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Real and financial cycles in EU countries: Stylised facts and modelling implications

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Contents

Abstract

This paper studies the cyclical properties of real GDP, house prices, credit, and nominal liquid financial assets in 17 EU countries, by applying several methods to extract cycles. The estimates confirm earlier findings of large medium-term cycles in credit volumes and house prices. GDP appears to be subject to fluctuations at both business-cycle and medium-term frequencies, and GDP fluctuations at medium-term frequencies are strongly correlated with cycles in credit and house prices. Cycles in equity prices and long-term interest rates are considerably shorter than those in credit and house prices and have little in common with the latter. Credit and house price cycles are weakly synchronous across countries and their volatilities vary widely – these differences may be related to the structural properties of housing and mortgage markets. Finally, DSGE models can replicate the volatility of cycles in house and equity prices, but not the persistence of house price cycles.

Keywords: financial cycles, synchronicity, real-time estimates, DSGE models

JEL codes: C32, E32, E44

Executive summary

The role of the financial sector in the propagation of economic fluctuations has been at the heart of both macroeconomic research and economic policy since the financial crisis. One recent strand of the related literature has provided evidence for the presence of large medium-term cycles in financial series, notably credit volumes and house prices. Estimates of cyclical components provide an important input for the conduct of monetary policy, and are also relevant for macroprudential policy tools such as the countercyclical capital buffers foreseen by Basel III regulations (BIS, 2010). A number of other studies have examined cycles in the prices of liquid financial assets using factor analysis to extract common components.

This paper presents research conducted by a team of experts from the European System of Central Banks (ESCB) – i.e. the 28 national central banks of the European Union (EU) and the European Central Bank -– to estimate financial cycles in EU countries and to assess their properties and their relationship to business cycles. The analysis covers eight series in each of 17 countries, including real GDP, real total credit to the private non-financial sector (and its separate household and corporate components), an index of real house prices, a nominal equity price index, nominal long-term rates, and the interest rate term spread.

The individual sections of the paper address six research questions. First, what are the defining characteristics of financial cycles? Second, how are financial cycles related to GDP cycles? Third, how are financial cycles related to each other across EU countries? Fourth, how are cyclical properties related to the structural characteristics of national housing markets? Fifth, how reliable are real-time estimates of the cycles? Sixth, are current DSGE models that include housing markets able to replicate the stylised facts?

The key findings of the study are as follows:

First, estimates confirm the findings of earlier studies that medium-term cycles in credit volumes and house prices are large and closely related. Across countries, the length of credit and house price cycles is estimated to be 13 years on average. Cycles in equity prices and long-term interest rates are considerably shorter and only weakly related to those in house prices and credit. This suggests that separate indicators may be needed to evaluate the build-up of systemic risks related to cycles in house prices and credit against risks in liquid assets.

Second, cycles in real GDP are closely related to those in house prices and credit at medium-term frequencies of 8 to 15 years. GDP appears to be subject to fluctuations at both business-cycle (2 to 8 years) and medium-term frequencies (8 to 15 years). The medium-term fluctuations are shared by those in house prices and credit with major turning points being closely aligned. For most countries, GDP cycles therefore contain an important component beyond the threshold of 8 years, which is often considered to be the maximum length of business cycles. Nevertheless, they resemble output gap estimates by the IMF, suggesting that the relevant institutions take medium-term components into account when estimating output gaps.

Third, the synchronicity of house price and credit cycles across euro area countries is considerably lower than it is for GDP. There is also some evidence of a north-south divide, reflecting the different timing of cyclical turning points in some Mediterranean countries compared with Scandinavian countries.

Fourth, there are important differences across countries in the properties of cycles in credit and house prices. Among the major European economies, Germany is unique in that it has hardly any medium-term cycles. At the other end of the spectrum, Spain and the Baltic states have experienced extraordinarily wide cyclical fluctuations. In general, the volatility of cycles and their synchronicity appear to be related to the rate of private homeownership in individual countries.

Fifth, real-time estimates of credit and house price cycles are subject to considerable uncertainty. This paper finds this uncertainty to be of around the same order as it is for GDP cycles, when measured relative to the amplitude of the respective cycles. Real-time estimates usually identify the phase of a cycle correctly, but they tend to underestimate the scale of booms and busts. This emphasises the challenge of detecting financial booms in real time.

Sixth, DSGE models can replicate the volatility of cycles in house and equity prices, but not the persistence of house price cycles. The team investigated the properties of several DSGE models integrating a housing sector, including a model with real rigidities, a full-scale New Keynesian model with collateral constraints on mortgages, and one with information frictions. Model simulations can match the data for the volatility of house price or equity price cycles to that of GDP cycles. However, standard models struggle to reproduce the persistence of house price cycles observed in the data. Information frictions provide a potential solution to the issue of persistence.

Several findings of the paper have implications for further research and for the conduct of monetary and macroprudential policy. First, distinguishing between business cycles and medium-term financial cycles appears to be challenging. In particular, a distinction based on cycle length lacks economic justification, suggesting that structural models are required to disentangle shocks originating in housing and mortgage markets from aggregate macroeconomic and monetary policy shocks. Second, since the amplitudes of cycles in credit and house prices differ across countries and are only modestly correlated, country-specific policies may have substantial benefits. Third, macroprudential policies should consider the uncertainty surrounding real-time estimates of the financial cycle.

1 Introduction

The financial crisis focused attention on the linkages between the financial sector and the real economy, both in economic policy and in macroeconomic research. Against this backdrop, several studies have examined the relationships between credit, asset prices and real economic activity (e.g. Goodhart and Hoffman, 2008; Schularick and Taylor, 2012; and Hubrich et al., 2013). Hubrich et al. (2013) find that, overall, financial shocks account for about one-third of the variation in GDP, although this contribution is heterogeneous across countries and over time. Several studies have examined the forecasting power of financial indicators for economic activity or have developed leading indicators of financial distress (Borio and Lowe, 2002, 2004; English et al., 2005; Gerdesmeier et al., 2010; Alessi and Detken, 2011; and Hatzius et al. 2010; Ng, 2011).

One recent strand of literature deals with the estimation of cycles in financial series, especially credit volumes and house prices. Using univariate filtering methods, Drehmann et al. (2012) and Aikman et al. (2015) find evidence of large medium-term cycles in both series, while Claessens et al. (2012) reach similar conclusions using turning point analysis. Comin and Gertler (2006) have already reported important medium-term fluctuations in US GDP. Other studies have extracted the common component in financial cycles (Breitung and Eickmeier, 2016; Miranda-Agrippino; and Rey, 2015). Schüler et al. (2016) constructed synthetic financial cycle indicators for euro area countries using credit volumes and house, equity and bond prices.

Several studies address these questions using structural time series models (STSMs), as introduced by Harvey (1989), Harvey and Koopman (1997), De Bonis and Silvestrini (2013), and Galati et al. (2016). These models provide a more precise characterisation of the dynamic properties of cycles in house prices and credit in a multivariate context, offering insights into cyclical dynamics. Rünstler and Vlekke (2016) extend the standard multivariate STSM to estimate cyclical fluctuations in real GDP, credit volumes and house prices, modelling their interactions at different frequencies.

From a policy perspective, Gadanecz and Jayaram (2016) stress the need for a deeper understanding of financial cycle dynamics to evaluate the costs and benefits of macroprudential measures. For example, Basel III regulations governing countercyclical capital buffers (CCCB) explicitly refer to a measure of the credit cycle, suggesting that the buffers should be increased once the credit-to-GDP ratio has exceeded its long-run trend by two percentage points. Giese et al. (2014) suggest that CCCB requirements should be based on a wider range of indicators, including credit and house price gaps. Financial cycle estimates may also be used to fine-tune other policy instruments such as caps on loan-to-value and debt-service-to-income ratios, as discussed by Hanson et al. (2011), Cerutti et al. (2015a) and Hartmann (2015). In addition, the interaction between monetary policy and macroprudential policy requires a better understanding of the link between real and financial cycles. Monetary policy appears to affect the financial cycle, as indicated by a growing body of literature including Adrian et al. (2010), Schularick and Taylor (2012), Rey (2013), Bruno and Shin (2015), and Black and Rosen (2016). This link suggests that there may be scope for incorporating financial stability considerations into monetary policy decisions. By contrast, Praet (2016) argues that the first line of defence should be provided by fiscal, macroprudential and supervisory policies, since these can better target trends in individual assets, sectors or national economies.

Against this background, this paper estimates financial cycles in EU countries and assesses their properties and their relationship to GDP cycles. The analysis covers eight quarterly series in each of 17 countries, including real GDP, real house prices, several credit aggregates, an equity price index, and interest rates.

The paper is structured in six sections which address the following questions. First, what are the defining characteristics of house price and credit cycles? Second, how are financial cycles related to GDP cycles? Third, how are financial cycles related to each other across countries? Fourth, are cyclical properties related to structural characteristics of national housing markets? Fifth, how reliable are real-time estimates of the cycles? And sixth, can the stylised facts be replicated by current DSGE models that include housing markets?

Section 2 re-examines the basic properties of the cycles in the eight series using bandpass filters and wavelet analysis. Section 3 focuses on the relationships between cycles in GDP, house prices, and credit volumes using a multivariate structural time series model by Rünstler and Vlekke (2016). Consistent with the earlier literature, this study finds that in most countries cycles in credit volumes and house prices are much more volatile and somewhat longer than GDP cycles. Moreover, the cycles in these three variables share an important common component. By contrast, cycles in equity prices and interest rates are considerably shorter and only weakly correlated with cycles in GDP, house prices or credit volumes. The length of cycles in credit and house prices is estimated at about 10-12 years for most countries. These long fluctuations are clearly shared by GDP, since major turning points are closely aligned. However, GDP appears to be subject to additional fluctuations at the traditional business-cycle frequencies, resulting in a shorter average cycle length. For most countries, GDP cycles contain an important component beyond the threshold of 8 years, which is often considered to be the maximum length of business cycles. However, GDP cycle estimates resemble output gap estimates by the IMF, suggesting that estimates from multilateral institutions (including the OECD and the European Commission) take such medium-term fluctuations into account.

Section 4 examines the co-movements of cycles across countries. Several methods are used to assess the cross-country correlations and synchronicity for each series. These methods find that credit and house prices are only moderately synchronous across EU countries, much less so than GDP cycles. By contrast, equity prices and interest rates are highly synchronous.

Section 5 relates cyclical characteristics to various structural features of national housing markets. The analysis finds that GDP, house price, and credit cycles are larger and more synchronous for countries with high rates of private homeownership (see also Huber, 2016; and Rünstler and Vlekke, 2016). Furthermore, the volatility and synchronicity of cycles is related to current account imbalances.

Section 6 discusses the reliability of real-time estimates of the financial cycle. While booms are easily identified with the benefit of hindsight, policymakers have to rely on one-sided filters which only consider past observations. Real-time estimates of cycles therefore suffer from sizeable subsequent revisions. The issue has been studied extensively for business cycles (e.g. Orphanides and Van Norden, 2003; Basistha and Startz, 2007; and Trimbur, 2009), but there is less evidence for financial cycles. Section 6 examines the revisions to one-sided estimates from bandpass filters and the multivariate STSM. Overall, the uncertainty of real-time estimates of credit and house price cycles appears to be comparable with that of business cycles, when measured relative to the amplitude of the cycles.

Section 7 discusses the possible implications of the findings for DSGE models, asking whether they can suitably replicate the stylised facts revealed in this paper. Three model variants are considered: (i) a real business cycle model augmented by habit formation and capital adjustment costs; (ii) the EIRE model, a New Keynesian model, which features a housing market and collateral constraints (Lozej et al., 2017); and (iii) a model with information frictions. The EIRE and real rigidities models are successful at matching the volatility of house prices, but struggle to match their persistence. Simulations from a DSGE model with information frictions, in which agents use a learning rule to form expectations, suggest that deviations from rational expectations may help to increase the persistence of house price growth.

Section 8 concludes the paper with a discussion of policy implications and directions for future research.

2 Financial cycles: the basic stylised facts

The study considers 8 series for 17 EU countries.

This section studies the main properties of financial cycles as deduced from bandpass filters and wavelet analysis.

The paper considers 8 series, which are listed in Table 1, together with data sources and abbreviations. The quarterly data are taken from an update of the database by Hubrich et al. (2013). All series apart from interest rates are taken in logarithms. GDP, residential property prices and credit aggregates are deflated using the GDP deflator. Nominal long-term rates are the yields on 10-year government bonds. The term spread is defined as the nominal long-term rate less the 3-month interest rate. Equity prices and interest rates are expressed in nominal terms to facilitate the comparability of results with those of earlier studies (e.g. Rey, 2013; and Miranda-Aggripino and Rey, 2015).

Table 1
Data used in the analysis

Series	Abbreviation
Real GDP	GDP
Real residential property prices	RPP
Real total credit to the private nonfinancial sector	TCN
Real credit to private nonfinancial corporations	LNF
Real credit to households	LHH
Nominal equity price indices	EQP
Nominal long-term rates	LTN
Term spread	SPR

Source: ECB Data Warehouse, with the exception of credit volumes and residential property prices, which are obtained from publicly available data from the Bank for International Settlements.

For nine countries the data are available prior to 1982, while for many other countries they are only available after 1995. Results are shown separately for long and short datasets.

The dataset includes 17 EU countries. Data availability differs significantly across countries. For 9 countries the data are available prior to 1982. For Portugal and Hungary they are only available from 1988 Q1 and 1990 Q1 respectively, and for a further 6 countries from 1995 Q1, providing fewer than 25 years of data. Clearly, this is insufficient to provide a reliable analysis of cycles with a length of up to 15 years. For this reason, the paper shows results separately for the 10 countries with data available prior to 1988 Q1 (*long dataset*) and the remaining 7 countries (*short dataset*). In some cases, only results for the long dataset are shown. The data end in 2015 Q4.

Table 2
Data availability for individual countries

Series	Abbreviation
Long datasets	BE, DE, DK, ES, FI, FR, IT, LU, NL, PT
Short datasets	EE, GR, HR, HU, LT, LV, SI

Sources: see Table 1.
Notes: Long datasets start prior to 1988 Q1. Short datasets start between 1990 Q1 and 1998 Q1. All data end in 2015 Q4.

2.1 Results from a bandpass filter

Previous studies have extracted GDP, credit and house price cycles from bandpass filters with various pre-specified frequency bands.

Previous studies by Drehmann et al. (2012) and Aikman et al. (2015) have used bandpass filters to extract cycles in financial series. These filters are designed to extract cycles with certain lengths in the series. This study follows the earlier literature in that it uses the optimal asymmetric bandpass filter from Christiano and Fitzgerald (2003), assuming a unit root with drift. The frequency band of the filter, which defines the upper and lower boundary of the cycle lengths to be extracted, must be set in advance. In this study the filter band is set at 8-80 quarters.

For business cycles a frequency band of 8-32 quarters is traditionally used. Studies have found cycles in house prices and credit to be longer, reflecting so-called medium-term cycles of 32 to about 120 quarters.

For business cycles, Baxter and King (1996) have recommended a frequency band of 8-32 quarters, based on a wide range of evidence dating back to the seminal studies of Burns and Mitchell (1946). However, Comin and Gertler (2006) have documented the presence of so-called medium-term cycles in US GDP. Using a bandpass filter with a frequency band of 32-120 quarters they show that these fluctuations are about the same size as the shorter business cycle fluctuations. The studies by Drehmann et al. (2012) and Aikman et al. (2012) use the same medium-term frequency band to extract financial cycles, although Drehmann et al. (2012) restrict cycles in real GDP to the frequency band of 8-32 quarters.

When applying a bandpass filter, it is important to use the same frequency bands for all series …

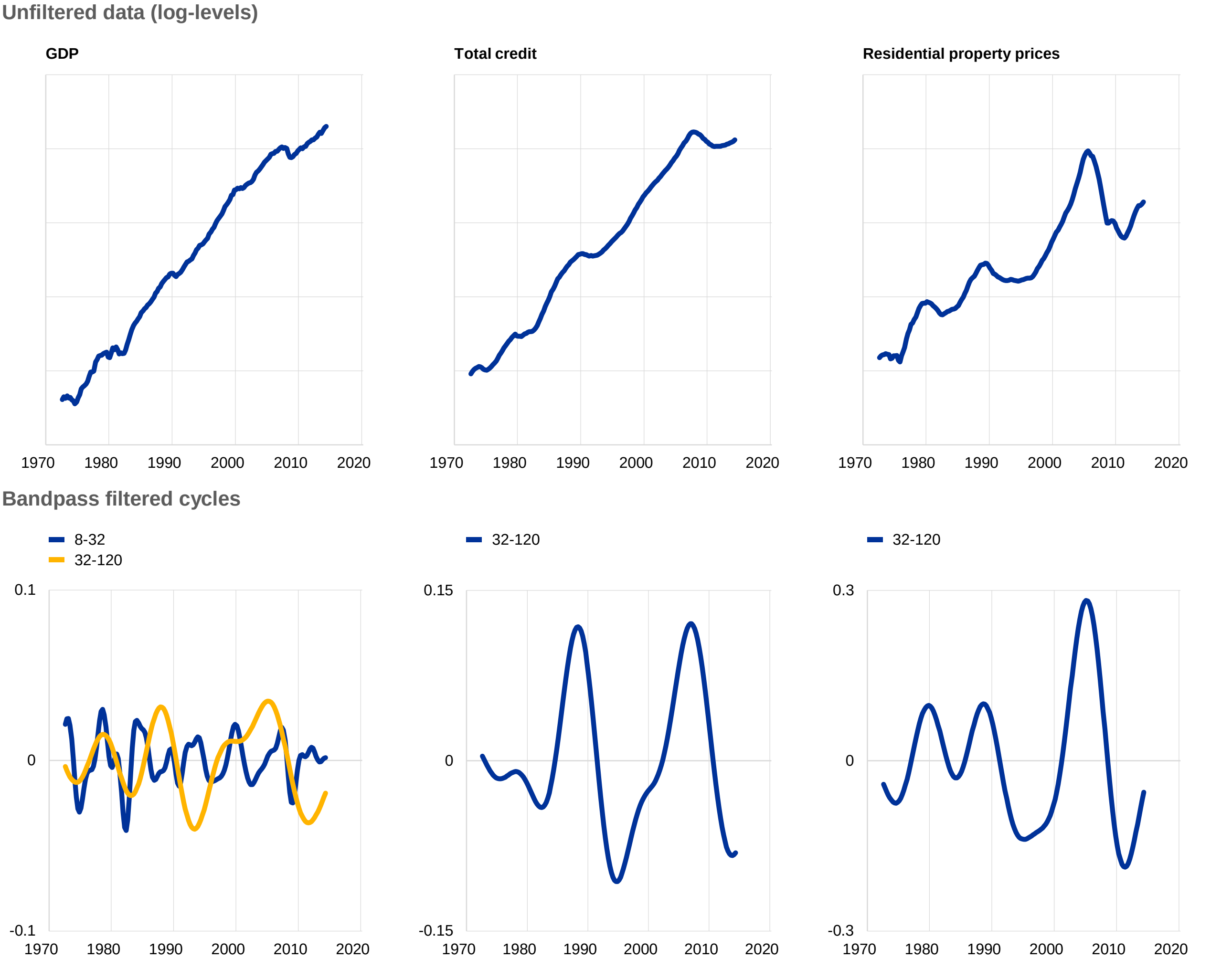
The fact that filter bands must be chosen in advance naturally introduces a certain arbitrariness in the results. In general, pre-specified filter bands imply the risk of missing parts of cyclical dynamics or, conversely, obtaining spurious cycles (Murray, 2003). In particular, if the frequency bands used to extract cycles in real GDP and financial variables do not overlap, the resulting estimates of cycles will be uncorrelated by construction. Hence, the conclusion of Drehmann et al. (2012) that "business and financial cycles are independent phenomena" may well be induced by their choice of filter bands.

… as shown for the US.

Chart 1 illustrates the issue for US data, showing the medium-term cycles for GDP, total credit, and house prices together with the traditional business cycle as extracted by the bandpass filter. Cycles in house prices and credit are large and persistent. There is also a medium-term cycle in GDP, although this is smaller than the house price and credit cycles. GDP is also subject to fluctuations at business-cycle frequencies of 8-32 quarters.

Chart 1

Bandpass filtered cycles for US data



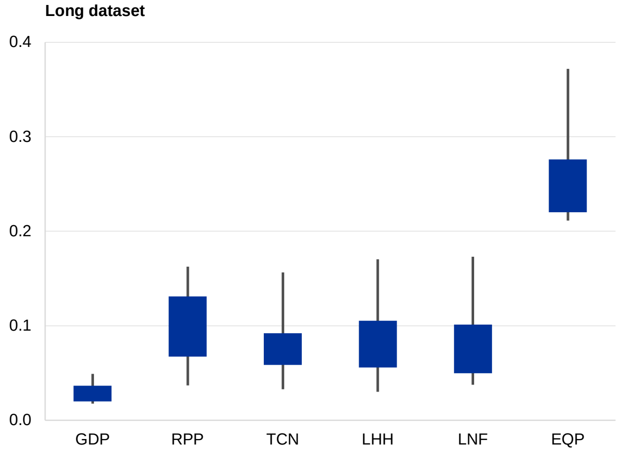
Sources: Own calculations.
Notes: The upper panel shows the series (in logarithms). The lower panel shows the cycles obtained from applying bandpass filters to the series. The frequency bands of the filters are shown in the legend in quarters. Cycles represent percentage deviations from trend. Please note the different scaling.

The box plots in this section display the distribution of cyclical properties across countries.

This section discusses the basic properties of the cycles that have been extracted from the bandpass filter with a frequency band of 8-80 quarters. This choice captures both traditional business cycle fluctuations and medium-term frequencies and is therefore neutral on whether they should be distinguished. The upper bound of 80 quarters is lower than that used by Drehmann et al. (2012), as the samples in this study are shorter. Charts 2 and 3 report the standard deviations and the average lengths of the cyclical components in the individual series. The charts use boxplots to illustrate the distribution of outcomes across countries. The box represents the [0.25; 0.75] quantiles of the distributions, while the lines extend to the [0.10; 0.90] quantiles. All statistics shown in the graphs apply to long datasets only, while Table 3 shows some statistics for both datasets.

Chart 2
Standard deviations of cyclical components

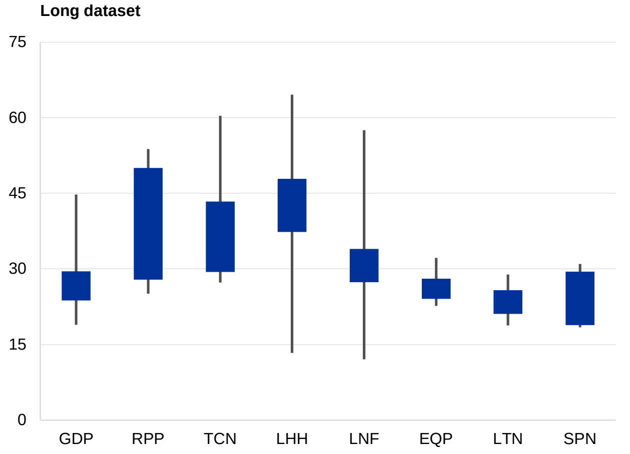
(percentage deviation from trend)



Sources: Own calculations.
Notes: For each variable, the chart shows the cross-country distribution of standard deviations of bandpass-filtered cycles (frequency band set at 8-80 quarters). The box represents the [0.25; 0.75] quantiles of the distribution, while the lines show the [0.10; 0.90] quantiles.

Chart 3
Average cycle length

(quarters)



Sources: Own calculations.
Notes: For each variable, the chart shows the cross-country distribution of cycle lengths – measured as the average distance between peaks – of bandpass-filtered cycles (frequency band set at 8-80 quarters). The box represents the [0.25; 0.75] quantiles of the distribution, while the lines show the [0.10; 0.90] quantiles.

Cycles in financial series are considerably larger than those in GDP.

Standard deviations of cycles in house prices and credit aggregates exceed those of GDP cycles by a wide margin. For the long dataset, the average standard deviation is 2.8% for GDP cycles, while it is close to 10% for house prices and credit aggregates. Not surprisingly, the average standard deviation for equity prices is even higher, at 28%. Values for interest rates are not reported, because these series are not taken in logarithms and the numbers are therefore not comparable.

Cycles in house prices and credit are longer than those in GDP, while cycles in equity prices and bond yields are shorter.

Cycle lengths are measured by taking the average distance between the peaks of the cycles, as obtained by applying standard turning point analysis (TPA) to the bandpass filtered cycles. For the long dataset, the average length of GDP cycles is 7.3 years. Cycles in credit volumes and house prices are considerably longer, although there is also more dispersion across countries. Cycle lengths of house prices are on average 9.6 years, while those of loans to households are 10.3 years. By contrast, cycles in equity prices and interest rates are somewhat shorter than those in GDP and are notably shorter than those in house prices and credit. The averages across countries range from 5.8 to 6.6 years.

The notion of a common financial cycle requires a certain degree of co-movement between financial series.

The remainder of this section discusses co-movements between cyclical components. Clearly, the notion of a financial cycle requires the presence of a common cyclical component, i.e. a certain degree of co-movement between the individual cycles, as is the case for business cycles, which have been characterised as “a high number of series moving together at business-cycle frequencies” (Sargent, 1980).

Table 3

Basic properties of bandpass filtered cycles

Long datasets	GDP	RPP	TCN	LHH	LNF	EQP	LTN	SPR
Standard deviation (*100)	2.88	9.82	8.13	8.81	8.56	28.81		
Cycle length (years)	7.31	9.61	9.45	10.29	8.06	6.62	5.83	5.90
Loadings PCA 1	.72	.86		.51	.61	.02	.30	-.51
Loadings PCA 2	.32	.10		.09	-.21	.52	-.45	-.14
Short datasets	**GDP**	**RPP**	**TCN**	**LHH**	**LNF**	**EQP**	**LTN**	**SPR**
Standard deviation (*100)	6.24	17.93	16.08	24.04	15.68	32.62		
Cycle length (years)	8.70	8.32	9.41	13.79	8.22	5.98	6.18	5.68
Loadings PCA 1	.90	.93		.82	.54	.63	-.25	-.51
Loadings PCA 2	.28	.06		.01	-.01	.18	.01	.24

Sources: Own calculations.
Notes: The table shows the median values of the respective statistics across countries. See Table 1 for series abbreviations and Table 2 for the country composition of long and short datasets. Cycle lengths are measured as average distances between the peaks of bandpass filtered cycles as obtained from turning point analysis. Loadings PCA 1 and PCA 2 refer to the factor loadings of the series on the first two principal components from factor analysis of the eight series applied individually to each country.

This issue has so far not been fully addressed in the literature. Various studies have investigated cyclical co-movements either among liquid financial assets (Breitung and Eickmeier, 2016; Miranda-Agrippino and Rey, 2015) or between GDP, house prices, and credit (Rünstler and Vlekke, 2016). Using a panel VAR, Hubrich et al. (2013) identify an important role for a common component in the annual growth rates of these series during the financial crisis. However, even though studies have built synthetic financial cycle indicators that combine equity prices and bond yields with credit and house prices, the co-movements between these two groups of cycles have not yet been assessed.

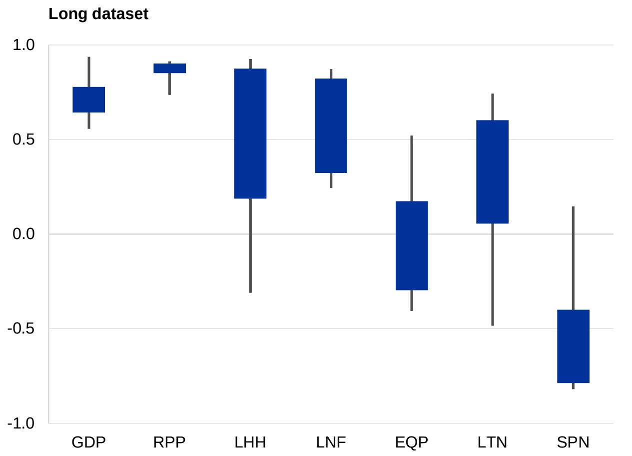
Cyclical co-movements can be studied by applying principal component analysis (PCA) to the bandpass filtered cycles. PCA is designed to extract the common components of the series under consideration. For each country, a PCA is performed for seven series in our dataset (total credit is excluded, as it is the sum of loans to households and to non-financial corporations). The analysis finds that two principal components are sufficient to model co-movements between the seven series. Charts 4 and 5 plot the distributions of factor loadings across countries, while Table 3 shows their median values.

GDP, house prices and credit cycles share a high degree of commonality across almost all countries, …

Most importantly, in all countries the cycles in GDP, house prices, and credit have high loadings on the first PCA. This suggests that these series share a common cycle. With one exception, factor loadings of GDP and residential property prices are larger than 0.65, while the loadings of loans to households and non-financial corporations remain above 0.5 on average.

Chart 4

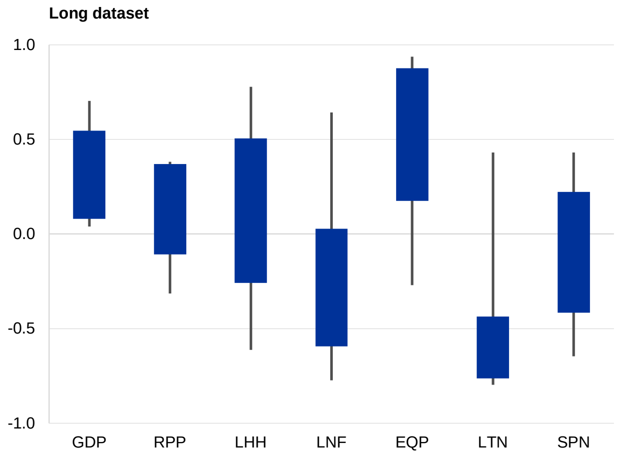
Loadings on the first principal component



Sources: Own calculations.
Notes: For each variable, the chart shows the cross-country distribution of loadings on the first principal components from factor analyses of the seven bandpass-filtered cycles within each individual country (frequency band set at 8-80 quarters). The box represents the [0.1; 0.9] quantile of the distribution, the horizontal line inside the box is the mean. Lines show min and max values.

Chart 5

Loadings on the second principal component



Sources: Own calculations.
Notes: For each variable, the chart shows the cross-country distribution of loadings on the second principal components from factor analyses of the seven bandpass-filtered cycles for each individual country (frequency band set at 8-80 quarters). The box represents the [0.1; 0.9] quantile of the distribution, the horizontal line inside the box is the mean. Lines show min and max values.

… whereas cycles in equity prices and long-term rates are only weakly related to the former.

For equity prices and long-term interest rates the loadings are lower and more dispersed. Note that the spread is defined as long-term rates minus short-term rates. Hence, given that short-term rates are more volatile than long-term rates, the spread turns countercyclical with loadings that are moderate, but consistently negative. The second PCA loads heavily on equity prices and long-term interest rates. By contrast, the loadings of GDP, credit aggregates, house prices and the spread are generally low. With the exception of GDP, the loadings are of inconsistent sign across countries.

As Table 3 shows, results for the short dataset are similar overall. One important difference is the larger standard deviations of cycles in GDP, credit and house prices, reflecting the prevalence of housing boom-bust cycles after 2000. Moreover, equity prices are subject to higher loadings on the first principal component.

2.2 Results from wavelet analysis

Another method used to assess cyclical properties is wavelet analysis. This is an extension of spectral analysis that allows for an assessment of time variation in cyclical properties.

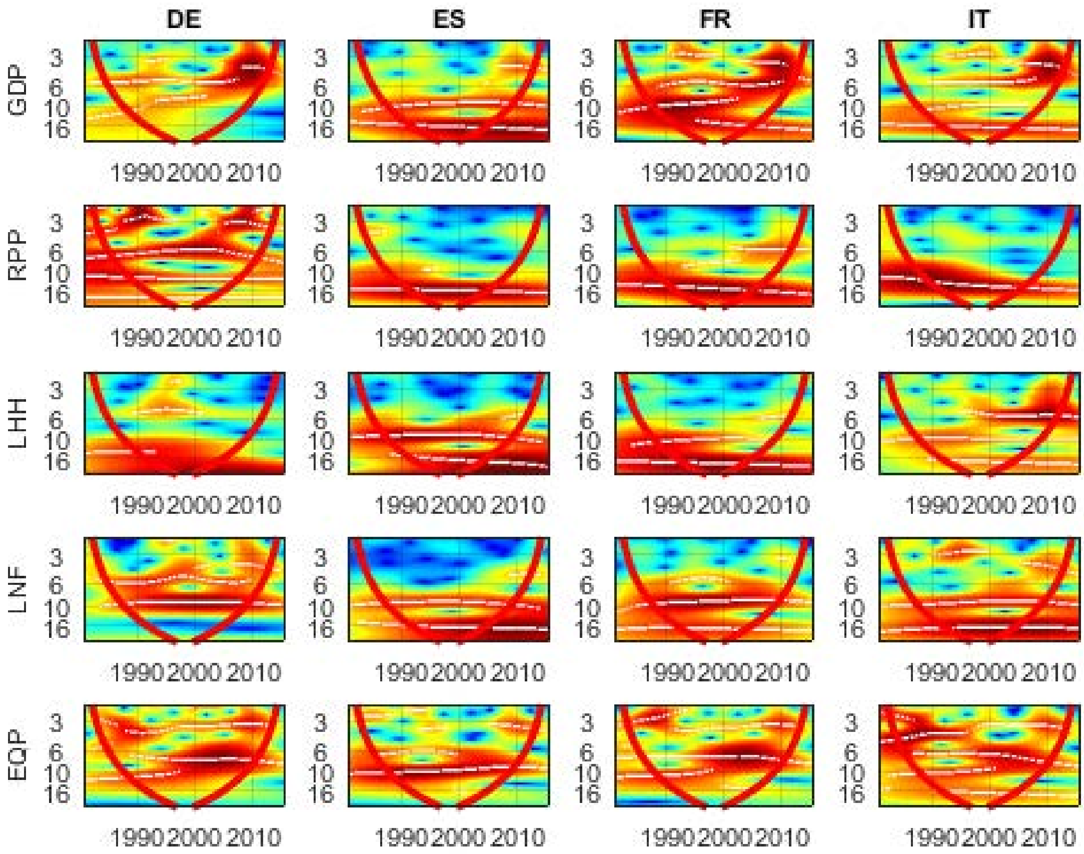
Wavelet analysis is another, highly flexible, method used to assess the cyclical properties of time series. It does not rely on filtering, but is instead applied directly to (annual) growth rates of the series. In essence, wavelet analysis is an extension of spectral analysis that allows for time variation. Spectral analysis interprets a time series as the weighted sum of cycles with specific periodicities, and estimates the contribution of these cycles to the overall variance of the series. Wavelet analysis extends spectral analysis by allowing for time variation in these contributions (see the Annex for more explanations). The study thereby extends the work of Schüler et al. (2016), who utilised spectral analysis and found a fairly high level of coherence between GDP and credit and house prices.

The analysis below considers the four main euro area economies (DE, ES, FR, IT) using data ranging from 1980 Q1 to 2015 Q4. The frequencies of the most important cycles in the individual time series can be inferred from the series' wavelet power spectra. Chart 6 uses heat maps to show these power spectra for the four largest euro area economies. The findings are, overall, in line with those from the bandpass filter presented in Section 2.2.

Chart 6

Wavelet power spectra

(cycle length (years))



Sources: Own calculations.
Notes: The x-axis represents time, while the length (periodicity) of the cycles is shown on the y-axis in annual terms. The power spectrum (i.e. the contribution of the specific periodicity to the overall series) is represented by colour. Dark red indicates high power, which means that cycles of the corresponding periodicity generate an important contribution to the overall variance of the series. Dark blue indicates low power. The left and right red lines for each plot represent the so-called cone of influence. The area outside the red lines is affected by end-of-sample problems and results outside these bands should not be interpreted. See Table 1 for series abbreviations.

Again, wavelet analysis finds long cycles in credit and house prices, with the exception of Germany.

For loans to non-financial corporations (LNF), loans to households (LHH), and house prices (RPP), the dominant cycles emerge at lengths of between 10 and 16 years. The respective boundaries are displayed on the graph as white lines, and cycle lengths are relatively stable over time. Only Germany stands out, showing an absence of such medium-term cycles – instead, cycles with durations of about 6 years dominate.

Cycles in GDP are somewhat shorter, with components at both business-cycle and medium-term frequencies, while the results for equity prices are more mixed.

Similar patterns emerge for GDP, although business cycle frequencies attain a higher weight. For Germany and Italy, the graphs indicate a dominant role for business cycles of about 6 years. By contrast, medium-term cycles of more than 10 years dominate in Spain, whereas France shows a mix of both. The findings for equity prices contrast with those for the other series. For all countries, the heat maps show much more dispersion, with an overall lack of dominant cycles of certain lengths and more time variation in the importance of different cycle lengths.

GDP cycles display high coherence with cycles in credit and house prices at medium-term frequencies, once again with the exception of Germany.

Wavelet analysis also provides an assessment of cyclical co-movements from an estimation of coherences between the series.[1] Chart 7 shows the relationship between GDP and the financial variables, with heat maps of the respective coherences. The results confirm the above findings of strong relationships between medium-term cycles in financial variables and GDP. However, Germany once again stands out as an exception, showing weak relationships.

Loans to non-financial corporations and real GDP (top panel) show high coherence for cycles with a duration of between 6 and 10 years in Spain and Italy throughout the sample period. In France coherence is high and significant across a broad frequency band, although it weakens in the 2000s. In Germany there is no evidence of high coherence at longer durations.

The results for lending to households are broadly similar, with a narrower range of frequencies showing significant coherence. Once again, for Spain and Italy significant and stable coherence emerges at low frequencies, while for France coherence is highest at a duration of between 6 and 10 years. Coherence between house prices and real GDP is close to one and stable in Spain and France at periodicities of around 16 years. For Germany, there is no evidence of significant co-movements between real GDP and real house prices at any frequency and for Italy this only occurs in the late 1980s and early 1990s. Finally, for real equity prices we estimate significant coherence in France and Italy for cycles with durations of 10 to 16 years and of around 16 years, respectively.[2]

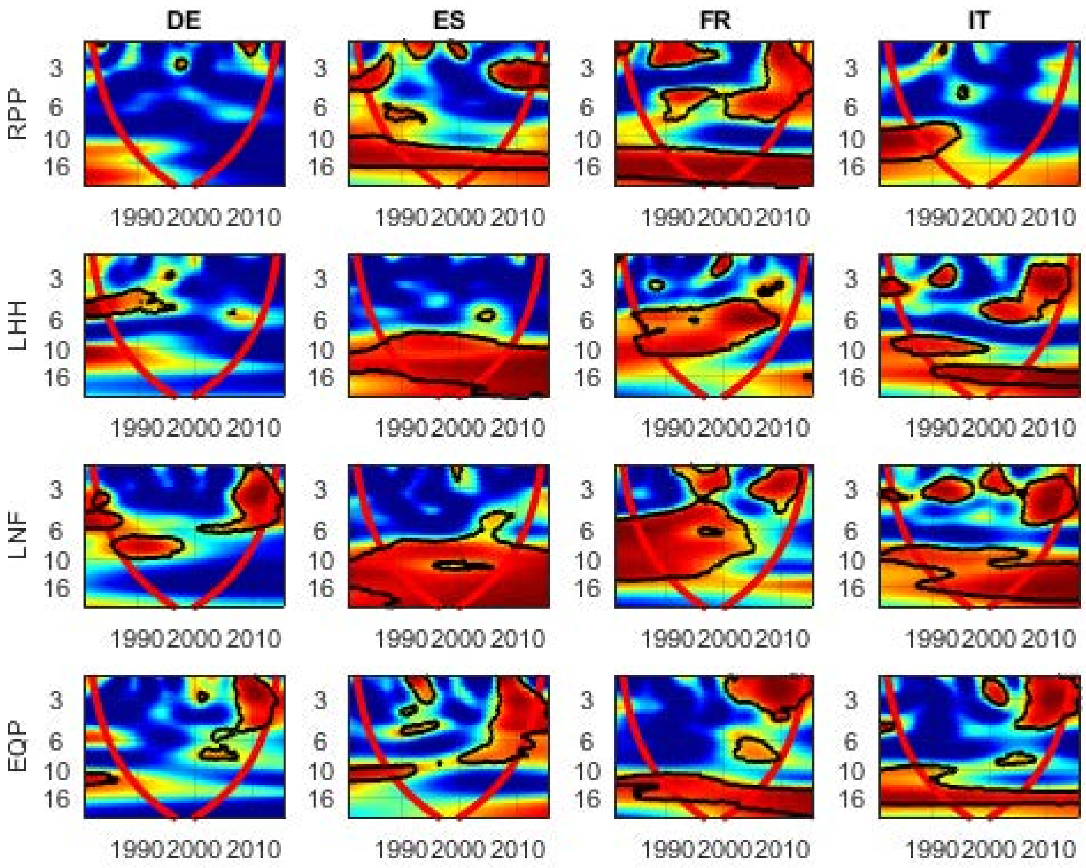
1 Coherence measures the strength of co-movement between two series at a certain cycle length. It ranges from zero to one.

2 For further results see Scharnagl and Mandler (2016).

Chart 7

Coherences of financial variables with real GDP

(cycle length (years))



Sources: Own calculations.
Notes: The x-axis represents time, while the length (periodicity) of the cycles is shown on the y-axis in annual terms. Coherence is represented by colour, with dark red and dark blue indicating high and low values, respectively. Black lines indicate regions with statistically significant coherence. The left and right red lines in each plot represent the so-called cone of influence. The area outside the red lines is affected by end-of-sample problems and results outside these bands should not be interpreted. See Table 1 for series abbreviations.

3 Cycles in GDP, credit, and house prices

Multivariate structural time series models provide tailored filters for extracting cyclical components, as parameters defining the frequency bands of the filters are estimated. They also provide a more precise characterisation of cyclical co-movements.

This section delves deeper into the relationships between cycles in output, house prices and credit at both traditional business-cycle and medium-term frequencies. For this purpose, a version of a multivariate structural time series model (STSM) is used. STSMs are designed to decompose a set of series into trends and cycles. The key difference to the bandpass filter is that the trend and cyclical components are explicitly specified as parametric time series models, the parameters of which are estimated. Thus, the resulting filter is tailored to the observed time series, which not only allows cyclical dynamics in a multivariate context to be more precisely characterised, but also reduces the risk of obtaining spurious cycles, as documented in the case of bandpass filters (Murray, 2003).

These models have been widely used to estimate output gaps and the NAIRU, but less so financial cycles.

STSMs have been widely used to estimate cyclical components in real activity, in particular the output gap and the NAIRU (Gerlach and Smets, 1999; Rünstler 2002; and Jarocinski and Lenza, 2016), but applications to credit and house prices are limited to a few studies. De Bonis and Silvestrini (2013) study an annual historical series of credit volumes in Italy, while Galati et al. (2016) apply univariate models to credit and house prices in major economies. These studies report cycle lengths of 12 to 15 years, by and large confirming the findings obtained from bandpass filters.

In general, only a few studies have so far addressed the co-movements of cycles in GDP, house prices and credit. Some evidence has been provided by event studies based on long historical datasets (Jordá et al., 2015, 2016) showing that major recessions in economic activity are typically preceded by financial booms. Claessens et al. (2012) apply turning point analysis to post-war data from developed and emerging economies, while Hubrich et al. (2013) consider the euro area economies. Both studies report that the major turning points in GDP coincide with those in the financial series, but that GDP is also subject to some additional short-term fluctuations.

This section presents results from a version of a multivariate STSM that models the joint dynamics of GDP, total credit, and house prices at both business-cycle and medium-term frequencies.

This section presents results from a version of the multivariate STSM developed by Rünstler and Vlekke (2016), which aims to model the joint dynamics of GDP, total credit, and house prices at both business-cycle and medium-term frequencies. The model provides additional flexibility in modelling the persistence of medium-term cycles and cyclical co-movements at different frequencies. The model specification is described in the Annex.

One important practical issue is the estimation for short datasets: for seven out of 17 countries in our sample data are available only after 1988 (see Table 2). The estimates for these countries are based on Bayesian methods with reasonably tight priors on the cycle lengths and the smoothness of trends. Estimates for the remaining countries are based on the Maximum Likelihood approach.

Table 4 shows the country averages for the major cyclical characteristics, while Chart 8 plots the estimates of cyclical components for all countries. The graphs reveal some important differences across countries, which will be further discussed in Sections 4 and 5.

The average length of cycles in house prices and credit is about 14 years.

The findings with respect to the basic properties of the cycles are in line with those of Section 2 and earlier studies. For the long datasets, the average cycle length is estimated at 14.1 and 13.8 years for house prices and total credit, respectively. The average length of GDP cycles is estimated to be somewhat shorter, at 11.7 years. The standard deviations of the cycles are estimated at 9.5%, 7.3% and 3.0% for house prices, total credit and GDP, respectively.

The GDP cycle emerges as a mix of a medium-term cycle, which is shared with credit and house prices, and an idiosyncratic shorter cycle.

In line with the results from the PCA presented in Section 2, the co-movements between the cycles are fairly close. Pairwise coherences among the three cycles are moderately high, and the highest value of 0.60 emerges for GDP and house prices. Generally, coherences are somewhat higher at medium-term frequencies. The lower panel of Table 4 shows the breakdown of the overall coherences into medium-term and business-cycle frequencies. In all cases coherences are high in the medium term. Indeed, in the estimates, the GDP cycle emerges as a mix of a medium-term cycle, which is shared by credit and house prices, and an idiosyncratic shorter business cycle, mostly three to five years in length. This also explains the lower average length of the GDP cycles in the upper panel of Table 4.

Table 4

Main estimate from multivariate STSM: averages across countries

	LONG DATASET			SHORT DATASET		
Main properties	**GDP**	**RPP**	**TCN**	**GDP**	**RPP**	**TCN**
Cycle length (years)	11.67	14.16	13.83	11.99	11.70	14.33
Standard deviation (%)	3.00	9.51	7.32	4.87	12.97	14.37
	LONG DATASET			**SHORT DATASET**		
Coherence	**GDP-RPP**	**GDP-TCN**	**RPP-TCN**	**GDP-RPP**	**GDP-TCN**	**RPP-TCN**
Coherence overall	.60	.57	.45	.67	.64	.69
Coherence 32-80	.63	.62	.48	.70	.66	.71
Coherence 8-32	.49	.36	.33	.52	.41	.52
Phase shift	-.40	-.19	.28	-.30	-.56	.02

Sources: Own calculations.
Notes: The lower panel of the table shows pairwise coherence and phase shift between cycles. Coherence is a measure between 0 and 1 that expresses the degree of co-movement between two series, abstracting from their lead-lag relationships (phase shifts). In addition to overall coherence, the values for business cycle and medium-term frequencies are shown separately. A negative value for the phase means that the first series leads the second series. See Table 2 for the country composition of long and short datasets.

Estimates of phase shifts between the cycles are fairly small (Table 4). On average, cyclical fluctuations in house prices and credit volumes tend to lag those in GDP by about six months. These results probably reflect a certain inertia in house prices and the fact that credit volume is a stock variable.

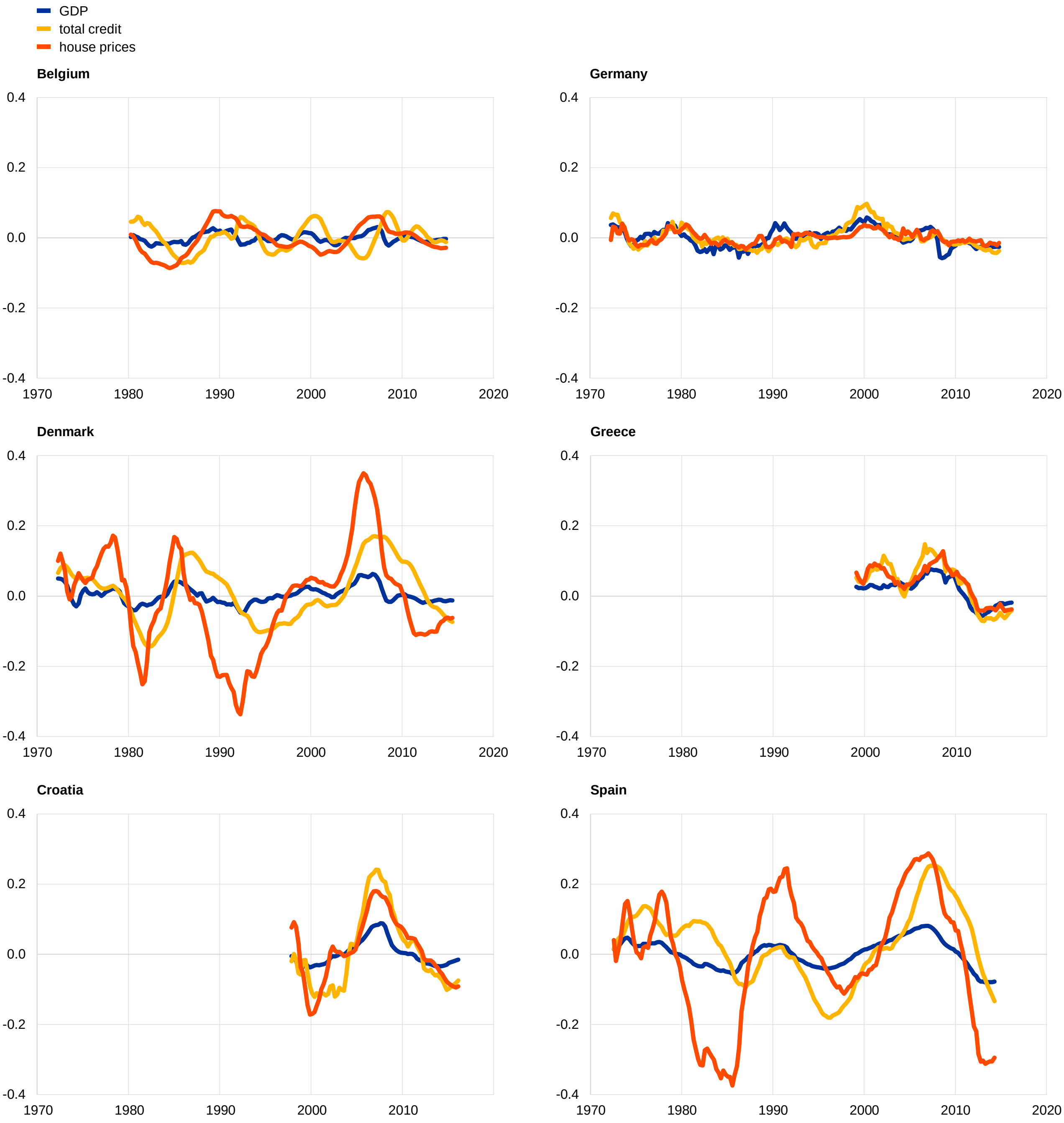
Results for countries with short datasets are similar, although they partly reflect the choice of priors.

For countries with short datasets, the estimated cyclical properties reflect, to some extent, the choice of priors. This holds in particular for the estimates of cycle lengths and volatilities, for which the priors are set to match the findings obtained from earlier studies.

Chart 8

Estimates of cyclical components from multivariate structural time series models

(percentage deviation from trend)



Sources: Own calculations.
Notes: The different scaling of the graphs should be noted. Countries are ordered by the scaling of graphs and, within the same scale, in alphabetical order.

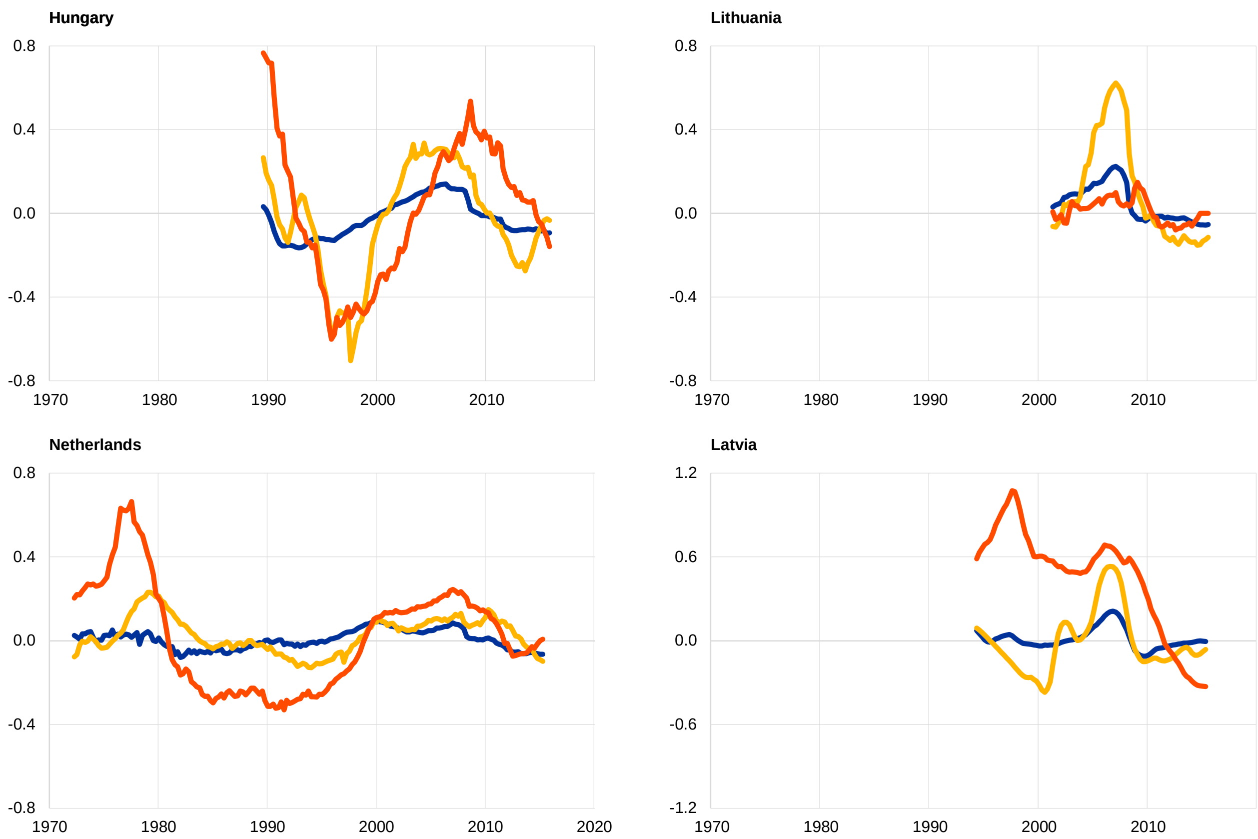
Chart 8 (cont.)

Estimates of cyclical components from multivariate structural time series models

Sources: Own calculations.
Notes: The different scaling of the graphs should be noted. Countries are ordered by the scaling of graphs and, within the same scale, in alphabetical order.

Chart 8 (cont.)

Estimates of cyclical components from multivariate structural time series models



Sources: Own calculations.
Notes: The different scaling of the graphs should be noted. Countries are ordered by the scaling of graphs and, within the same scale, in alphabetical order.

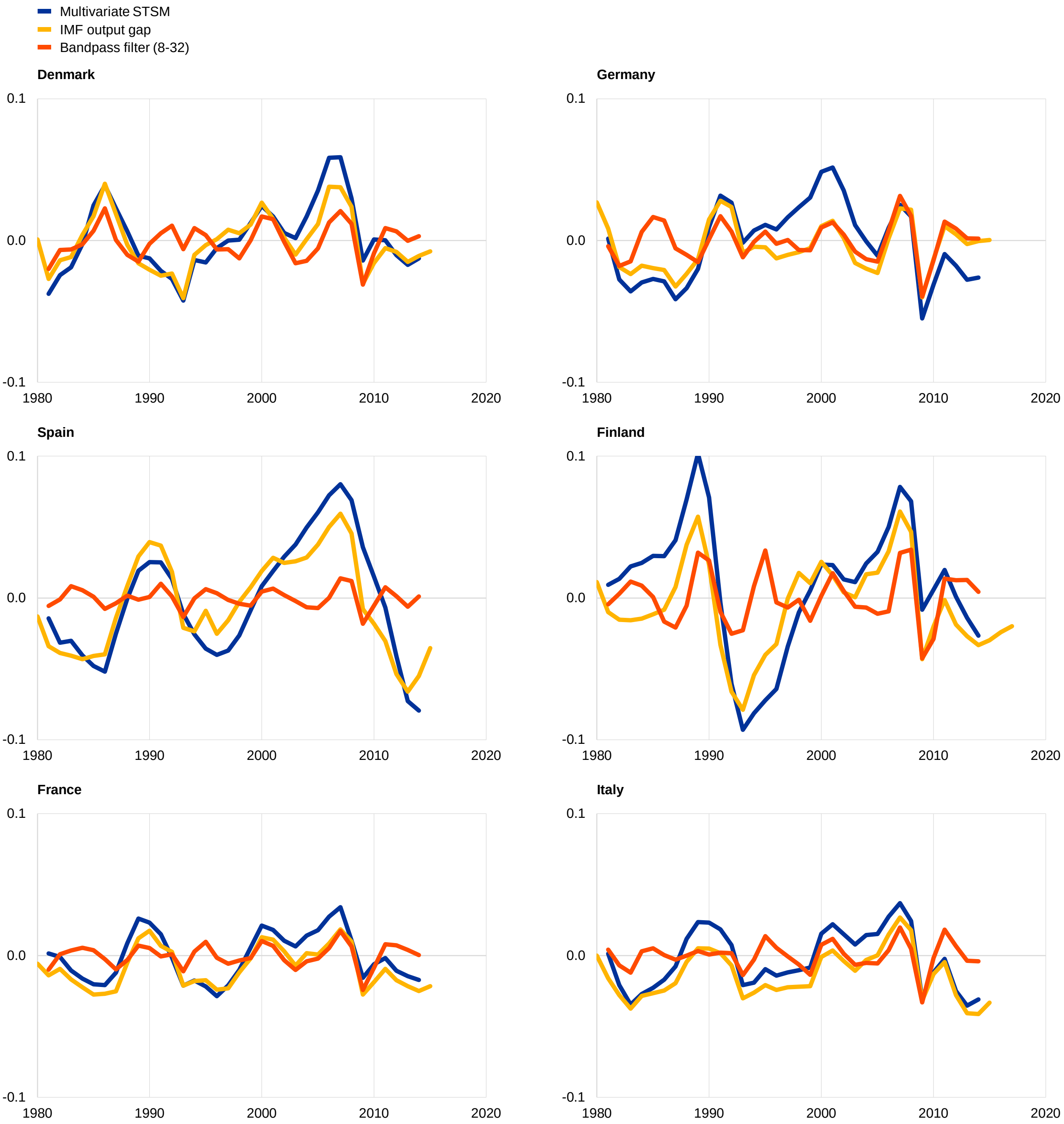
The priors are largely uninformative with respect to coherence, but the posterior results are still very similar to those obtained for countries with long datasets. One major difference is the higher volatility of cycles, in particular that of credit cycles. This reflects especially volatile recent boom/bust cycles in a number of countries in our short dataset, specifically the three Baltic states.

The output gap estimates of the IMF are very similar to the GDP cycles estimates from the multivariate STSM. They therefore account for medium-term components in the GDP cycle.

The above empirical findings indicate that estimating the GDP cycles in a multivariate context in conjunction with cycles in financial series has important consequences for these estimates. The financial series emphasise the presence of medium-term fluctuations in the GDP cycle which would otherwise be missed. This results in average estimated cycle lengths outside the frequency band of 8-32 quarters which has usually been used to extract business cycles with bandpass filters (Baxter and King, 1993). However, as shown in Chart 9, with only a few exceptions the output gap estimates published by the IMF are very similar to the GDP cycles estimates obtained from the multivariate STSMs. The IMF output gap estimates therefore appear to contain medium-term components beyond the 32-quarter cut-off point.

Chart 9

Estimates of GDP cycles and IMF output gaps



Sources: Own calculations, IMF.
Notes: The chart compares estimates of GDP cycles from the multivariate STSM and the bandpass filter with a frequency band of 8-32 quarters with output gap estimates published by the IMF in its regular World Economic Outlook (IMF, 2016).

By contrast, estimates of GDP cycles from the 8-32 bandpass filter differ considerably, which casts doubt on its usefulness for economic policy purposes.

By contrast, cycles obtained from the bandpass filter with the standard frequency band of 8-32 quarters differ substantially from these estimates in a number of cases. This holds in particular for countries with large cycles in house prices and credit, such as Spain and Finland. Some important differences also emerge for other countries with recessions in the mid-1990s and after 2007 being underestimated or entirely missed by the bandpass filter. Germany emerges as an exception, where the

STSM differs from the IMF estimate: in this case the STSM reveals a pronounced boom in the 1990s, related to a boom in credit.[3]

Given that the above output gap estimates are an important reference point for economic policy analysis, these differences cast some doubt on the appropriateness of a 32-quarter cut-off point for output gap estimation. Medium-term fluctuations may be policy-relevant, while the 32-quarter cut-off point entails a certain degree of arbitrariness.

3 Another important source of output gap estimates is the OECD. These estimates are very close to those of the IMF and give rise to very similar conclusions.

4 Cyclical co-movement among countries

The degree of co-movement in financial cycles across European countries has implications for policy coordination. First, there are implications as to whether common policies should be applied across countries. Second, national macroprudential authorities may wish to integrate foreign developments into their decision making. If cycles are sufficiently synchronous across (clusters of) countries, international developments might be informative for policies at national levels (see also Hubrich et al., 2013). This section analyses the cyclical co-movements of macro-financial variables across European countries based on principal component analysis (PCA) and measures of synchronicity and similarity.

Studies document a substantial degree of synchronicity of GDP cycles within Europe (Afonso and Sequeira, 2010; Giannone et al., 2009; Mink at al., 2012; and Ciccarelli et al., 2016), although Camacho et al. (2006) reject the idea of a single common cycle. More recently, Belke et al. (2016) have shown that GDP cycles for euro area countries are subject to different amplitudes. With regard to other macro-financial variables, the degree of international co-movement varies greatly, depending on the nature of the series being analysed. Breitung and Eickmeier (2016) note that commonality is particularly high for fast-moving financial variables such as stock prices and interest rates, but is considerably lower for monetary and credit aggregates, and for house prices. Miranda-Agrippino and Rey (2015) and Rey (2013) find that one global factor explains a major part of a large cross-section of the returns of risky financial assets around the world. Breitung and Eickmeier (2016) argue that the low synchronicity of house prices is not surprising given the differences in regulation and financing across Europe (see also Cerutti et al., 2015b). Similarly, credit cycles in Europe are fairly asynchronous across countries (De Backer et al., 2006; Meller and Metiu, 2015; and Aikman et al., 2015).

4.1 Principal component analysis

This section presents a principal component analysis for each of the eight series, based on annual growth rates of equity prices, house prices, GDP and credit stocks. Interest rates/spreads enter the PCA in levels. The analysis is limited to countries in the long dataset.

Table 5

Fraction of total variance explained by the first three principal components

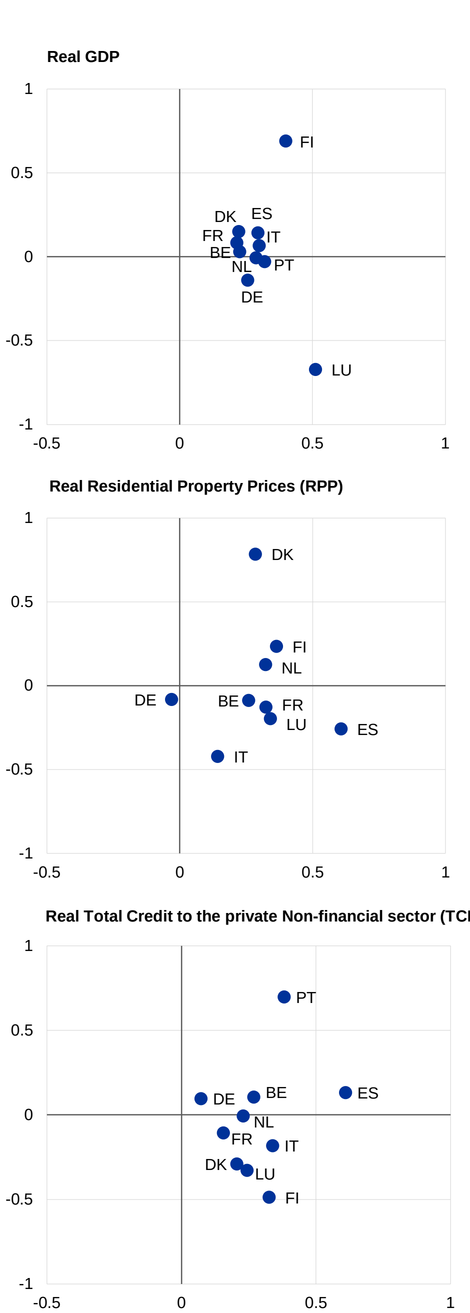
Long dataset	GDP	RPP	TCN	LHH	LNF	EQP	LTN	SPR
PC 1	62.3	41.8	40.2	44.4	42.0	64.0	93.1	48.5
PC 2	13.2	21.8	22.8	27.6	20.1	12.2	4.2	31.7
PC 3	8.1	16.9	10.6	9.4	16.2	8.4	1.2	10.1

Sources: Own calculations.
Note: See Table 1 for series abbreviations and Table 2 for the country composition of the long dataset.

Chart 10

Principal component analyses of co-movements across countries

(x-axis: PC1; y-axis: PC2)

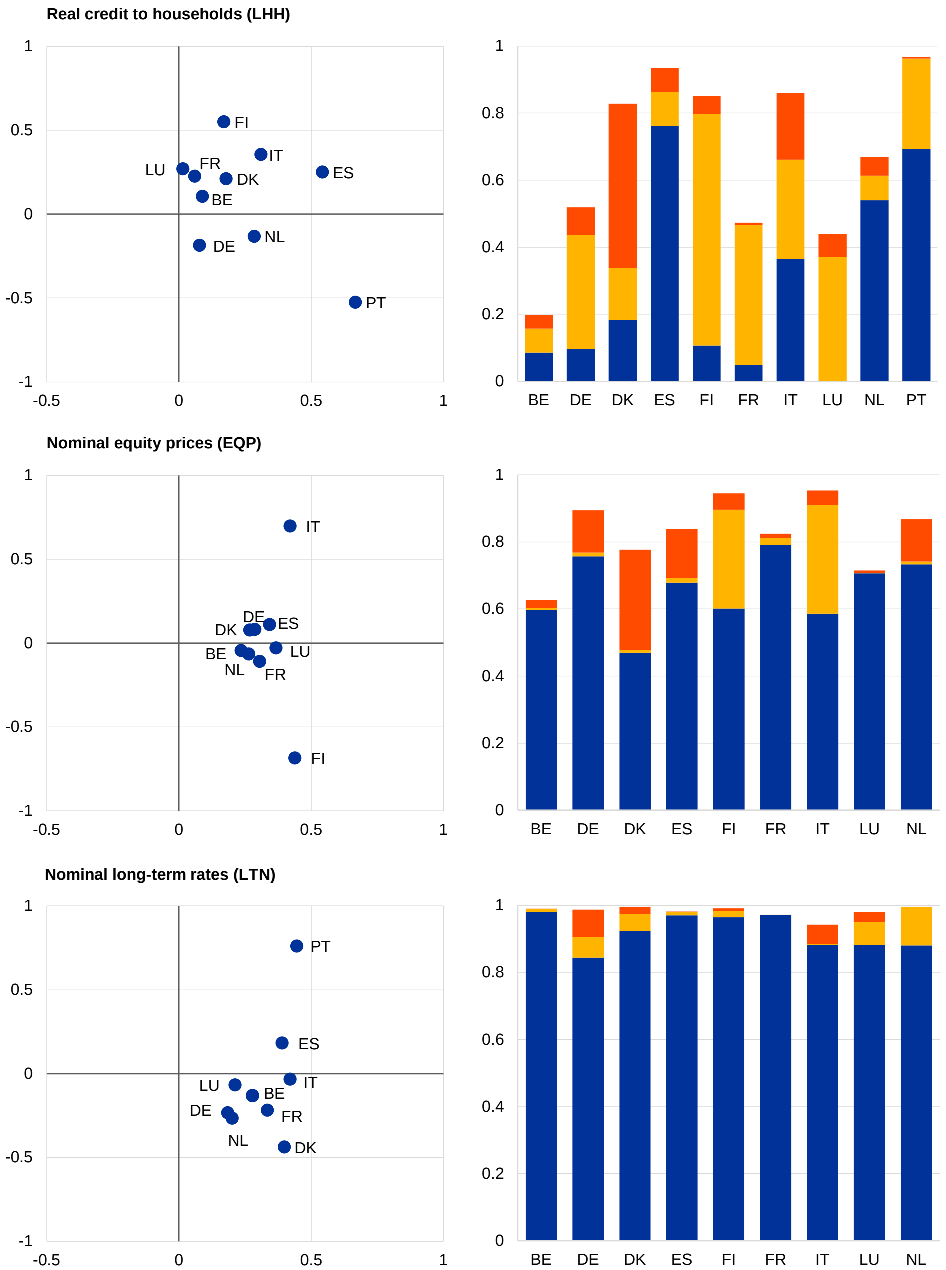


Sources: Own calculations.

Notes: The left-hand graphs show the loadings of the individual countries on the first two PCs. The right-hand graphs show the country-specific variances explained by the first three PCs. They are obtained from the R^2 of regressions of the country-specific series on an intercept and the PCs.

Chart 10 (cont.)

Principal component analyses of co-movements across countries



Sources: Own calculations.
Notes: The left-hand graphs show the loadings of the individual countries on the first two PCs. The right-hand graphs show the country-specific variances explained by the first three PCs. They are obtained from the R² of regressions of the country-specific series on an intercept and the PCs.

Co-movement across countries is strong for interest rates and, to a lesser extent, for equity prices and GDP...

Table 5 reports the fraction of total variance explained by the first three principal components (PCs). All eight series share some common dynamics across countries, and two or three PCs explain the bulk of the variation across countries. However, there are important differences between the series in terms of degree of commonality. Specifically, credit and house prices show substantially lower commonality across countries than GDP and liquid financial assets. While the first

PC explains 93% of the total variance for long-term rates, and 62% and 64% for GDP and equity prices, respectively, the corresponding values drop to less than 45% for credit and house prices.

These differences are reflected in the loadings of the individual countries on the first two PCs, and the country-specific variances explained by the first three PCs, which are shown in Chart 10. For long-term rates, all countries load positively on the first PC, which explains at least 80% of the variance of the series in each country. These extremely high shares of explained variance reflect longer-term developments, i.e. the downward trend in the series in advanced economies over the past 35 years.

The degree of co-movement is lower for GDP and equity prices, although still relatively high. Loadings on the first PC are once again all positive, with 50% to 80% of the variance of individual countries being explained by the latter.

… but weak for credit and house prices. Germany stands out with small cycles in credit and house prices that are unrelated to those of the remaining countries.

The results for credit and house prices contrast with those for GDP and equity prices. For these series, there is no evidence of a common cycle in Europe, as loadings on the first PC are highly dispersed across countries. Germany stands out through the entirely idiosyncratic behaviour of its credit and housing markets, as indicated by the zero loadings on the first PC for these series. Regarding total credit, the loadings of Italy, Portugal and Spain on the first PC are particularly large. For these countries, the first PC appears to reflect the credit boom/bust cycles that occurred around the end of the 1980s as well as the recent financial crises.[4]

For house prices the second principal component appears to capture a north-south divide in cyclical co-movements.

With regard to house prices, the second PC suggests a north-south divide in cyclical co-movements. Countries with real house price growth broadly increasing in the first half of the 1990s and then decreasing in the second half – such as Denmark and Finland – load with positive weights, whereas countries with opposite developments – such as Italy and Spain – load with negative weights.

4.2 Synchronicity and similarity

Synchronicity and similarity measures complement the analysis above. These measures are based on binary indicators and are therefore more robust, allowing time variation in co-movement to be examined.

This section complements the above analysis by examining the synchronicity and similarity measures proposed by Mink et al. (2012). Synchronicity between two cycles is based on binary indicators: in each period, a value of one indicates that two cycles have the same sign. The similarity measure is based on the average absolute differences between the levels of the two cycles. The two measures are described in the Annex. To examine the overall synchronicity and similarity among a set of countries, a reference cycle is formed, which is defined as the median of the individual cycles. Synchronicity and similarity of the individual country cycles with the reference cycle are then calculated and averaged across countries.

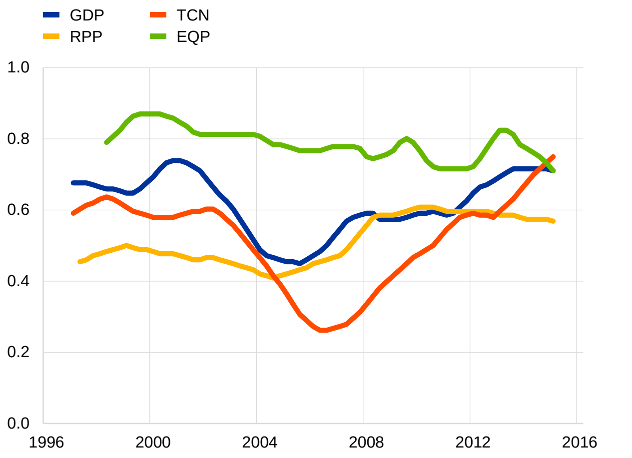
4 Various robustness checks confirm these results. First, the analysis above was based on annual growth rates, but results for bandpass filtered cycles (frequency band set at 8-80 quarters) are very similar. Second, results are similar for the sample of all 17 countries (with shorter datasets), although commonalities are somewhat higher.

These measures may provide additional insights to an approach based solely on correlations (as in PCA), because the latter may fail to detect certain non-linear patterns in cyclical co-movements. For instance, a correlation based approach may not accurately reflect synchronicity between two co-moving cycles with opposite signs (above and below trend).

This section examines the synchronicity and similarity of the bandpass-filtered cycles presented in Section 2, based on a frequency band of 8-80 quarters. The focus is on GDP, real total credit, residential property prices and equity price indices for the nine countries with long datasets.

Chart 11

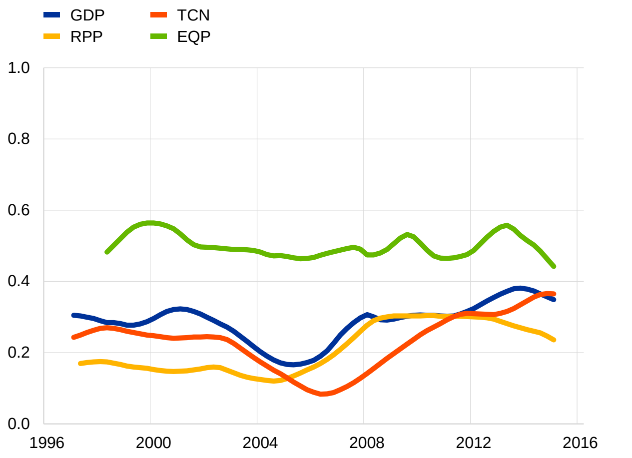
Overall synchronicity



Sources: Own calculations.
Note: Synchronicity and similarity measures are transformed to 8-year moving averages.

Chart 12

Overall similarity



Sources: Own calculations.
Note: Synchronicity and similarity measures are transformed to 8-year moving averages.

The synchronicity and similarity of cyclical components in credit and GDP house prices drop during the boom in the early 2000s.

Charts 11 and 12 compare cyclical synchronicity and similarity across countries for the four series. Equity price cycles are both more synchronous and more similar across countries than are other series. This is in line with findings from the principal component analysis above. Second, the synchronicity and similarity of cyclical components in other series – especially in credit and house prices – are generally lower and show more variation over time. In particular, the synchronicity and the similarity of credit and GDP cycles drop during the build-up to the boom in the early 2000s, reaching a trough just before the recent financial crisis. After that, all measures suggest increased synchronicity and similarity between cycles, reflecting slower growth in house prices and credit. Both measures increase during the subsequent recovery.

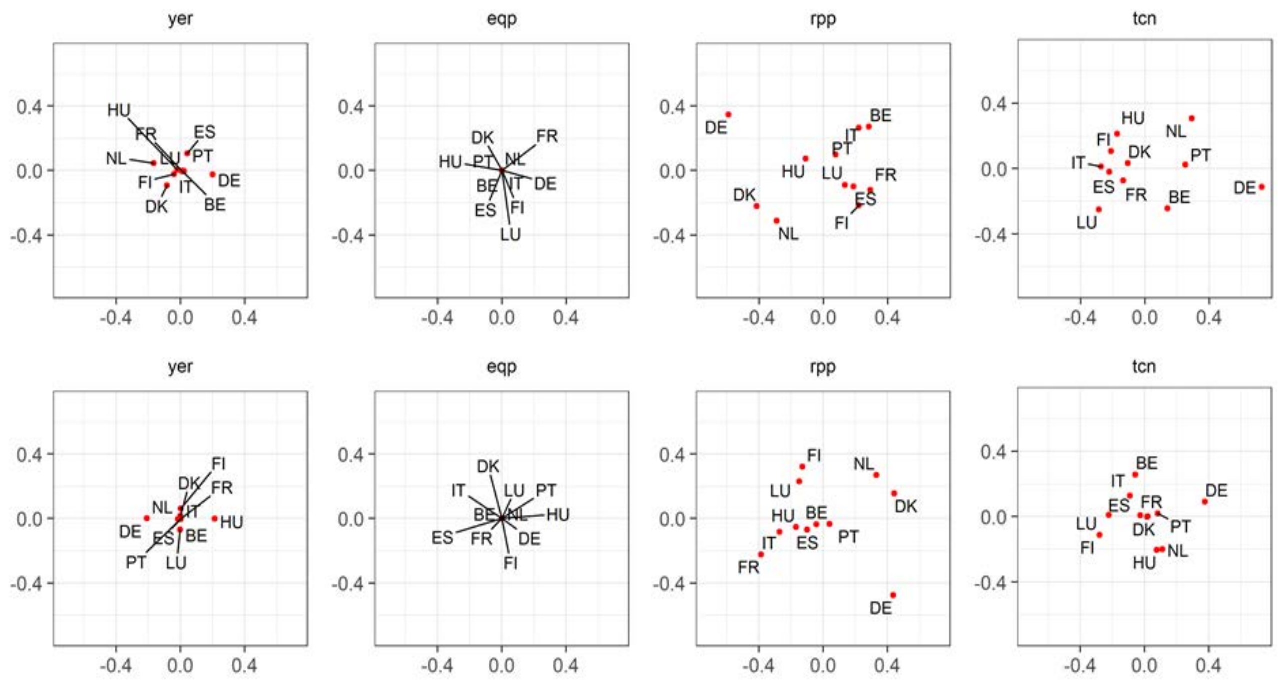
A multidimensional scaling map of phase and swing synchronicity.

The relevant literature often attempts to test for phase synchronicity of a group of the time series. The analysis below adopts the framework proposed by Meller and Metiu (2015), described in the Annex. To measure phase synchronicity, the extracted cycles are mapped into two distinct binary indicators – one reflecting the upswings/downswings (swing synchronicity) in cycles, and the second reflecting the sign of the cycle (gap synchronicity). An average measure is calculated for the phase synchronicity between cycles of each country pair. The statistics are summarised in two-dimensional graphs – multidimensional scaling maps.

Chart 13 compares scaling maps for medium-term cycles in the four series under analysis. Two countries that are close to each other on the map are likely to share a common cycle. The maps for gap and swing synchronicity confirm our previous findings, suggesting several conclusions. First, for both measures, medium-term components in equity prices are strongly synchronous for all country pairs, and therefore seem to share a single common cycle. In contrast, real house prices and credit aggregates diverge much more across countries at medium-term frequencies. In addition, there are some indications of countries grouping into separate clusters. Consistent with previous findings, house prices and credit cycles in Germany share relatively little commonality with the other countries under analysis. Finally, real GDP at medium-term frequencies seems to be highly synchronous across countries for both measures.

Chart 13

Gap and swing synchronicity



Sources: Own calculations.

Notes: Dissimilarities between two countries are based on p-values from a statistical test of phase synchronicity (see the Annex). A small distance for any country pair reflects a small associated p-value, i.e. a significant synchronicity between the two cycles and the existence of a common cycle for that country pair.

5 The role of structural properties

Recent studies relate differences in cyclical characteristics to the structural properties of national mortgage and housing markets.

The estimates of GDP, credit, and house price cycles presented in Section 3 are subject to substantial cross-country heterogeneity. Two recent studies by Huber (2016) and Rünstler and Vlekke (2016), suggest that these differences are related to various structural characteristics of national housing and mortgage markets. In particular, countries with a high rate of private homeownership appear to have larger and longer house price and credit cycles. The first study also finds some weaker relationships with characteristics of national mortgage markets such as LTV ratios.

This section inspects the relationship between the volatility and synchronicity of cycles and various macro-financial indicators.

This section looks at the relationship between this heterogeneity and various structural macro-financial indicators across countries. It considers two properties of the cycles, i.e. their standard deviations and, as a novel feature, the pairwise synchronicities between cycles. The synchronicity measure is the same as the one used in Section 4 and is described in the Annex. Cycles are estimated from the Christiano-Fitzgerald bandpass filter with a frequency band of 8-80 quarters.

Macro-financial indicators include private homeownership rates, maximum loan-to-value (LTV) ratios, and the share of flexible rate mortgages. A high rate of private homeownership indicates a higher share of homeownership by middle-class households and, therefore, greater importance of mortgage-based housing finance, which should raise the relevance of collateral constraints. The LTV ratio is a proxy for borrowing constraints, while the share of flexible rate mortgages affects households' exposure to interest rate risk.[5] Finally, among macroeconomic indicators, we include the current account and a measure of current account misalignments from Comunale (2017a, 2017b). The data sources and details are provided in the Annex.[6]

It should be stressed that these relations should be interpreted cautiously in respect of underlying causal relationships.

For the six macro-financial indicators the average values over the entire sample period are used. Table 6 shows the correlations between the six indicators and the two cyclical properties across countries. It should be stressed right from the start that these correlations do not necessarily indicate that the indicator has a uni-directional causal impact on the cyclical properties. A correlation might also arise due to a reverse causal impact or to other latent characteristics (such as cultural differences) that influence both the indicator and cyclical properties.

Countries with higher homeownership rates also have larger and more synchronous cycles in GDP, house prices and credit.

Both the standard deviations of cycles and the synchronicity between GDP and house price cycles appear to be closely related to the rate of private homeownership. All correlations are significant, the only exception being the synchronicity between house prices and loans to households. Correlations are weak for the two measures of mortgage market characteristics, i.e. maximum LTV ratios and the share of flexible rate mortgages, although the LTV ratio is negatively related to the synchronicity between GDP and loans to non-financial corporations. The relationships between

5 More precisely, regulatory maximum LTV caps represent occasionally binding constraints, while banks may occasionally use tighter internal credit standards.

6 More detailed results for this section may be found in Comunale (2017c).

private homeownership and cyclical volatility in GDP and house prices and their synchronicity are shown in Charts 14 and 15.

The same holds, although to a lesser extent, for countries with low loan-to-value ratios and flexible rate mortgages.

However, the interaction of LTV ratios and flexible rate mortgages appears to matter for credit (see also IMF, 2008; Rubio and Comunale, 2017a, b). For countries with both low LTV ratios and flexible rate mortgages (such as Portugal, Slovenia, and the Baltic states) GDP and credit cycles are subject to higher volatility. Moreover, these countries also experience higher cyclical synchronicity between GDP and loans to NFCs. However, the interaction term does not have a significant impact on house prices.

The results indicate that collateral constraints are an important factor in the build-up of house price cycles.

Overall, countries with a high rate of private homeownership, and a combination of low LTV ratios and flexible rate mortgages, display larger and more synchronous cycles in GDP, credit and house prices. These features make households vulnerable to cyclical variations in financing conditions. The results therefore provide some support for the view that collateral constraints are an important source of cycles in house prices. As suggested by Leamer (2007), the synchronicity of GDP and house prices may arise from the contribution of private residential investment to output fluctuations. Private residential investment has provided a substantial contribution to GDP growth in countries such as the Netherlands, Denmark and Ireland, albeit less so in Germany, Italy, France and Finland (IMF, 2008).

Table 6

Correlations between structural cyclical characteristics

(correlations, bootstrapped errors)

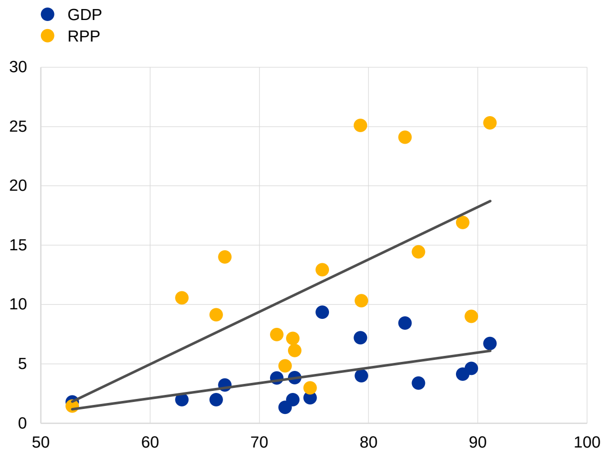
Volatility	GDP	RPP	TCN	LHH	LNF	EQP
Homeownership rate	***0.54	***0.61	***0.50	***0.67	***0.47	0.11
LTV ratio	-0.16	0.17	0.03	-0.06	0.18	-0.33
LTV ratio x Flex rate	*0.37	0.37	**0.55	**0.40	***0.57	0.27
VAD financial sector	-0.12	-0.24	-0.13	-0.29	0.05	-0.12
Current account	**-0.53	**-0.49	*-0.38	**-0.56	-0.23	0.02
CA misalignment	0.28	0.20	0.26	0.26	0.14	-0.05
Synchronicity	**GDP-LHH**	**GDP-LNF**	**GDP-RPP**	**GDP-TCN**	**GDP-LTN**	**LHH-RPP**
Homeownership rate	**0.48	***0.70	***0.60	0.40	**-0.51	0.13
LTV ratio	0.11	***-0.47	-0.07	-0.14	0.42	0.16
LTV ratio x Flex rate	0.13	***0.54	0.33	0.25	-0.28	-0.31
VAD financial sector	-0.51	-0.23	-0.25	-0.46	0.02	-0.41
Current account	***-0.62	***-0.66	*-0.43	***-0.58	0.25	-0.04
CA misalignment	*0.48	***0.59	*0.41	*0.58	-0.20	0.08

Sources: Own calculations.
Notes: The table shows the correlations between structural characteristics (rows) and the standard deviations of the series or the synchronicity of the individual indicators (column) across all 17 countries, with data starting from 1999. The stars indicate significance levels at 1% (***), 5% (**) and 10% (*). Significance levels are obtained from regressions of indicators and a constant, and calculated from bootstrapped errors. LTV ratio is the maximum loan-to-value ratio. Homeownership rate is the homeownership rate as a percentage of the total population. VAD financial sector is the gross value-added of the financial sector as a percentage of GDP. CA misalignment is the average current account misalignment. Current account is the current account balance over GDP. LTV ratio x Flex rate is the interaction term between maximum LTV ratios and the share of flexible rate mortgages of total mortgage volumes.

Chart 14

Homeownership rates and cyclical volatility

(x-axis: homeownership rate; y-axis: standard deviations*100)

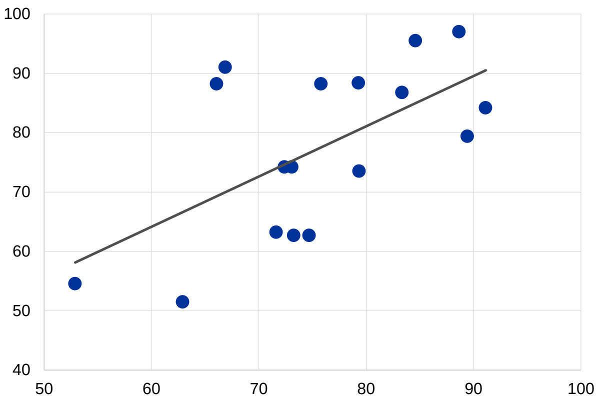


Sources: Own calculations.
Notes: The chart plots the rate of private homeownership (horizontal axis) against the standard deviations of cycles in GDP and house prices. Cycles are obtained from the bandpass filter with a frequency band of 8-80 quarters as described in Section 2. The solid line represents the regression of volatility on private homeownership.

Chart 15

Homeownership rates and synchronicity

(x-axis: homeownership rate; y-axis: synchronicity of GDP with RPP)



Sources: Own calculations.
Notes: The chart plots the rate of private homeownership (horizontal axis) against the pairwise synchronicity of cycles in GDP and house prices. Cycles are obtained from the bandpass filter with a frequency band of 8 80 quarters as described in Section 2. The solid lines represent regressions of synchronicity on private homeownership.

EU countries with larger and more synchronous cycles also show more negative current account balances.

Finally, in our sample from 1999 to 2015, cycles in credit and house prices appear to be linked to current accounts and their misalignments: countries with larger and more synchronous cycles have more negative current account balances (see Charts 16 and 17). Economies generally tend to lose competitiveness in boom periods: real effective exchange rates rise above equilibrium levels and current accounts become more misaligned due to the shift of funding towards less tradable and productive sectors (Dell'Ariccia et al., 2012).

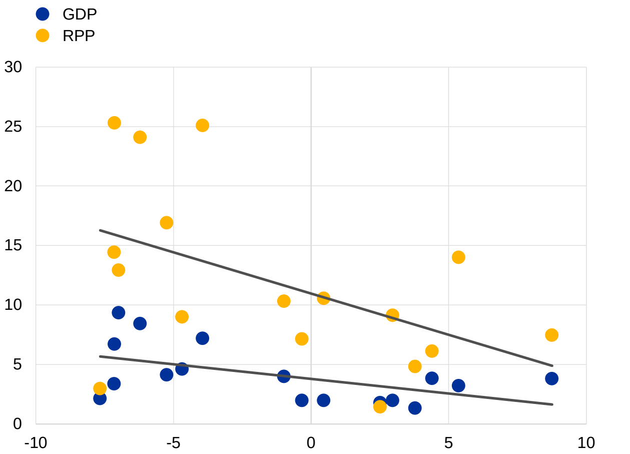
This may reflect the specifics of the most recent boom-bust cycle. More fundamentally, countries with a large negative net foreign asset position appear more prone to disruptions in external finance.

The underlying causes of these correlations may well operate in both directions. Certainly, the economic expansion in the periphery prior to the financial crisis was, to some extent, driven by easier access to external finance due to increased financial integration within the euro area. This resulted in current account deficits as well as a high synchronicity of GDP and credit cycles. More fundamentally, countries with chronic current account deficits and a negative net foreign asset position may have to rely more heavily on external finance for an expansion real activity, and are therefore more prone to sudden stops (e.g. Mendoza, 2016). This may result in a higher synchronicity of fluctuations in credit and GDP. In line with this argument, Avdjiev et al. (2017) find that large foreign capital flows and a higher share of external lending are associated with a higher likelihood of credit booms. Capital flows that fuelled non-tradable sectors of the economy would worsen both the internal and the external terms of trade and would shift the current account into negative territory (Comunale, 2017a; and Dell'Ariccia et al., 2012). In the medium term, the boom would end in a sharp correction, in particular if the economy has a negative net foreign asset position.

Chart 16

Current account balances and cyclical volatility

(x-axis: current account balance (percent of GDP); y-axis: standard deviations*100)

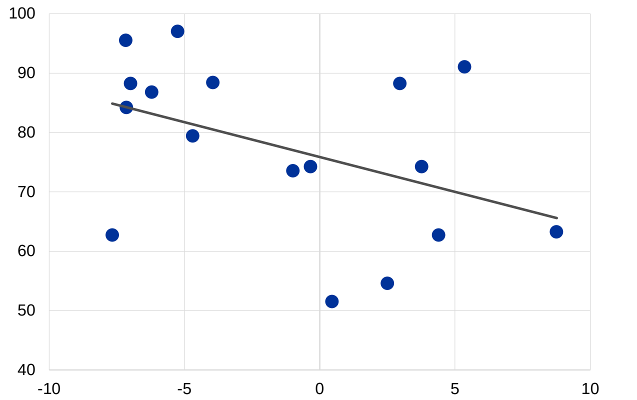


Sources: Own calculations.
Notes: The chart plots current account balances as a % of GDP (horizontal axis) against the volatilities of cycles in GDP and house prices. Cycles are obtained from the bandpass filter with a frequency band of 8 80 quarters as described in Section 2. The solid line represents the regression of volatility on current account balances.

Chart 17

Current account balances and synchronicity

(x-axis: current account balance (percent of GDP); y-axis: synchronicity of GDP and RPP)



Sources: Own calculations.
Notes: The chart plots current account balances as a % of GDP (horizontal axis) against the pairwise synchronicity of cycles in GDP and house prices. Cycles are obtained from the bandpass filter with a frequency band of 8- 80 quarters as described in Section 2. The solid line represents the regression of synchronicity on current account balances.

6 Can cycles be assessed in real time?

Studies usually report historical estimates of cycles, but policymakers have to rely on real-time estimates which are subject to considerably higher uncertainty.

Studies usually report historical estimates of cycles based on full-sample information (including the estimates presented so far in this paper). Policymakers, however, necessarily have to rely on real-time estimates, based only on past and current observations. Real-time estimates are subject to considerably higher uncertainty than those based on full-sample information. The resulting difficulties in detecting housing booms and busts in real time have been documented by Gadea-Rivas and Perez-Quiros (2015).

This section examines the real-time performance of the multivariate STSM and the bandpass filters. While the true cycles are unknown, a great deal can be learned from comparing real-time and final estimates across different methods. Final estimates are a reasonable benchmark, given that they are subject to considerably lower uncertainty.

When assessing revisions, it is important to make a distinction between three different sources of uncertainty:

1. The impact of data revisions.
2. Model and parameter uncertainty.
3. Filter uncertainty: even with model parameters being fully known, estimates of cycles can be subject to a high degree of uncertainty. Since both trends and cycles follow stochastic processes, any decomposition contains to a stochastic element. This holds in particular for real-time estimates: historical estimates of cycles are based on symmetric two-sided filters that make use of both past and future observations, while real-time estimates are necessarily based on one-sided filters. The latter are subject to potentially higher uncertainty, and, as a result, large subsequent revisions to one-sided estimates may be required.

A number of studies have assessed the reliability of real-time estimates of the output gap (e.g. Orphanides and van Norden, 2002; Nelson and Nikolov, 2003; and Watson, 2007), and credit cycles (Edge and Meisenzahl, 2011). In their seminal article, Orphanides and van Norden (2002) find that revisions to US real-time output gap estimates using different detrending methods could be of the same order of magnitude as the final output gap estimate itself. The discrepancies are mostly due to the poor reliability of end-of-sample estimates arising from model and filter uncertainty, while data revisions play a relatively minor role. This has been confirmed by various subsequent studies, including Marcellino and Musso (2011) for the euro area output gap and Edge and Meisenzahl (2011) for the US credit-to-GDP ratio.

Studies have attempted to improve estimates by using multivariate detrending methods.

Other studies have attempted to alleviate end-of-sample uncertainty by expanding the amount of information used in estimation. In the context of univariate filters, Gomez (2001) proposed to extend the data to include forecast and backcast values of the series (see also Mise et al, 2005; and Watson, 2007). Several authors have considered multivariate detrending methods, expanding the information set by adding variables which should, according to economic theory and empirical evidence, be informative about the cycle. Early examples of this approach are Clark (1989) and Kuttner (1994), who created bivariate models of the output gap based on Okun's law (using unemployment data) and the Phillips curve (using inflation data). Rünstler (2002), Doménech and Gómez (2006), Basistha and Startz (2007), and Trimbur (2009) found that multivariate models significantly improved the accuracy of real-time gap measures compared to univariate detrending techniques. Multivariate filters exploiting information from a large number of variables were designed by Valle e Azevedo et al. (2006), Altissimo et al. (2010) and Creal et al. (2010).

Two exercises are carried out in this section to study the properties of real-time estimates from the multivariate STSM and the bandpass filter. Section 6.1 assesses filter uncertainty based on full-sample parameter estimates (as reported in Section 3). Section 6.2 studies the joint effects of filter and parameter uncertainty for multivariate STSM estimates, by re-estimating the model parameters from certain sub-samples (i.e. data ranging only until 1999 Q4 and 2007 Q4, respectively), and then assessing the properties of one-sided estimates for the remainder of the sample. This exercise provides some evidence as to whether the most recent booms would have been detected by the models in real time.

6.1 Filter uncertainty

This subsection assesses the effect of filter uncertainty by comparing one-sided and two-sided (final) estimates of cycles. Thus, estimates of the cycle in period t given the information available in period t are compared with estimates in period t given the information in period t+20. The latter are very close to the final estimates.

One- and two-sided estimates of cycles are taken from the Christiano-Fitzgerald bandpass filter and from the multivariate STSMs presented in Sections 2 and 3. Three statistics are used to assess the quality of real-time estimates: first, the *degree of co-movement* between real-time and final estimates, which is measured by sample correlation and sign concordance (share of observations when real-time and final estimates have the same sign); second, the *volatility* of the one-sided estimate relative to the final estimate; and third, the *noise ratio*, i.e. the volatility of revisions (the difference between real-time and final estimates), relative to the volatility of the final estimates.

Ideally, correlations and sign concordance should be close to one. This also holds for the (relative) volatility of one-sided estimates, while noise ratios (reflecting the relative size of the error) should be close to zero.

Table 7

Properties of one-sided estimates

Long dataset	NOISE RATIO			VOLATILITY		
	GDP	RPP	TCN	GDP	RPP	TCN
Bandpass filter	0.83	0.76	0.87	0.73	0.62	0.79
STSM	0.71	0.66	0.79	0.77	0.63	0.58
	CORRELATION			**SIGN CONCORDANCE**		
	GDP	**RPP**	**TCN**	**GDP**	**RPP**	**TCN**
Bandpass filter	0.65	0.67	0.66	0.68	0.76	0.71
STSM	0.74	0.74	0.70	0.78	0.81	0.68

Sources: Own calculations.
Notes: The table shows median values across countries for various statistics to compare one-sided and the two-sided estimates from the Christiano-Fitzgerald bandpass filter and the multivariate STSM described in Section 3. Ideally, correlations, sign concordance, and relative volatilities should be close to one, while noise ratios should be close to zero.

The precision of one-sided estimates is comparable for GDP and house price cycles, but slightly lower for credit cycles.

Table 7 presents median values for the group of ten countries for which longer time series are available. The results for GDP and house prices are comparable overall. The one-sided estimates underestimate the volatility of cycles by about 25-45% in most cases, while noise ratios are between 66% and 83%. Correlations and sign concordance are between 0.65 and 0.81. In general, the precision of estimates increases with the volatility of cycles, but declines for longer cycles (Rünstler and Vlekke, 2016). In the case of GDP and house price cycles, the two effects appear to offset each other, leading to comparable outcomes. For credit cycles, however, lower volatility results in somewhat less precise estimates.

The multivariate STSM tends to perform better than the univariate bandpass filter.

The results also suggest that the multivariate model tends to produce more reliable real-time estimates than the univariate bandpass filter. This holds in particular for the noise ratios and the degree of co-movement between the one-sided and the final estimates. Real-time estimates of the cycle appear to be more accurate for house prices – with stronger co-movement and smaller revisions – than for GDP and credit.

Table 8 presents the equivalent results for the group of countries with shorter time series, again reporting the median values across countries. Not surprisingly, the filter uncertainty of one-sided estimates increases with the shorter sample, resulting in noise ratios close to, or even above, one. At the same time, the one-sided estimates of the cycles in GDP and house prices tend to be more strongly correlated with the final estimates. However, due to the different sample sizes and the different properties of the cycles in the short dataset, the results are not directly comparable.

Table 8

Properties of one-sided estimates

Short dataset	NOISE RATIO			VOLATILITY		
	GDP	RPP	TCN	GDP	RPP	TCN
Bandpass filter	0.96	0.89	1.16	0.75	0.67	1.06
STSM	1.01	1.00	0.77	0.72	0.67	0.65
	CORRELATION			SIGN CONCORDANCE		
	GDP	RPP	TCN	GDP	RPP	TCN
Bandpass filter	.72	.72	33	.73	.71	.60
STSM	.89	.80	.62	.75	.73	.70

Sources: Own calculations. See notes to Table 7.

6.2 Would the last boom have been detected in real time?

The house price and credit boom in the early 2000s would have been detected for most countries in real time. However, its scale would have been substantially underestimated.

This section examines out-of-sample one-sided estimates. The comparison accounts for both filter uncertainty and parameter uncertainty. For this purpose, the multivariate STSM is re-estimated over two sub-samples, one with data until 1999 Q4 and the other until 2007 Q4. One-sided estimates of the cycles are then obtained for the remainder of the sample as in Section 6.1, but based on the two sub-sample parameter estimates. Finally, they are compared with the two-sided estimates discussed in Section 6.1, which are based on full-sample parameter estimates. This exercise provides some evidence on how much of the credit and house price booms in the early 2000s would have been detected by the models in real time. The analysis is only conducted for the countries in the long dataset.

Chart 18 compares the final two-sided estimates with the out-of-sample one-sided estimates. For the GDP cycle the results are mixed: with the exception of Denmark, the model is not able to detect the upturn of the early 2000s in real time, while the subsequent recession is detected relatively successfully.

In the case of credit and house price cycles, the results are somewhat more favourable – the booms in the early 2000s are detected for most countries. However, in many cases, and in particular for France, Spain and Italy, the scale of the booms is underestimated and it is not clear whether the estimates would have been perceived as alarming signals in real time.

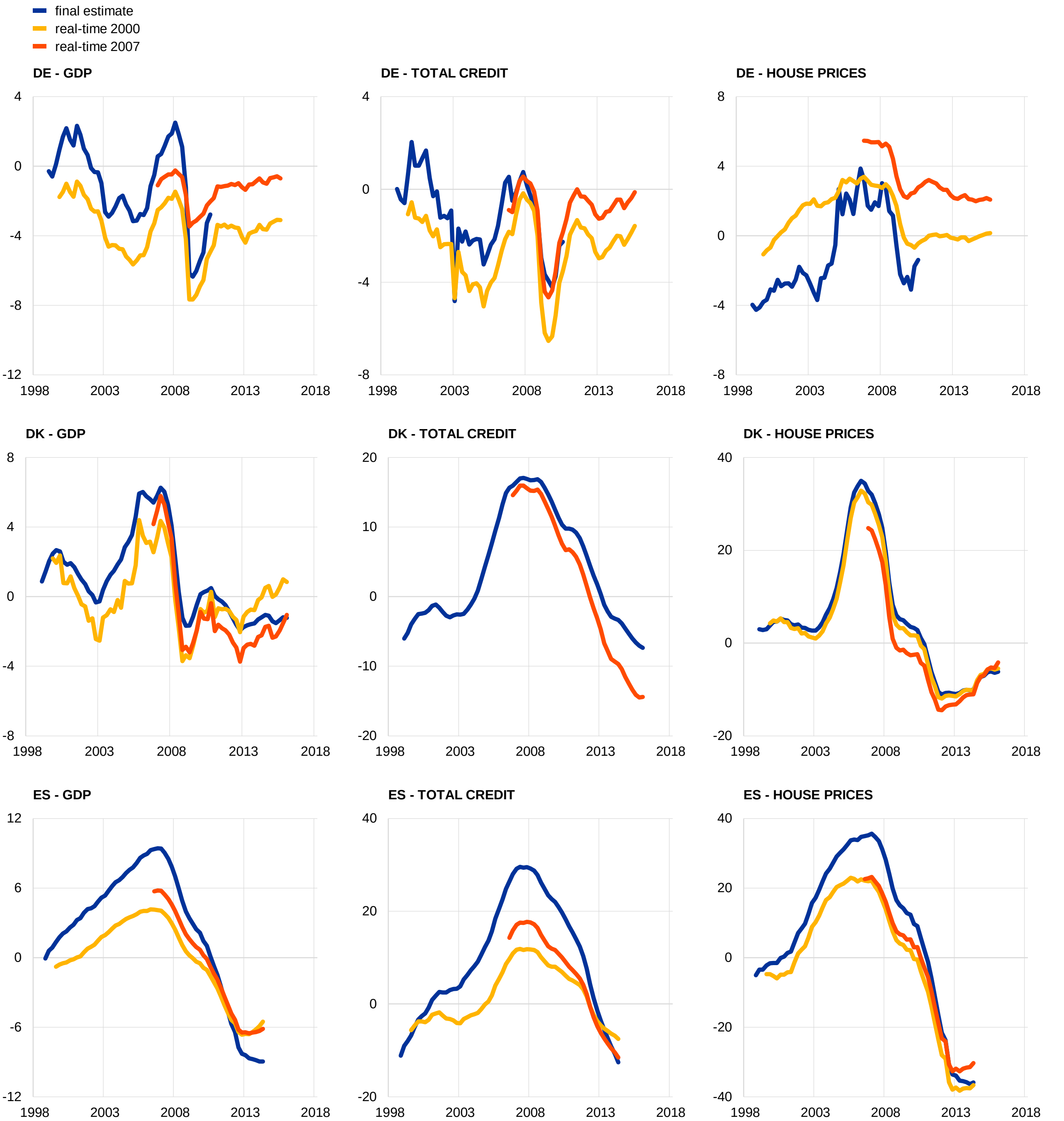
Overall, the uncertainty around real-time estimates of credit and house price cycles appears to be on approximately the same scale as it is for business cycles.

Overall, the results suggest that the uncertainty surrounding the real-time estimates of credit and house price cycles is of approximately the same scale as for business cycles, when measured relative to the amplitude of the cycles. For all series, real-time estimates generally tend to underestimate the scale of booms and busts. While multivariate time series models tend to perform better than bandpass filters, this paper provides only tentative conclusions on this subject, as the series are too short to reliably assess the effects of parameter uncertainty.

Chart 18

Out-of-sample one-sided estimates of cycles for selected countries

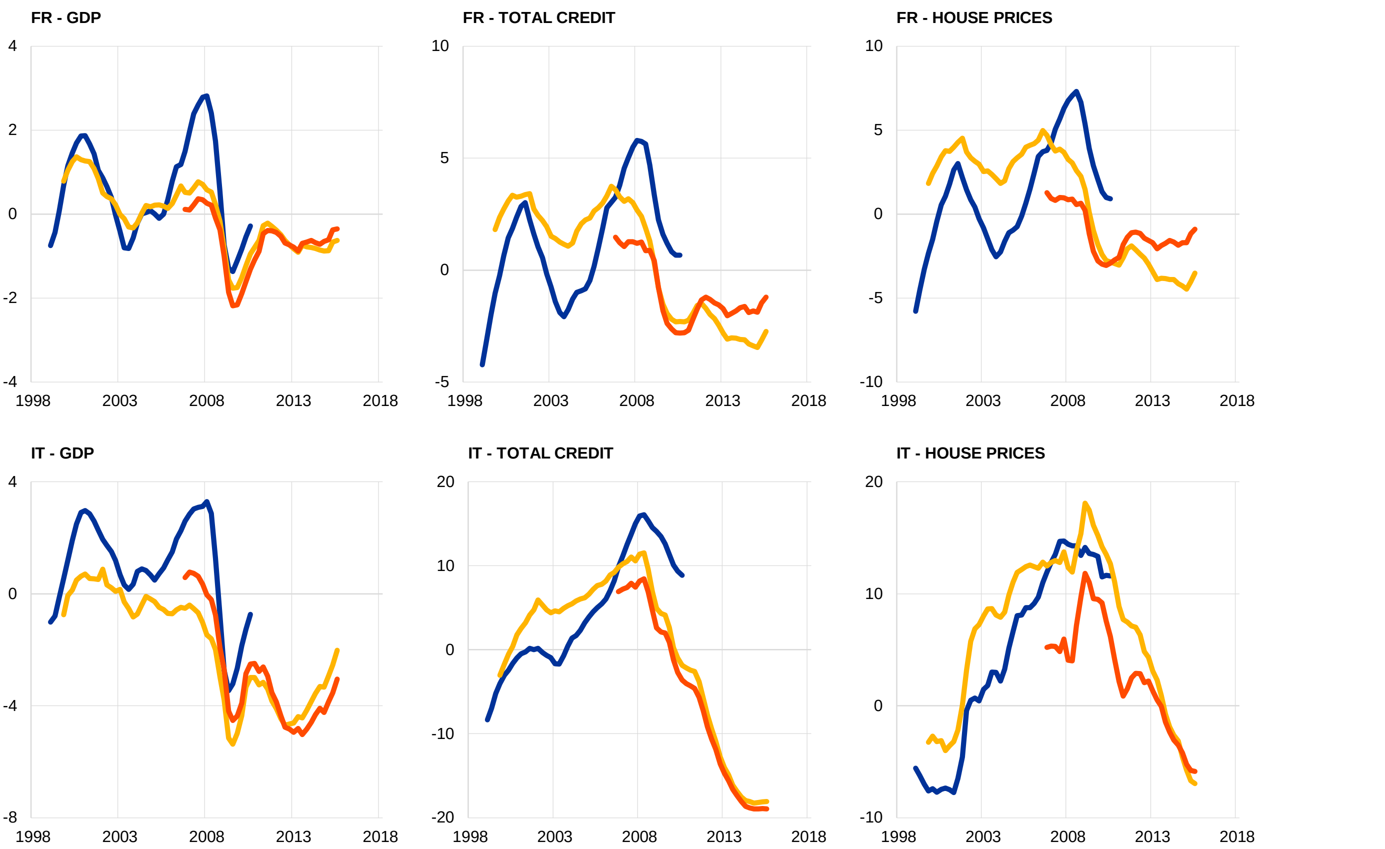
(percent*100)



Sources: Own calculations.
Notes: The graphs compare final (two-sided full-sample) estimates of cycles with one-sided estimates based on sub-sample parameter estimates, with two sub-samples ranging until 2000 Q4 and 2007 Q4, respectively. The latter estimates replicate the information sets available to economic policymakers in 2000 and 2007. Note the different scaling of the graphs.

Chart 18 (cont.)

Out-of-sample one-sided estimates of cycles for selected countries



Sources: Own calculations.
Notes: The graphs compare final (two-sided full-sample) estimates of cycles with one-sided estimates based on sub-sample parameter estimates, with two sub-samples ending in 2000 Q4 and 2007 Q4, respectively. The one-sided estimates replicate the information sets available to economic policymakers in 2000 and 2007. Note the different scaling of the graphs.

7 Implications for structural models

The recent financial crisis has highlighted the importance of developing structural models that can be used to study financial and real cycles within the same unified framework. Given that the development of DSGE and other structural models has always been guided by their ability to reproduce stylised facts, the main goal of this section is to compare the implications of existing frameworks with the empirical findings revealed in this paper. A second objective is to use the comparison between different model mechanisms and the data to identify directions for future research.

The comparison starts from three empirical findings that were highlighted in previous sections and that are particularly relevant for structural modelling. First, financial cycle variables such as equity prices, house prices and credit are considerably more volatile than GDP. Second, for house prices and credit, this high volatility is mostly due to medium-term fluctuations, as opposed to the fluctuations at higher frequencies that are usually associated with the business cycle. Correspondingly, cycles in house prices and credit are typically longer than their business cycle counterparts. Third, medium-term fluctuations play a much smaller role in driving the dynamics of equity prices.

Given that the housing market is an important dimension across which euro area countries are found to diverge, as discussed in Section 4, this section focuses on structural models that incorporate a housing sector. The dynamics of equity prices implied by the current generation of DSGE models are also briefly discussed.

It would be beyond the scope of this paper to cover all possible categories of structural models. This section focuses on dynamic stochastic general equilibrium (DSGE) models, as these are particularly useful for policy and welfare analysis. Three main categories of DSGE models are considered: (i) models with real rigidities, (ii) models with financial frictions, and (iii) models with information frictions.

7.1 Equity and housing in a DSGE model with real rigidities

A standard real business cycle model augmented by habit formation and capital adjustment costs …

This subsection starts by asking whether DSGE models with real rigidities can reproduce the stylised facts documented in this paper. The analysis is based on a neoclassical growth model in which technology shocks are the only source of business and financial cycle fluctuations.

The first model considered is a standard real business cycle model augmented by habit formation and capital adjustment costs, two types of real rigidities that are widely used in the literature. The literature on capital adjustment costs includes the work of Hayashi (1982), Pindyck (1982) and Abel (1983, 1985). In the context of asset pricing models, habit formation has, for instance, been studied by Abel (1990), Constantinides (1990) and Campbell and Cochrane (1999). Following Jermann et al.

(1998), this section asks whether a model augmented by real rigidities can reproduce the joint dynamics of output and equity prices observed in the data.

… is reasonably successful at reproducing the dynamics of equity prices ...

Model simulations suggest that the model is reasonably successful at reproducing the joint dynamics of output and equity prices observed in the data. The first column in Table 9 shows the volatility of year-on-year growth rates for output and equity prices. The model parameters are chosen to match these two moments. The second column reports the volatility of output and equity prices at business-cycle frequencies, i.e. cycles ranging from 8 to 32 quarters. The third column shows the volatility of the medium-term frequency, i.e. cycles with a duration of 32 to 120 quarters. The final column in Table 9 shows the ratio between the standard deviations of medium-term cycles and those of business cycles. A value greater than one implies that medium-term fluctuations are more volatile than short-term fluctuations. Chart 19 reports the autocorrelations of year-on-year changes in equity prices, both for the model and for the data.

Table 9

Equity prices and GDP in a model with real rigidities

(cyclical volatilities)

	GROWTH RATES		CYCLE 8-32		CYCLE 32-120		RATIO CYCLES	
	DATA	MODEL	DATA	MODEL	DATA	MODEL	DATA	MODEL
GDP	1.9	1.9	1.0	1.0	1.9	2.2	1.9	2.2
EQUITY PRICES	21.2	21.2	13.3	11.7	19.4	20.4	1.5	1.7

Sources: Own calculations.
Notes: Growth rates are expressed in annual terms. CYCLE 8-32 and CYCLE 32-120 show the standard deviations of cyclical components as derived from the bandpass filter described in Section 2, with bandwidths of 8-32 and 32-120 quarters, respectively. RATIO CYCLES shows the ratio of the two bandpass-filtered cycles. Data source: ECB and Euro Area Business Cycle Network. The data are for the euro area and range from 1987 Q1-2015 Q4. Model simulations are based on Jaccard (2014).

Substantial progress has been made in the modelling of equity prices since Mehra and Prescott (1985) published their paper on the equity premium puzzle. In the context of DSGE models, contributions to the literature include the work of Jermann (1998), Boldrin et al. (2001), Danthine and Donaldson (2002), Campanale et al. (2010), Gourio (2012), Croce (2014) and Jaccard (2014, 2017). These models are also able to match the high equity premium and low mean risk-free rate observed in the data. Overall, the current generation of DSGE models has the potential to reproduce the dynamics of equity prices documented in this paper.

… but fails to reproduce the high volatility of medium-term house price cycles…

By contrast, the DSGE model augmented by real rigidities fails to reproduce the high volatility of medium-term house price cycles. The framework used to generate these artificial data is a real business cycle model with endogenous housing supply (e.g. Davis and Heathcote, 2005), augmented by habit formation and capital adjustment costs. It is possible to find a combination of parameter values that enables the modified model to reproduce the fact that house prices are about twice as volatile as output (see column 1). It is not, however, possible to reproduce the fluctuations in house prices observed at different frequency ranges. As illustrated in Table 10, the model overstates the volatility of house prices at business cycle frequencies, i.e. 2.0 vs. 0.9, and cannot match the high volatility of house prices observed at medium-term frequencies.

Table 10

House prices and GDP in a model with real rigidities

(cyclical volatilities)

	GROWTH RATES		CYCLE 8-32		CYCLE 32-120		RATIO CYCLES	
	DATA	MODEL	DATA	MODEL	DATA	MODEL	DATA	MODEL
GDP	1.7	1.7	1.0	1.0	1.9	1.9	1.9	1.9
HOUSE PRICES	3.6	3.6	0.9	2.0	6.6	3.9	7.3	2.0

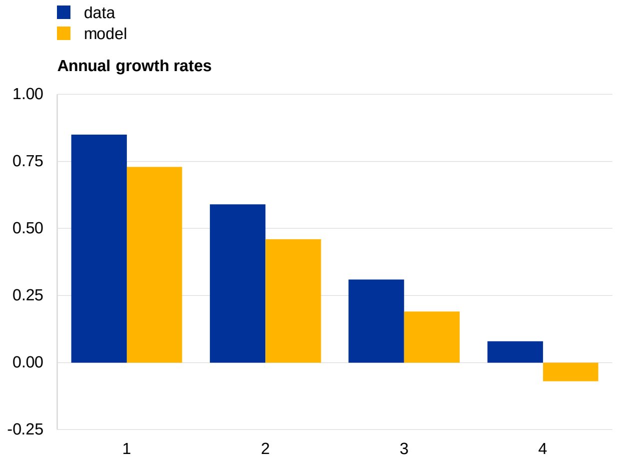
Sources: Own calculations.
Notes: See Table 9 for further explanations. Model simulations are based on Jaccard (2014). Data source: BIS and Euro Area Business Cycle Network, euro area data. The data range from 1980 Q1 to 2015 Q4.

… and their persistence.

As shown in Chart 20, the real rigidities model also fails to reproduce the high persistence of house prices observed in the data. Compared to the frictionless model with endogenous housing supply considered by Davis and Heathcote (2005), introducing real rigidities helps to generate more volatile fluctuations in house prices. When the increase in the volatilities at different frequencies is broken down, the analysis shows that this mechanism again mostly increases the short-term volatility of house price cycles (i.e. from 8-32 quarters). However, as discussed in Sections 2 and 3 of this paper, the total variance of house prices is mostly due to medium-term fluctuations, with a cycle length of 32 to 120 quarters.

Chart 19

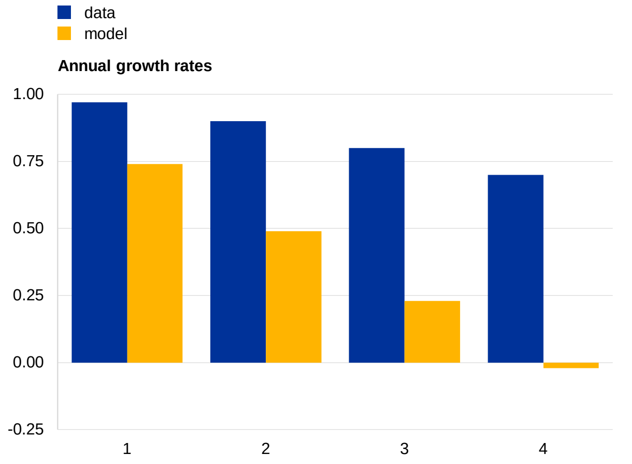
Autocorrelation of equity prices



Sources: Own calculations.
Notes: The chart compares autocorrelations of annual growth in equity prices at lags 1 to 4 in the data and model simulations based on Jaccard (2014). See the notes to Table 9 for further explanations.

Chart 20

Autocorrelation of house prices



Sources: Own calculations.
Notes: The chart compares autocorrelations of annual growth in house prices at lags 1 to 4 in the data and model simulations based on Jaccard (2014). See the notes to Table 10 for further explanations.

7.2 Housing in a DSGE model with borrowing constraints

This subsection looks at a standard medium-sized DSGE model with housing and collateral constraints.

This subsection examines the extent to which models with financial market imperfections can replicate the joint dynamics of GDP and house prices. It uses the EIRE model developed by Lozej et al. (2017), a medium-sized DSGE model developed for the Irish economy, building on earlier work by Clancy and Merola (2014). In this model, households and firms borrow from banks to fund their expenditure. Their real estate wealth is then subjected to idiosyncratic shocks, as a result of which some households find themselves in negative equity at the beginning of the quarter and subsequently default. Defaulting households face a utility cost equivalent to the defaulted amount, which may be thought of as the social stigma or the legal cost associated with bankruptcy. Costly default creates a relationship between the non-financial sectors' cost of external finance and housing wealth, implying that house price fluctuations affect private consumption and non-residential investment.

Apart from the borrower-creditor relationship including credit constraints…

Macro-financial interactions resulting from the link between the ease with which borrowers obtain funds in imperfect credit markets and an asset price have been the defining feature of the integration of credit market frictions into DSGE models since the financial accelerator model of Bernanke et al. (1999). Iacoviello (2005) extended this approach to the housing market. The EIRE model differs from the framework developed by Iacoviello (2005) and Iacoviello and Neri (2010) in that default occurs in equilibrium. Hence, there is an external financial premium which varies over the business cycle, similar to that featured in Bernanke et al. (1999). Furthermore, as outlined by Jakab and Kumhof (2015), and in contrast to most DSGE models with credit constraints, banks create credit not only to intermediate savings from savers to borrowers, but also to fund transactions. This dual role of lending renders credit to the non-financial sector more volatile relative to GDP than in traditional models with credit constraints.

… the model features sticky wages and prices, habit formation in consumption, investment adjustment costs and tradeable and non-tradeable goods producing sectors.

Apart from the borrower-creditor relationship, the EIRE-model is a standard open economy New Keynesian model with sticky wages and prices, habit formation in consumption, investment adjustment costs and tradeable and non-tradeable goods producing sectors. International capital flows are intermediated by a banking sector subject to a minimum capital requirement. Lozej et al. (2017) estimated key model parameters by matching the impulse response functions from an identified VAR featuring GDP, the GDP deflator, house prices, exports and the overnight interest rate (EONIA) as an exogenous variable. The authors identify supply, housing demand, export demand, and monetary policy shocks using sign restrictions.

Table 11

House prices and GDP in a model with borrowing constraints

(cyclical volatilities)

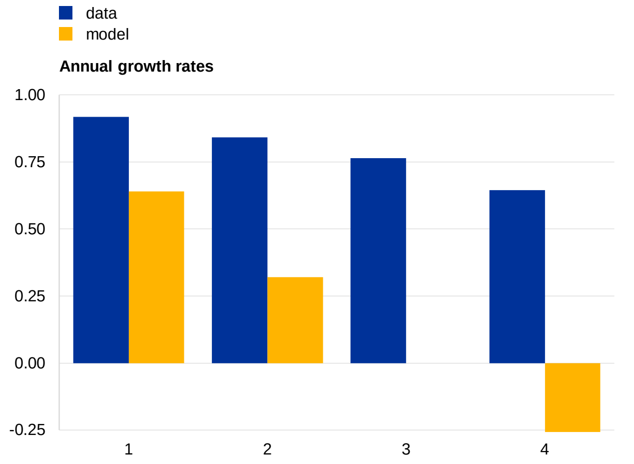
	GROWTH RATES		CYCLE 8-32		CYCLE 32-120		RATIO CYCLES	
Model with default	DATA	MODEL	DATA	MODEL	DATA	MODEL	DATA	MODEL
GDP	4.6	2.8	1.6	1.9	8.7	2.9	5.4	1.2
EQUITY PRICES	9.5	6.8	3.2	3.6	17.5	6.0	5.6	1.3
	GROWTH RATES		CYCLE 8-32		CYCLE 32-120		RATIO CYCLES	
Model w/o default	DATA	MODEL	DATA	MODEL	DATA	MODEL	DATA	MODEL
GDP	4.6	1.8	1.6	1.2	8.7	1.2	5.4	1.3
EQUITY PRICES	9.5	3.4	3.2	2.0	17.5	3.5	5.6	1.6

Sources: Own calculations.
Notes: Growth rates are expressed in annual terms. CYCLE 8-32 and CYCLE 32-120 show the standard deviations of cyclical components as derived from the bandpass filter described in Section 2 with bandwidths of 8-32 and 32-120 quarters, respectively. RATIO CYCLES shows the ratio of the two bandpass-filtered cycles. Model simulations are based on Lozej et al. (2017). Data source: CSO, Central Bank of Ireland. In “Model with default”, households face a utility cost of defaulting, while in “Model w/o default”, this cost is set to zero.

The model performs reasonably well at matching the response of macroeconomic variables, …

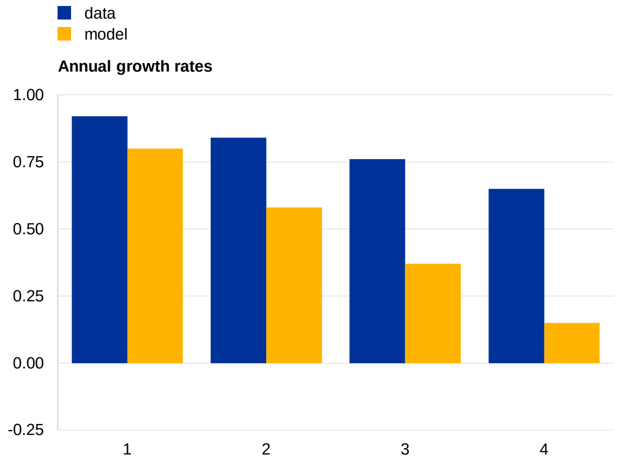
The model performs reasonably well at matching the response of GDP, the GDP deflator and exports to the various shocks, and also generates house price fluctuations of the right order of magnitude (see Lozej et al., 2017). The costly default assumption represents an important amplification mechanism of the response of GDP and house prices to export demand and housing demand shocks, thus adding to the overall volatility of GDP and house prices.

Chart 21
Autocorrelation of house prices



Sources: Own calculations.
Notes: The chart compares autocorrelations in annual growth rates of house prices at lags 1 to 4 in the data and model simulations from Lozej et. al (2017). See the notes to Table 11 for details.

Chart 12
Autocorrelation of house prices in a model with learning



Sources: Own calculations.
Notes: The chart compares autocorrelations in annual growth rates of house prices at lags 1 to 4 in the data and model simulations from a model variant of Jaccard (2014) with learning. See the notes to Table 10 for further details.

… especially in the case of costly default, …

As can be seen from Table 11, the model with costly default reproduces about 60-70% of the volatility of GDP and house price growth (which it has not been calibrated to match), an improvement on the model without financial frictions. Regarding the filtered series, the model with costly default is able to closely match the absolute and relative volatilities of GDP and house prices at the shorter frequencies, while the model without costly default underpredicts the relative volatility of house prices and the absolute volatility of both series.

… but once again underpredicts the volatility of long-term cycles versus short-term cycles and does not generate a hump-shaped response of house prices.

However, while imperfect credit markets enrich the model's macro-financial interactions, the problems outlined in the previous section persist. Both models underpredict the long-term volatility of the series as well as the relative volatility of long-term versus short-term cycles (see Table 11). Finally, the model is not able to replicate the estimated hump-shaped response of house prices. This is because the price of a house is modelled as an asset price, depending only on the current and future expected values of the marginal utility of consumption and housing, and the real cost of borrowing. The inability to generate hump-shaped responses is also reflected in the excessively rapid decay of the autocorrelation of house price growth compared with the data (see Chart 21).

7.3 House price dynamics with information frictions

This subsection complements the analysis above by discussing whether information frictions could help to generate more realistic house-price momentum in DSGE models. Information frictions generally imply that agents are unable to observe or process certain information about the state of the economy. As a result, agents form their expectations by relying on learning, based on the information available. The idea here is that learning increases optimism during booms and pessimism during recessions so, for example, in the face of a booming housing market, learning gradually generates the belief that house prices will continue to increase. This belief then becomes self-fulfilling and contributes to the increase. This conclusion is, therefore, that learning amplifies and propagates the response of house prices to shocks.

Incomplete information regarding housing fundamentals can generate cycles in house prices with higher persistence compared with the model presented in Section 7.1.

To illustrate the idea, consider the baseline model with real rigidities discussed in Section 7.1. First, augment the model by adding a persistent technology shock specific to the construction of new housing stock: this shock represents housing-market fundamentals (e.g. Iacoviello and Neri 2010). Second, suppose that agents base their expectations on a learning rule which assumes that housing-sector shocks are less persistent than they are in reality. Once the model has been augmented by these assumptions, it generates higher autocorrelations of house price growth, as reported in Chart 22. One reason for this improvement is that the housing-sector technology shock process is persistent, although the bulk of the additional momentum comes from the fact that agents are slow to recognise the shocks to housing-market fundamentals and adjust their expectations accordingly. As a result, house prices react gradually and sluggishly to these shocks.

A richer model of information frictions could be based on signal extraction problems …

The example above includes some important simplifying assumptions, since it introduces an arbitrarily persistent housing-sector shock as well as an ad hoc learning rule. The effective modelling of information frictions requires more discipline in respect of the relationship between the learning rule and the features of the exogenous shocks. To date the literature offers only two approaches to modelling information frictions and learning. One of these assumes that agents know the true law of motion that guides the exogenous shock processes, but cannot observe these processes perfectly – they face a signal-extraction problem. In this case, there is a learning rule that corresponds to the true law of motion and that describes the formation of rational expectations subject to imperfect information. For example, Kahn (2008) built a general-equilibrium model with a housing market and introduced a persistent Markov chain augmenting the growth rate of aggregate productivity. Under conditions of imperfect information, economic agents are unable to quickly distinguish regime switches from transient shocks, so the model can produce realistically sluggish and bubbly house-price dynamics. In a similar vein, Rots (2017) introduces exogenous shocks of different persistence into a DSGE model incorporating a housing sector. Under the assumption that transitory and persistent shock components cannot be observed individually, agents rely on learning to gradually disentangle one from the other. The slow recognition of the shocks' persistence adds momentum to house prices, albeit to a limited extend.

… or adaptive learning.

Another approach, which provides more freedom in the choice of a learning rule, includes adaptive learning rules that are not based on the true law of motion of the exogenous fundamentals. For a DSGE model with housing, this approach has been shown to help generate realistic house-price momentum and volatility (e.g. Adam et al. 2011; and Gelain et al. 2013). Studies in this strand of the literature assume that agents predict one or more variables of immediate relevance to their choices but outside their control (e.g. an asset price) using a simple forecasting rule based on only a subset of the state variables. The studies typically proceed to show that the agents are not able to distinguish the perceived from the actual law of motion, since the data are insufficient. For example, the learning rule in Adam et al. (2011) implies that house price growth follows a unit root process, whereas actual house price growth is assumed to be stationary, two hypotheses that are empirically difficult to disentangle (e.g. Christiano and Eichenbaum, 1990). Beyond housing markets, a number of recent studies have presented DSGE models that employ adaptive learning to better mimic the dynamics of consumption, investment, inflation or labour hours (e.g. Eusepi and Preston, 2011; Huang et al. 2009; Milani, 2007; and Orphanides and Williams, 2004).

The assumption that agents rely on learning to form expectations enjoys empirical support.

The assumption that agents rely on learning to form expectations enjoys empirical support. For example, Edge et al. (2007) show that the projections of economists and professional forecasters for long-run growth in total factor productivity for the US are close to those obtained using a linear steady-state Kalman filter. In line with the intuition that learning creates optimism during booms, Foote et al. (2012) argue that US housing-market participants acted rationally at the onset of the 2007-2009 financial crisis, holding beliefs that turned out to be overly optimistic ex post. Similarly, Garriga et al. (2014) show that, given housing-market fundamentals observed in the US prior to the crisis, a general-equilibrium model including the housing market can replicate an observed housing boom only when expectations about housing market fundamentals are assumed to be over-optimistic.

Information frictions have also been successfully introduced into search and matching models of the housing market to generate house-price momentum (e.g. Piazzesi and Schneider, 2009; and Glaeser and Nathanson, 2015). Burnside et al. (2011) created a model including heterogeneous beliefs about imperfectly observable housing-market fundamentals. In their model, an infectious mechanism spreads the prevailing belief regarding fundamentals and creates a housing boom that may be followed by a bust if the dominant belief turns out to be incorrect.

7.4 Discussion

It is a challenge for DSGE models to generate the large and persistent fluctuations observed in house prices and credit.

The empirical facts revealed in this paper have important implications for DSGE modelling. Our analysis shows that generating the large and persistent fluctuations observed in financial variables such as house prices can be a challenge for models of the type normally used in central banks for policy analysis. By contrast, existing frameworks are considerably more successful at reproducing the joint dynamics of financial market returns and business cycle aggregates. One reason for the difference may be that financial market returns have received considerable attention – in comparison with the vast body of research on financial market returns, the macroeconomic literature on housing markets remains at a relatively early stage of development (e.g. Piazzesi and Schneider 2016).

It should be emphasised that the results presented in this section have been obtained by studying a limited number of theoretical mechanisms. It should also be borne in mind that the models above were not developed with the aim of explaining medium-term fluctuations in house prices but, rather, to address a different issue.

Models with real rigidities and financial frictions bring the frictionless benchmark into closer conformity with the data …

Our review of different model mechanisms reveals that introducing real rigidities or financial frictions into DSGE models that include housing markets helps to increase the volatility of house prices. With regard to the macro-housing model developed by Davis and Heathcote (2005), introducing these features therefore helps to bring the frictionless benchmark into closer conformity with the data. However, our analysis also shows that reproducing the medium-term volatility of house prices still represents a formidable challenge for standard models.

This section also reports simulations obtained using models in which learning rules have been introduced. The findings confirm that introducing deviations from the rational expectations paradigm may help to resolve the puzzle of missing house price persistence documented in this section. Given the exploratory nature of the analysis, it should be emphasised that this result is subject to a number of simplifying assumptions such as, for instance, the introduction of ad hoc learning rules. Developing a more sophisticated model mechanism is beyond the scope of this section and more disciplined approaches to learning that have recently been proposed are discussed in a selective literature review.

… but further research is required. Models with imperfect information would appear to be an interesting option.

In terms of future research, the analysis suggests that the challenge will be to develop models that can simultaneously reproduce the dynamics of house prices and equity returns within the same unified framework. Introducing imperfect information into DSGE models with real rigidities and financial frictions may be an interesting direction for future exploration.

8 Conclusions

Perhaps the most important stylised fact found in the present study (and in the studies it builds on) is the important role of medium-term fluctuations in GDP, credit and house prices, and the close co-movements between these three cycles.

Whether these fluctuations should be called medium-term business cycles or financial cycles may be largely a matter of semantics. However, the fact that IMF (and OECD) output gap estimates seem to include medium-term fluctuations in GDP lends support to the former term (Section 3). On the other hand, GDP appears to be subject to additional short-term fluctuations that are not shared by credit and house prices and may, therefore, reflect other types of disturbances and transmission mechanisms. Overall, the close co-movement of these three series at medium-term frequencies most certainly does not support the view that business and financial cycles should be regarded as “independent phenomena” as suggested by Drehmann et al. (2012). Whatever the preferred terminology, there is no economic justification for a distinction based on cycle lengths.

The links between medium-term cycles in real activity, house prices, and credit emphasise the urgent need for both theoretical and empirical models to analyse the innovations and propagation mechanisms driving real economic activity and housing markets. The aim is to disentangle aggregate demand and supply innovations from those arising in the credit and housing markets, and to assess the impact of both types of innovation on aggregate fluctuations and housing markets. Such an analysis would also provide a deeper understanding of the links between monetary and macroprudential policies.

Although research in this direction has made some progress, there are still few studies assessing the effects of credit supply shocks (e.g. Mumtaz et al., 2015; Gambetti and Musso, 2016). Similarly, studies on the effects of macroprudential policies are still scarce, partly due to the lack of data on past policy implementation (for a recent review see Galati and Moessner, 2013). With regard to theoretical models, the challenge of the future is to reproduce the dynamics of both house prices and equity returns within a unified framework that can account for the persistence of cycles in house prices and credit. Introducing imperfect information into DSGE models with real rigidities and financial frictions may be one promising direction.

Another policy-relevant finding is that the volatilities of cycles in house prices and credit vary dramatically across EU countries and are only weakly synchronous. These differences may partly reflect the links between private homeownership, the share of mortgage financing held by middle-income households, and the role played by collateral constraints in driving medium-term cycles. Cross-country differences suggest that potential benefits could arise from implementing country-specific macroprudential policies. To the extent that leverage cycles also imply weakly synchronous medium-term fluctuations in GDP, macroprudential policies aimed at limiting leverage cycles could also contribute to containing macroeconomic imbalances.

Finally, the findings in this paper have a number of implications for the construction and use of financial cycle indicators. First, the cyclical properties of equity prices and bond yields appear to differ significantly from those of credit volumes and house prices: the former are subject to fairly short cycles that are highly synchronous across countries. This suggests that it is important to distinguish between cycles in credit and house prices and those in liquid assets. Separate indicators may be required to evaluate the build-up of systemic risks in each of these spheres. Second, real-time estimates of cycles in house prices and credit are subject to high uncertainty on a scale similar to that affecting estimates of the output gap. This suggests that policymakers should interpret estimates cautiously and need to combine them with other information sources. At the same time, real-time uncertainty could be reduced by using multivariate approaches that combine real and financial information to estimate medium-term cycles.

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Methodological annex

Wavelet analysis

Wavelet analysis is an extension of spectral analysis that allows for time variation. It is therefore able to distinguish a case where a series is the sum of several cycles at different frequencies from a case where a series is characterised by structural change, i.e. it consists of a single cycle with a frequency that shifts across subsamples.

Specifically, wavelet analysis decomposes a time series into periodic functions (waves) with only finite support, facilitating the location of changes in the importance of specific cyclical frequencies over time (Cazelles et al. 2008). Its advantage over rolling window Fourier analysis is that it uses efficient windowing, since the window width is adjusted endogenously, depending on the frequency as the wavelet is stretched or compressed.

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

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

where s represents the scale (which is inversely related to frequency) and τ the location over time. It is calculated for all combinations of scales and time and provides information simultaneously for both time and frequency.

Specifically, the empirical analysis is based on the Morlet wavelet:

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

The Morlet wavelet may be described as a Gaussian modulated sine wave. At its centre it behaves like a sine wave, although towards its tails it dies out fairly quickly. The Morlet wavelet with $\omega_0 = 6$ has optimal time-frequency localisation and a direct relationship between scale and frequency ($\omega \approx 1/s$). The wavelet power spectrum $WPS_x(\tau, s) = |W_x(\tau, s)|^2$ measures the relative contribution to the variance of the time series at each scale and at each point in time. The larger $WPS_x(\tau, s)$ at frequency s_i around τ_i, the more important the fluctuations at this frequency.

Finally, the co-movement of two time series may be estimated by dynamic correlation:

$$\rho_{ij}(\tau, s) = \frac{\mathcal{R}\left(W_{x_i x_j}(\tau, s)\right)}{\sqrt{WPS_{x_i}(\tau, s)\sqrt{WPS_{x_j}(\tau, s)}}}$$

where $\mathcal{R}$ denotes the real part of the cross-wavelet transform $W_{x_i x_j}(\tau, s)$. The latter represents the local covariance between series x_i and x_j at each point in time τ_i and frequency s_i. Based on dynamic correlation, Rua and Silva Lopes (2015) propose a measure of cohesion, which is a weighted average of all pairwise dynamic correlations with certain weights w_i and w_j representing weights (e.g. GDP weights):

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

Significance of cohesion is tested by a parametric bootstrap. A number of simulated replications for each series are generated, based on estimated uncorrelated autoregressive processes. Using the dynamic correlations for these replications it is possible to derive the simulated distribution of cohesion under the null hypothesis of unrelated time series.

The structural time series model

The analysis in Section 3 is based on a version of the multivariate STSM from Rünstler and Vlekke (2016). As in the original model created by Harvey and Koopman (1997), cyclical dynamics is modelled from stochastic cycles (SCs), albeit with various extensions to allow for (i) different cycle lengths of individual series (ii) phase shifts among these (Rünstler, 2004); and (iii) extended dynamics (an additional autoregressive root) to account for the high persistence of medium-term cycles.

The model decomposes GDP, credit, and house prices into trend and cyclical components and explicitly models the dynamics of each of these. Cyclical components emerge as mixtures of three latent stochastic cyclical processes of potentially different lengths and persistence. This approach thereby models the joint cyclical dynamics of GDP, credit and house prices, while allowing for differences in the dynamics of the individual series.

Consider the vector of three non-stationary series $y_t = (y_{1,t}, y_{2,t}, y_{3,t})'$ for $1 \leq t \leq T$. The multivariate STSM decomposes these series into the trend $\mu_t = (\mu_{1,t}, \mu_{2,t}, \mu_{3,t})'$ and cyclical components $c_t = (c_{1,t}, c_{2,t}, c_{3,t})'$ as follows.

$$y_t = \mu_t + c_t + e_t$$

$$\mu_t = \beta_t + \mu_{t-1} + v_t$$

$$\beta_t = \beta_{t-1} + u_t$$

$$c_t = (A, A^*) \binom{\varphi_t}{\varphi_t^*}$$

The trend component μ_t is modelled, as in Harvey and Koopman (1996), as a local linear trend, i.e. a multivariate random walk with time-varying drift β_t. Both $v_t \sim N(0, \Sigma_v)$ and $u_t \sim N(0, \Sigma_u)$ are independently normally distributed. Irregular component $e_t \sim N(0, \Sigma_e)$ is a white noise term.

Cyclical component c_t is modelled as a mixture of three independent latent stochastic cycles (SCs), with loadings given by 3x3 matrices (A, A^*). The stochastic cycle is defined as

$$\left[(1-\omega_i L)(1-\rho_i \begin{pmatrix} \cos\lambda_i & \sin\lambda_i \\ -\sin\lambda_i & \cos\lambda_i \end{pmatrix} L\right] \begin{pmatrix} \varphi_{i,t} \\ \varphi_{i,t}^* \end{pmatrix} = \begin{pmatrix} \varepsilon_{i,t} \\ \varepsilon_{i,t}^* \end{pmatrix}$$

where L is the lag operator and innovations $\left(\varepsilon_{i,t}, \varepsilon_{i,t}^*\right)' \sim N(0, I_2)$ follow a bivariate standard normal distribution.

The SC is a stationary process that gives rise to cyclical fluctuations, which are of length $2\pi/\lambda_i$, while parameters $0 \leq \omega_i < 1$ and $0 \leq \rho_i < 1$ govern their persistence. The case of $\omega_i = 0$ corresponds to Harvey and Koopman (1997). Rünstler and Vlekke (2016) propose a more general specification to account for the high persistence of medium-term cycles.

Finally, vector $(\varphi_t, \varphi_t^*)'$ is given as $\varphi_t = (\varphi_{1,t}, \varphi_{2,t}, \varphi_{3,t})$ and $\varphi_t^* = \left(\varphi_{1,t}^*, \varphi_{2,t}^*, \varphi_{3,t}^*\right)$.

The parameters of this model $(\Sigma_v, \Sigma_u, A, A^*, \omega_i, \rho_i, \lambda_i)$ for $i = 1, \dots, 3$ are estimated either by the maximum likelihood or by the Bayesian techniques via the Kalman filter. Finally, based on parameter estimates, estimates of trend and cyclical components are obtained.

For countries with long datasets, we estimate the parameters from the maximum-likelihood approach. For countries with short data, the team has implemented a Bayesian routine. Priors have been selected as follows:

1. Fairly informative priors have been imposed on the parameters governing cyclical dynamics $\omega_i, \rho_i, \lambda_i$. The prior for parameter λ_i, has been centred at cycle length 7.85 years and normal prior uncertainty. The priors on autoregressive parameters ω_i and ρ_i are given by a Beta distribution centred at 0.75. These choices are based on existing empirical evidence concerning the dynamics of real and financial cycles. They are, however, somewhat conservative in the sense that they favour business as opposed to medium-term cyclical dynamics.

2. Largely uninformative normal priors are used for the loading coefficients of the two matrices (A, A^*), since these are expected to be driven by country-specific factors. All loading parameters, with the exception of the diagonal elements of A, are centred at zero and have normal prior uncertainty. The diagonal elements of A, which are required to be non-negative, have inverse-Gamma priors.

3. For trend innovations, the inverse-Gamma priors specify the volatility of shocks e_t and v_t to be five times as large as that for the stochastic slope innovation u_t. This specific choice of priors is driven by the findings of earlier studies.

Although implementing a STSM is more expensive than running a bandpass filter, the model-based approach results in a filter that is tailored to the observed time series, which has various advantages over bandpass filters. First, it allows for a more precise characterisation of cyclical dynamics in a multivariate context. Second, it reduces the risk that spurious cycles will be obtained – as documented for bandpass filters (Murray, 2003). Third, the multivariate approach uses the information contained in the co-movements of the series, thereby potentially allowing more precise estimates to be achieved.

Synchronicity and similarity indices

Define a binary synchronicity measure between cycles $c_i\ (t)$ and $c_j\ (t)$ at time *t* as $\varphi_{ij}(t) = 1$ if $c_i\ (t)$ and $c_j\ (t)$ are of the same sign and $\varphi_{ij}(t) = -1$ if not. The average synchronicity between the two series is then calculated as

$$\varphi_{ij} = -1 \leq \frac{1}{T}\sum_{t=1}^{T}\varphi_{ij}(t) \leq 1$$

If average synchronicity is $\varphi_{ij} = 1$, then the two series are perfectly synchronous. Furthermore, a measure of the overall synchronicity of a group of *n* countries (indexed by *i = 1,...,n*) with a certain reference cycle r at time *t*, $c_r\ (t)$ is obtained from

$$\varphi(t) = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}\varphi_{ir}(t).$$

Similarity measure $\gamma_{ir}(t)$, taking into account the absolute differences between the cycle of a country i and a reference cycle $c_r\ (t)$, is defined as

$$\gamma_{ir}(t) = 1 - \frac{|c_i(t) - c_r(t)|}{\sum_{\mathrm{i}=1}^{\mathrm{n}}|c_i(t)\,|/n}.$$

The overall similarity for a group of countries is obtained by averaging the measure above over all countries

$$\gamma(t) = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}\varphi_{ir}(t).$$

The reference cycle $c_r\ (t)$ is calculated as the median of cycles across all countries under analysis (i.e. the median computed at each point in time). Calculated in this way, the reference cycle maximises both overall synchronicity and similarity. These measures are now normalised to lie between zero (minimal cycle coherence) and unity (maximal cycle coherence). For details see Mink et al. (2012).

To measure phase synchronicity, the extracted cycles are mapped into two distinct binary indicators, with one reflecting the upswings/downswings (swing synchronicity) in cycles and the other reflecting the sign of the cycle (gap synchronicity): $B_i^{swing}(\mathrm{t}) = \frac{\Delta c_i(t)}{|\Delta c_i(t)|}$, and $B_i^{gap}(\mathrm{t}) = \frac{c_i(t)}{|c_i(t)|}$, where $\Delta c_i\ (t)$ denotes the first difference of $c_i\ (t)$. A time series of gap and swing synchronicity between countries *i* and *j* from is given by the products

$$S_{ij}^{swing}(t) = B_i^{swing}(\mathrm{t})B_j^{swing}(\mathrm{t})$$

$$S_{ij}^{gap}(t) = B_i^{gap}(\mathrm{t})B_j^{gap}(\mathrm{t})$$

Note that the perfect (negative) synchronicity of two cycles leads to the conditions $\mathrm{E}[S_{ij}(t)] = 1$ ($\mathrm{E}[S_{ij}(t)] = -1$), while non-synchronicity (cycles being in the same phase and the opposite phase with the same probability) leads to $\mathrm{E}[S_{ij}(t)] = 0$.

Meller and Metiu (2015) propose a statistical test on the null hypothesis that cycles are either not or are negatively synchronous on average H_0: $\mathrm{E}[S_{ij}(t)] \leq 0$ against the one-sided alternative H_1: $\mathrm{E}[S_{ij}(t)] > 0$ of positively synchronous cycles. This is based on the distribution of mean values of the time series $S_{ij}(t)$.

Bilateral synchronicity measures for all country pairs can be used to construct a symmetric matrix of dissimilarities between countries based on bilateral estimates of $\mathrm{E}[S_{ij}(t)]$

$$\boldsymbol{D}_{nxn} = [D_{ij}] = \left[1 - \mathrm{E}[S_{ij}]\right].$$

Finally, the dissimilarity matrix is used to calculate a multidimensional scaling map, i.e. a two-dimensional representation of the distances between the countries that approximately preserves the *n(n-1)/2* pairwise distances between countries given in the dissimilarity matrix.

Macro-financial indicators: data sources

Homeownership rates are taken from the Eurostat EU-SILC survey and the average is calculated over the sample period 2003-2015. Data for regulatory maximum LTV ratios are taken from ECB (2016) and integrated with information from the IMF (2011) and national sources for Lithuania, Slovenia, Greece, and Hungary. The data for the shares of flexible rate mortgages refer to loans to households for house purchases with different initial rate fixation periods (new business), provided by the ECB Statistical Data Warehouse. We consider the average value over the entire available period 2001-2017. The gross value added of the financial sector and the real estate and construction sector over GDP is from Eurostat and is averaged over 1995-2015. Similarly, current account balances (as percentages of GDP) from the IMF WEO database are averaged over the period 1994-2014. Finally, current misalignments are taken from Comunale (2006; 2017b). The estimates are based on the Macroeconomic Balance (MB) approach of the IMF CGER (Lee et al., 2008).

Abbreviations

Countries

BE	Belgium	**HR**	Croatia	**PL**	Poland
BG	Bulgaria	**IT**	Italy	**PT**	Portugal
CZ	Czech Republic	**CY**	Cyprus	**RO**	Romania
DK	Denmark	**LV**	Latvia	**SI**	Slovenia
DE	Germany	**LT**	Lithuania	**SK**	Slovakia
EE	Estonia	**LU**	Luxembourg	**FI**	Finland
IE	Ireland	**HU**	Hungary	**SE**	Sweden
GR	Greece	**MT**	Malta	**UK**	United Kingdom
ES	Spain	**NL**	Netherlands	**US**	United States
FR	France	**AT**	Austria		

In accordance with EU practice, the EU Member States are listed in this report using the alphabetical order of the country names in the national languages.

Others

BIS	Bank for International Settlements	GDP	gross domestic product
CPI	Consumer Price Index	HICP	Harmonised Index of Consumer Prices
DG ECFIN	Directorate General for Economic and Financial Affairs, European Commission	i.i.p.	international investment position
ECB	European Central Bank	ILO	International Labour Organization
EDP	excessive deficit procedure	IMF	International Monetary Fund
EER	effective exchange rate	MFI	monetary financial institution
EMI	European Monetary Institute	MIP	macroeconomic imbalance procedure
EMU	Economic and Monetary Union	NCB	national central bank
ERM	exchange rate mechanism	OECD	Organisation for Economic Co-operation and Development
ESA 95	European System of Accounts 1995	SSM	Single Supervisory Mechanism
ESCB	European System of Central Banks	TSCG	Treaty on Stability, Coordination and Governance in the Economic and Monetary Union
ESRB	European Systemic Risk Board		
EU	European Union		
EUR	euro		

Conventions used in the tables

"-" data do not exist/data are not applicable
"." data are not yet available

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