequencies. The right side illustrates the shift of the Morlet wavelet across the time axis.

The CWT of a time series is obtained by projecting the time series $x(t)$ onto the wavelet function ψ ⁵⁷

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

where $*$ denotes the complex conjugate wavelet function. The transform is calculated for all combinations of scales s and points in time t . It measures the correlation between the time series $x(t)$ and the wavelet in question. The more the two resemble each other, the higher the value of $W_x(\tau, s)$.

The wavelet power spectrum (WPS) represents the relative contribution made by the various cycles to the total variance of the time series for each scale and point in time. It is defined as:

$$\text{WPS}_x(\tau, s) = |W_x(\tau, s)|^2.$$

The higher the value of the power spectrum, the more important the fluctuations are in the corres-

ponding frequency range at the relevant point in time.

For the purposes of illustration, the bottom chart on p. 73 shows a simulated time series containing a structural break in period 50, after which the cycle length changes from four to eight years. The estimated power spectrum based on the Fourier transform, which does not allow for time variation, captures both cycles. It is not clear, however, whether the two cycles move simultaneously across the entire period or whether a change has taken place over time. The WPS can provide information on the matter.⁵⁸ It is depicted as a heatmap with power spectrum values increasing from dark to light colours. The curved lines mark the boundaries of what is referred to as the cone of influence. The number of observations close to the borders is insufficient to accurately calculate the wavelet coefficients, due to which only the results within the two lines should be interpreted. The black and largely horizontal lines show the key cycle lengths (local maxima of the WPS). It is discernible that a structural break occurred midway through the observation period.

The interaction between two time series $x(t)$ and $y(t)$ can be analysed by means of the cross-wavelet transform

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

Given that the Morlet wavelet is complex, the cross-wavelet transform, too, exhibits complex values.

This allows phase shifts and phase differences between two time series, i.e. lead-lag relationships, to be analysed. The phase angle of a time series is defined as:

$$\varphi_x(\tau, s) = \tan^{-1} \left[\frac{\Im\{W_x(\tau, s)\}}{\Re\{W_x(\tau, s)\}} \right],$$

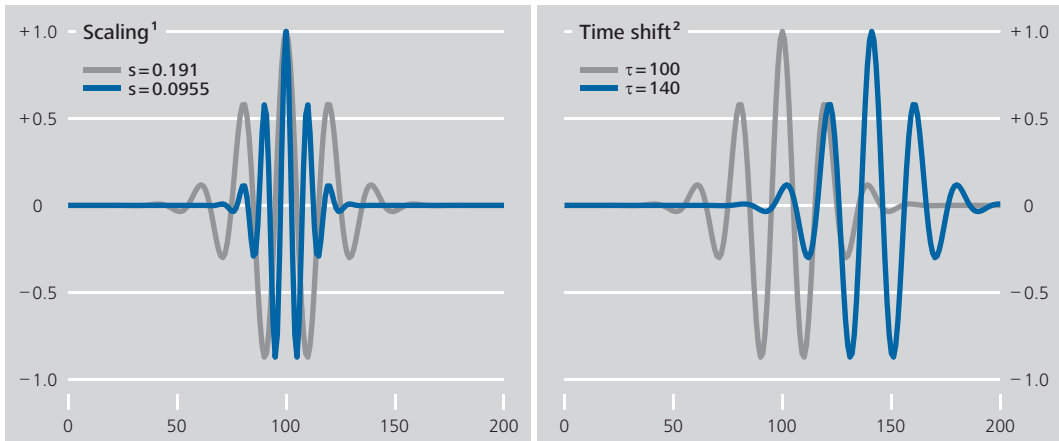
where $\Re\{W_x\}$ is the real and $\Im\{W_x\}$ is the imaginary part of the wavelet transform W_x . The phase angle indicates the oscillation position of the time series for a specific time-frequency combination. In

⁵⁶ The real part of the Morlet wavelet is a cosine function (Euler's formula).

⁵⁷ See L. Aguiar-Conraria and M. Soares (2014), op. cit.

⁵⁸ The estimates of the WPS were produced using a modified version of the ASToolbox for Matlab: <https://sites.google.com/site/aguiarconraria/joanasoares-wavelets/> See L. Aguiar-Conraria and M. Soares (2014), op. cit.

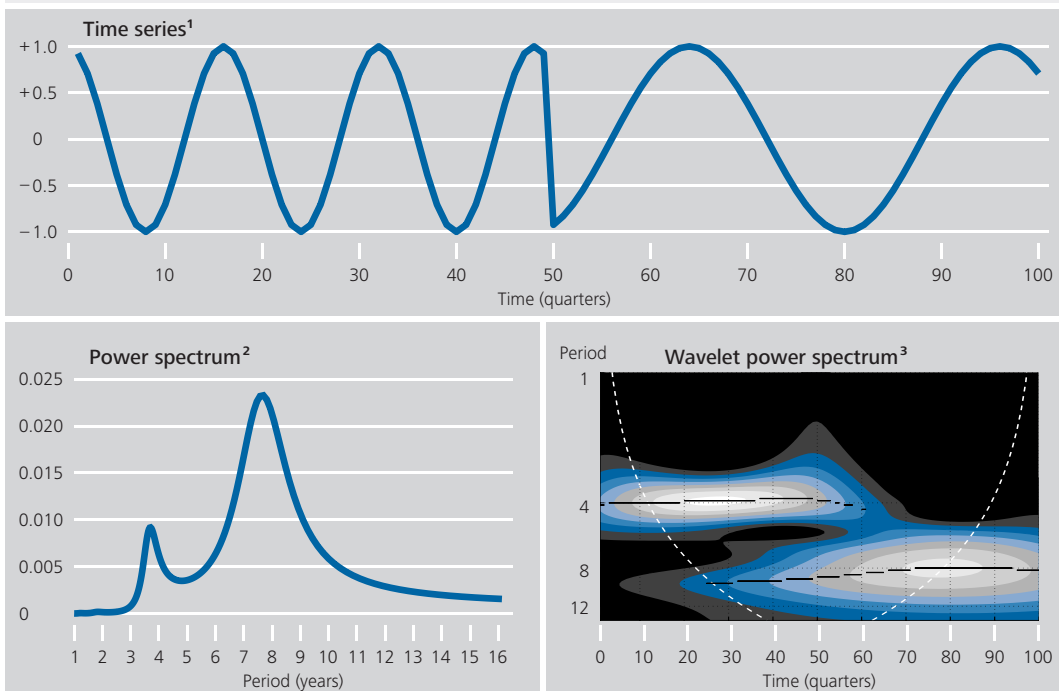
Scaling and time shift of the Morlet wavelet



1 Scaling to adjust the Morlet wavelet to higher frequencies. **2** Shift of the Morlet wavelet along the time axis.

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A comparison of spectral and wavelet analysis



1 Simulated time series with cycles having a length of four years up until period 50, thereafter having a length of eight years. **2** Power spectrum does not reflect time variation. **3** The horizontal axis shows the time, while the vertical axis shows the oscillation period. The thin black lines represent local maxima of the power spectrum over time, while the curved white lines depict the cone of influence. The values of the wavelet power spectrum increase from dark to light colours.

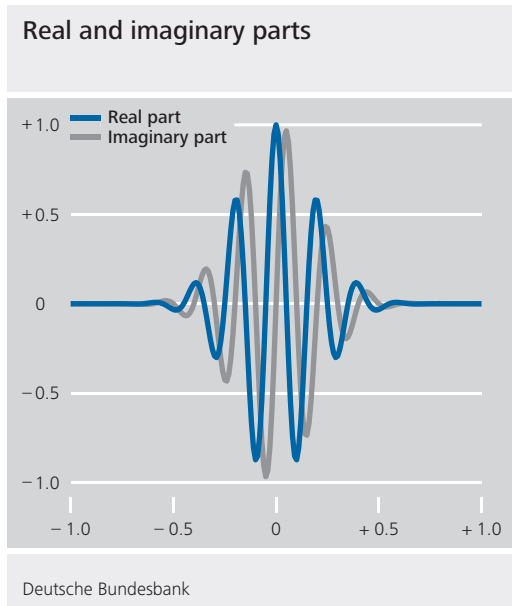
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the bivariate case, the corresponding information from the cross-wavelet transform is examined:

$$\varphi_{xy}(\tau, s) = \tan^{-1} \left[\frac{\Im\{W_{xy}(\tau, s)\}}{\Re\{W_{xy}(\tau, s)\}} \right].$$

$\varphi_{xy}(\tau, s)$ denotes the phase difference. In the case of $\varphi_{xy} \in (0, \pi)$, time series $x(t)$ leads $y(t)$. For a given frequency $\omega(s)$, the phase difference can be converted into the corresponding time difference

$$\Delta_{xy}^T = \frac{\varphi_{xy}}{\omega(s)}.$$



w_i and w_j represent the weights of time series $x(t)$ and $y(t)$.⁶⁰ The dynamic correlation is defined as:

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

where \Re denotes the real part of the cross-wavelet transform W_{xy} .⁶¹

The statistical significance of coherence or cohesion is tested by means of a parametric bootstrap procedure.⁶² For each time series, a certain number of artificial time series are simulated on the basis of univariate ARMA models. The corresponding null hypothesis assumes that the time series are not correlated with one another. The test is based on the simulated distribution of coherence and cohesion under the null hypothesis.

Coherence can be interpreted as a local correlation between two time series. It is defined as:

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

A measure of the strength of common cycles pertaining to multiple time series is cohesion. This is a weighted average of all pairwise combinations of the dynamic correlation⁵⁹

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

⁵⁹ See A. Rua and A. Silva Lopes (2015), Cohesion Within the Euro Area and the US: A Wavelet-Based View, *OECD Journal: Journal of Business Cycle Measurement and Analysis*, 2014/2, pp. 63-76.

⁶⁰ In the application in the main text, countries' real GDP is used for weighting purposes.

⁶¹ See A. Rua (2010), Measuring Comovement in the Time-Frequency Space, *Journal of Macroeconomics*, Vol. 32, pp. 685-691.

⁶² See B. Cazelles, M. Chavez, D. Berteaux, F. Menard, J. Vik, S. Jenouvrier and N. Stenseth (2008), Wavelet Analysis of Ecological Time Series, *Oecologia*, Vol. 156 (2), pp. 287-304.