EUROPEAN CENTRAL BANK

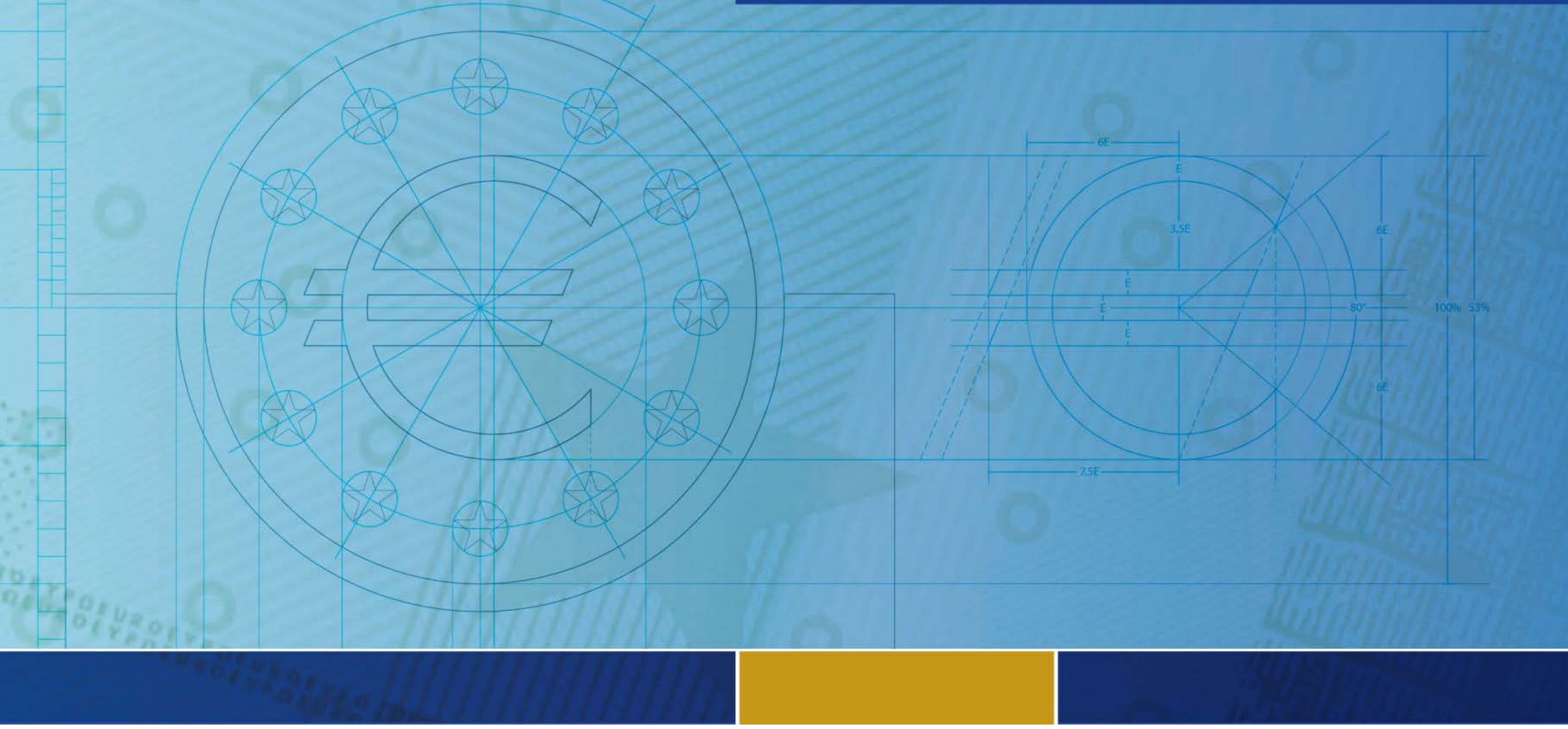
EUROSYSTEM

Working Paper Series

Hanno Stremmel

Capturing the financial cycle in Europe

No 1811 / June 2015



ABSTRACT

In this study, we approximate the financial cycle in Europe by combining potential common and relevant financial indicators. We consider different credit aggregates and asset prices but also incorporate banking sector indicators for 11 European countries. We develop seven different synthetic financial cycle measures in order to best capture the characteristics of the financial cycle. We assess the various financial cycle measures using both graphical and statistical investigation techniques. The best-fitted financial cycle measure includes the following financial ingredients: credit-to-GDP ratio, credit growth and house-prices-to-income ratio. This study also highlights potential applications for the financial cycle measure in the macro-prudential policy context.

JEL Classification: E30, E44, E61, G18, G28
Keywords: financial cycle, financial regulation, medium term, financial crises.

Non-technical Summary

The global financial crisis of 2007 has drawn significant attention to the analysis of financial stability and the causes of financial crises. Macro-prudential policy has emerged as an important policy area designated to safeguard financial stability. The vulnerabilities within the financial system are often based on cyclical movements of financial variables (e.g. booms or busts phases). These are fraught with risks and may lead to serious financial and macroeconomic tensions. Therefore, the understanding of the financial cycle and its drivers is essential for the conduct of macro-prudential policy. This has particular relevance for activating certain macro-prudential tools, such as time-varying capital buffers, that are linked to certain stages in the financial cycle.

In contrast to cyclical movements in the real economy (business cycle), no "natural" cycle measure is available for the financial sector. In comparison to business cycles, financial cycles evolve over the medium term and their analysis goes beyond the shorter-term focus of business cycle theory. The cyclical movements of financial variables may amplify economic fluctuations, trigger imbalances, lead to macroeconomic destabilisation and/or threaten financial stability.

In this paper, we review different construction techniques to create a financial cycle for European countries. We consider various financial indicators (e.g. asset prices, credit aggregates and banking sector variables) in the process. We create different synthetic financial cycle measures that vary in the involved variables and identify the most appropriate measure by employing graphical and statistical assessment techniques. The key ingredients of the best fitted financial cycle measure for Europe include credit aggregates (credit-to-GDP ratio, credit growth) and assets prices (house-prices-to-income ratio).

Our paper contributes to the literature by developing a commonly applicable financial cycle measure for Europe. This paper further highlights potential applications of the financial cycle metric in financial stability analysis and contributes to the ongoing discussion on macro-prudential policy. We investigate the characteristics of business and financial cycles and provide evidence that financial cycles are often associated with the onset of financial crises. We also investigate the synchronicity of financial cycles across various European countries and find evidence that financial cycles are more correlated during stress times than in boom periods - an insight that should be taken into account in the policy-making process. Lastly, the paper provides a starting point for further analysis regarding the potential drivers of the duration and amplitude of the financial cycle as well as their importance for macro-prudential policy.

1 Introduction

The recent global financial crisis of 2007 has triggered a re-evaluation of the macroeconomic policy. In particular the crisis has drawn significant attention to the analysis of financial stability and the causes of financial crises, such as financial linkages and systemic risks. As a response to the crisis, more attention is paid to the development of macro-prudential policy tools and the establishment of a new institutional framework for the conduct of macro-prudential policy. The new institutional setting is often similar to that of monetary policy and comes with the definition of new policy mandates and objectives. However, macro-prudential policy faces huge challenges. In the literature there is an ongoing debate on how to define macro-prudential objectives and how to measure systemic risk or the financial cycle (Hansen, 2012). This uncertainty may lead to either inactivity of policy makers by deferring necessary policy decisions or to dubious decisions that are not accepted or properly understood by market participants. Despite these open issues, the newly designed macro-prudential entities in Europe have begun to conduct macro-prudential policy (ESRB, 2014). Overall, policy making seems to be ahead of the empirical underpinning.

Cyclical movements of the financial indicators are a recurring influencing factor for vulnerabilities within the financial system. During the last few decades academics have started endeavours to obtain a better understanding of empirical regularities of the "financial cycle". Cyclical financial movements such as expansions or booms and contractions (or busts) phases are fraught with risks and may lead to serious financial and macroeconomic tensions. In particular, the behaviour and development of the credit cycle has been explored for a long time. Although credit booms are the foundation of credit crunches, causes of financial crises and vulnerabilities may have more than just the credit dimensions. Moreover, also other financial variables with unstable expansion may contribute to the vulnerability.

The understanding of the financial cycle and its drivers, as well as policy-makers' awareness of the actual phase in the financial cycle, is essential for the conduct of macro-prudential policy (e.g. Borio, 2013). The activation of macro-prudential measures, such as time-varying capital buffers, refers to stages in the financial cycle (Detken et al, 2013).

In contrast to business cycles, no obvious "natural" financial cycle measure is available. Recent literature shares a broad description of the financial cycle but struggles to come up with an appropriate indicator. Financial cycles can be distinguished from business cycles through their amplitude and frequency. Financial cycles evolve over the medium term and their analysis should go beyond the shorter-term focus of business cycle theory. This means that the completion of full peak-to-trough cycles may last up to decades (Aikman et al, 2010, 2014). Borio (2012) defines financial cycles as "self-reinforcing interactions between perceptions of value and risk, attitudes towards risk and financing constraints, which translate into booms followed by busts". The interactions may amplify economic fluctuations, trigger imbalance and lead to macroeconomic destabilisation and/or threaten financial stability. In this study, we follow this financial cycle definition.

In this paper, we aim to reduce the uncertainty arising from the unclear definition of the financial cycle by creating a synthetic or artificial financial cycle measure. Individual cyclical measures may neglect important developments in other financial market segments. Accordingly, it appears more sensible to construct cycle measures for the whole financial sector. We try to capture the financial cycle in Europe by accounting for and combining the different influences of financial indicators. A synthetic measure allows us to analyse the joint behaviour of different potential influence factors. Our goal is to come up with a common synthetic measure that is suitable to capture the financial cycle for European countries. It should be emphasised that a common measure is needed to ensure accountability and comparability of the cycle among countries and for macro-prudential policy purposes.

Before capturing financial cyclical movements and creating a synthetic financial cycle, we briefly review the literature. One strand of literature describes financial cycles indirectly and obtains findings of financial cycles en passant their respective analytical goals. Studies relate financial indicators such as asset prices or credit aggregates to economic activities (e.g. Detken and Smets (2004), Goodhart and Hofmann (2008), Schularick and Taylor (2012), Aizenman et al. (2013), Borio et al. (2013), Bracke (2013)). Others use financial factors as leading indicators in early warning systems (e.g. Borio and Lowe (2002, 2004), English et al. (2005), Borio and Drehmann (2009), Alessi and Detken (2011), Ng (2011)).

The direct way of characterising the financial cycles started in the aftermath of the Global Financial Crisis. Aikman et al. (2010, 2014) investigate credit cycle characteristics across 14 advanced countries over a long period (1870–2008). Claessens et al. (2011a, b) analyse cyclical movements of credit, housing and equity prices for 21 advanced countries from 1960 to 2007. Both analyses provide evidence of high synchronicity of the individual series, in particular between the credit and house price cycle. The paper by Drehmann et al. (2012) is the first attempt to construct a synthetic financial cycle measure by combining medium-term fluctuations of financial variables for seven advanced countries from 1960 to 2011. The combination of credit aggregates and house prices works well, whereas equity prices tend to be destructive rather than beneficial. They also show that a financial cycle's amplitude and duration have increased since the mid-1980s. Aikman et al. (2010, 2014) and Drehmann et al. (2012) exhibit tight links between peaks of financial cycles and systemic banking crises. Although the literature employs different metrics, it provides similar conclusions and insights: Compared to business cycles, financial cycles tend to have a higher amplitude and lower frequency.[1]

Closely linked to the literature on financial cycles, our study is also related to the macro-prudential policy framework. An increasing amount of literature is devoted to investigating the effectiveness of the cyclical movement of credit measures (e.g. credit-to-GDP gap) for defining the counter-cyclical capital buffer rate. The cyclical movement of this credit measure is used as an early warning indicator to spot the build-up of financial vulnerabilities, although the predictive power of various credit aggregate measures varies (e.g. Detken et al. (2014), Drehmann and Tsatsaronis (2014), Wezel (2014)). Recent studies confirm the ability of the credit-to-GDP gap to spot vulnerabilities within the financial system in a cross-country framework (e.g. Bush et al. (2014), Detken et al. (2014), Giese et al. (2014), Hiebert et al. (2014)). In addition to these studies on the effectiveness, there is also an emerging strand of literature providing guidance on the implementation and calibration of the counter-cyclical capital buffer (e.g. Behn et al. (2013), Detken et al. (2014), Drehmann and Juselius (2014)).

Our paper contributes to the literature in four ways. First, we use a wider country sample to determine the financial cycle measure. Thereby, we focus on European countries and incorporate as many countries as possible. In doing so, we develop a commonly applicable financial cycle measure. Second, we enlarge the scope of financial indicators. Besides traditional credit and asset price indicators, we also include banking sector variables. Third, we perform a 'horse race' of different financial cycle measures using graphical and statistical techniques to determine the potentially best measure to describe the financial cycle. Lastly, our paper highlights various potential application options of the financial cycle metric.

The remainder of this paper is organised as follows. In the next section we describe the underlying data for the construction of the financial cycle. The third section explains the methodologies used for constructing financial cycles, whereas Section 4 constructs different financial cycle measures for a European sample. The fifth section employs various tools to assess the different synthetic financial cycle measures with respect to their fit. Section 6 elaborates on potential applications of these financial cycle measures, before concluding and discussing the policy implications in Section 7.

2 Data Description

To capture the financial cycle we aim to incorporate as many European countries as possible in our empirical exercise. The selection of EU Member States in our sample is driven purely by the data availability. We require a country's variables to have long time spans to be able to characterise financial cycle patterns and to draw conclusions regarding the

[1] Busch (2012) confirms these findings for Germany by exploring the cyclical nature of credit measures and business cycles.

appropriateness of financial cycle measures. Accounting for these constraints and using quarterly data, we construct financial cycle measures for 11 countries (Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Spain, and United Kingdom) for the period of 1980Q1 to 2012Q4.

The literature on financial cycles is relatively new and less researched than business cycle theory. In constructing the synthetic financial cycle we follow the approach by Drehmann et al. (2012) and combine different individual filtered time series. The variable choice is not obvious due to the lack of a common financial cycle definition. Also the requirement of long time horizons cancels out many potential financial variables (e.g. default rates or risk premiums).

In total, we consider seven different potential components of financial cycles. Four potential ingredients describe financial sector developments (asset prices and credit aggregates). The choice of the financial sector variables follows the spirit of Kindleberger (1978) and Minsky (1972, 1982, 1986) as well as recent financial cycle literature (Aikman et al. (2010, 2013), Claessens et al. (2011a, b), Drehmann et al. (2012)):

a) For assets prices we include the development of property prices by using the *nominal house prices-to-nominal disposable income* (per head). Both underlying time series are sourced through the ECB Statistical Data Warehouse (SDW) and are based on European Member States national statistics.
b) To capture credit developments we incorporate the *credit-to-GDP ratio*. This measure is often employed in macro-prudential literature (e.g. Detken et al, 2014). As a credit measure we use the 'nominal bank credit to households and non-financial counterparties' from the BIS credit database. The GDP is sourced via the IMF's International Financial Statistic database and is included in nominal terms.[2]

In addition, we calculate growth rates using the data series from (a) and (b), respectively. These growth figures are designed to capture different movements of acceleration and speed of the indicators:

c) *Annual growth rates of the nominal bank credit to households and non-financial counterparties.*
d) *Annual growth rates of house prices*.

Moreover, we incorporate three bank balance sheet data variables which characterise the behaviour of the banking institutions directly. We source the potential banking sector variables through the OECD Banking Statistics database.[3] This database is not an optimal

[2] We also applied various credit data (series of credit levels vs growth rate) and the credit source (IMF vs BIS), but our results do not depend on this choice. The results are available upon request.
[3] OECD series are yearly data and only available until the year 2010. The series are transformed from annual into quarterly series to meet the units of the remaining variables.

source, since the availability of the data is heavily constrained in comparison to the former financial indicators.[4] However, to the best of our knowledge, this is the most comprehensive database on balance sheet variables from the banking sector. We consider the following variables:

- *e) (Short-term) Funding-to-total assets* accounts for cyclical behaviour in bank funding.
- *f) Net income-to-total assets* captures profitability of the banking sector over the cycle.
- *g) Proportion of loans to total assets* captures banking sector lending over the cycle.

All indicators are incorporated in nominal terms and are normalised to a common level to ensure comparability of their units. The two growth variables are the four-quarter difference in log-levels, whereas the other indicators are in percentage points. We also incorporate real variables, but the results do not depend on this choice.

For assessment and evaluation purposes of the potential synthetic cycle measures, we utilise two banking crises databases. On the one hand, we adopt the European System of Central Banks (ESCB) *Heads of Research Group Banking Crises Database* as described in Detken et al. (2014). On the other hand, we cross-check the results with the Laeven and Valencia (2008, 2010, 2012, 2013) *Systemic Banking Crises Database*. The two databases contain different crisis events due to the diverging compiling strategies. The former one condenses different banking crisis databases but also involves a discretionary judgment by local authorities whereas the latter database follows a purely rule-based approach. To overcome potential divergences and issues, we employ both crisis indicators for investigating the coincidence of synthetic financial cycle measures with financial crises. We adjust and control both measures for the post-crisis bias identified by Bussiere and Fratzscher (2006) by considering only the start period of the crisis. Remaining periods of the on-going crisis are omitted to avoid any influences to the leading indicators after the onset of the crisis.

3 Methods to Construct the Financial Cycle

Previous literature has delivered first insights in financial cycles but falls short of developing a commonly accepted medium-term financial cycle measure for a heterogeneous set of countries. Indeed, the literature diverges both on the construction techniques and the ingredients of the cycle. We try to tackle this by creating and analysing various synthetically combined financial cycle measures for European countries. Our goal is to identify the best measure for approximating empirically the financial cycle.

Synthetic cycles are obtained by aggregating individual financial indicator cycles. The idea behind synthetic measures is to capture a range of potential influences without quantifying

[4] The database does not provide any data for the United Kingdom. For other countries such as Ireland or Italy certain years are not available.

their exact relationship. Before presenting the creation and selection process of the synthetic financial cycle indicators, it is important to discuss the range of construction techniques. The methodologies used are adapted from business cycle literature. Recent financial cycle literature portrays two analytical approaches (e.g. Aikman et al. (2010, 2013), Claessens et al. (2011a, b), Drehmann et al. (2012)). The turning point analysis determines cyclical peaks and troughs within the time series using an algorithm, whereas the frequency-based filter analysis is a statistical filter technique to isolate fluctuations with different frequencies.

The *turning point analysis* allows peaks and troughs of a certain underlying time series to be determined. The algorithm was developed to identify the turning points of business cycles (e.g. Burns and Mitchell (1946), Bry and Boschan (1971), Harding and Pagan (2002)). The intuition behind the procedure is to identify local minima and maxima of a time series. This enables the algorithm to disentangle contraction and expansion phases of the time series.[5]

The *frequency-based filter* is a technique to study the behaviour of cyclical movements by isolating the cyclical pattern of the underlying time series. In recent literature two dominant types of frequency-based filters are used to visualise cyclical behaviours: the Hodrick-Prescott (HP) filter and the band-pass filter (BP). The HP filter, developed by Hodrick and Prescott (1981, 1997)[6], basically splits the data series into trend and cycle components by applying a criterion function to penalise deviations from the trend by using pre-specified weights (Comin and Gertler, 2006). The two-sided HP filter incorporates both historic and future information on the time series, whereas the one-sided HP filter only employs historical data. One-sided HP filters are often used in the macro-prudential literature due to using only past information (e.g. Dekten et al, 2014).[7] The second frequency-based filter technique is the BP filter developed by Christiano and Fitzgerald (2003). This is basically a two-sided moving average filter isolating certain frequencies in the time series.

In the following, we employ the frequency-based filters due to their favourable characteristics from an analytical perspective. Given that single frequency filtered time series are additive (Drehmann et al, 2012), we consider them as a proper tool to construct a synthetic financial cycle measure. In this study, we opt for the band-pass filter, although the results do not depend on the choice of filter used.[8]

---

[5] The procedure requires certain conditions. One of these conditions is an alternating pattern of peaks and troughs. Details of this procedure are explained in Bry and Boschan (1971), and Harding and Pagan (2002).

[6] The filter technique was originally proposed by Leser (1961, 1963) and employs methods that were developed earlier by Whittaker (1923).

[7] This development is mainly driven by the literature on the counter-cycle capital buffer and the implied work on the Credit-to-GDP ratio (e.g. Borio and Lowe (2002), Borio and Drehmann (2009), Basel Committee on Banking Supervision (2010, 2011), Drehmann et al. (2011)). It is obvious that a prudential tool has to rely purely on historic information, so that it is equipped to be handy in the future.

[8] See Drehmann et al. (2012) for more information.

4 Creating a Financial Cycle Measure

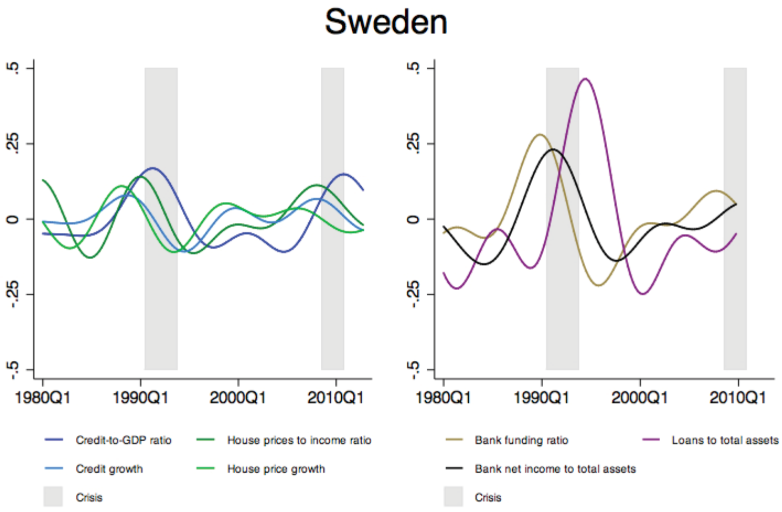
The construction of synthetic financial cycle measures involves two steps. In the first step, we apply the frequency-based band-pass filter to each individual series to compare the behaviour of medium-term cycles. In the second step, we combine several financial indicators to build the synthetic financial cycle measures.

To ensure consistency within the macro-prudential literature, we rely on the recommended settings for frequency-based filters. In detail, we transfer the proposed HP filter settings (lambda of 400.000) by the Basel Committee on Banking Supervision (2010), Borio (2012) and Detken et al. (2014) to the BP filter. The resulting parameter choice is in line with recent financial cycle literature (Drehmann et al, 2012), however the choice of the parameter remains more or less arbitrary. Recent literature argues that the length of the financial cycle is four times the length of a business cycle (Ravn and Uhlig (2002), Gerdrup et al. (2013), Detken et al. (2014)). Therefore, the duration of a financial cycle spans from 32 to 120 quarters (or 8 to 30 years) using this band-pass methodology. The rationale behind choosing the BP-filtered time series is not only that their cycles are smoother than HP filtered series but also the comparison of time series is easier. [9]

In the first step, we develop medium-term cyclical components for each of the six individual indicators: *credit-to-GDP ratio*, *house-prices-to-income ratio*, *credit growth*, *house price growth*, *bank funding ratio*, *bank-net-income-to-total-assets ratio* and *loans-to-total-assets ratio*. However, due to the data constraints not all series are available for all countries at all points in time. In Figure 1, we exemplify the patterns of individual cycles by illustrating them for Sweden. The individual graphs of the cyclical movements of the seven financial indicators for the remaining countries suggest a similar conclusion and are provided in the Appendix (Figure A1). The grey shaded areas in the figures reflect financial crisis periods identified by the ESCB Heads of Research Group Banking Crises Database.

[9] Comin and Gertler (2006) apply the settings of 2 and 32 quarters for business cycles. Alternatively, one may argue to use these BP settings for medium-frequency components by Comin and Gertler (2006). However both lines of reasoning imply the same parameters. Like Drehmann et al. (2012), we restrict the upper bound to 30 years due to the constrained data availability.

Figure 1: Cyclical Movements of Financial Indicators



The left panel of Figure 1 shows the cyclical components of the *credit-to-GDP ratio*, *house prices-to-income ratio,* as well as *credit growth* and *house price growth*, whereas the right panel outlines the cyclical components of *bank-funding*, *loans-to-total-assets* and *bank-net-income-to-total-assets ratios*. Both panels help us to characterise the underlying indicators and to make statements about their potential usefulness. An obvious caveat of this investigation is the limited number of full cycles incorporated in this time period.

The left panel reveals that cyclical components of credit aggregates and asset prices concur closely. The peaks and troughs of the individual time series occur within a tight time frame. In addition, the frequencies of the time series are similar, whereas the amplitudes appear to be divergent. Two of the four measures – both growth rates – tend to pick up quickly, whereas the other indicators adjust more gradually. In total, both growth rates tend to behave as leading indicators, whereas the *credit-to-GDP ratio* seems to be rather a lagging one. All asset and credit indicators peak around the outbreak of financial distress in the early 1990s and the late 2000s.

The data coverage in the right panel is a major concern and potential interpretations should be drawn carefully considering that for some countries the available data is much more constrained (e.g. United Kingdom). The explanatory power and the concurrence of the banking sector variables tend to diverge among countries. The frequencies but also the amplitudes appear to be different. In detail, for Sweden the peaks of the individual series in the right panel are less closely aligned than in the left panel. The *funding* and *income ratios* pick up the development more quickly than the *loans-to-total-assets ratio*. In comparison to asset prices and credit aggregates, banking variables are lagging and feature higher amplitudes.

Combining both panel interpretations, the graphical investigation reveals that variables capturing asset prices and credit aggregates are more suitable for visualising cyclical patterns of the financial variables than banking sector variables.

These results provide a first indication of the relative importance of individual financial indicators for characterising the financial cycle. However, the validity of these cyclical movements is limited because single measures may miss certain developments in the financial markets. Accordingly, we construct cycle measures for the whole financial sector. Since no obvious financial cycle measure is available, we derive synthetic measures. Of course, synthetic financial cycles have to be checked for their appropriateness before drawing any conclusion. Due to the favourable characteristics of frequency-based filter series, we are able to create aggregated synthetic financial cycle measures by averaging the underlying frequency-based filtered individual cycles for each point in time.[10]

In total, we construct seven potential financial cycle measures (*FC*) with different ingredients. Table 1 exhibits the seven synthetic financial cycle and the corresponding variables included in the combined measures. All cycle indicators include core component(s) but also vary with regard to additional variables considered in the analysis. FC1 is not a synthetic measure but is a single component financial cycle measure. Recent macro-prudential literature is in favour of using this indicator, arguing that filtered credit-to-GDP time series is helpful in predicting financial crises and that the explanatory power can only be increased gradually by adding further indicators (Detken et al, 2014). Therefore, we use this variable as our starting point.

Table 1: Financial Cycle Measures

Financial Cycle	Ingredients
FC1	Credit-to-GDP ratio
FC2	Credit-to-GDP ratio, House prices to income ratio
FC3	Credit-to-GDP ratio, House prices to income ratio, Credit growth
FC4	Credit-to-GDP ratio, House prices to income ratio, Credit growth, House price growth
FC5	Credit-to-GDP ratio, House prices to income ratio, Credit growth, Bank funding ratio
FC6	Credit-to-GDP ratio, House prices to income ratio, Credit growth, Bank net income to total assets
FC7	Credit-to-GDP ratio, House prices to income ratio, Credit growth, Loans to total assets

The data coverage is a major concern of this study. By incorporating only asset and credit variables we are able to cover nearly all time periods. For FC measures 1–4, 1446 out of 1452 possible observations can be included.[11] For banking sector variables the picture is different. By employing banking sector variables we lose nearly one-third of the

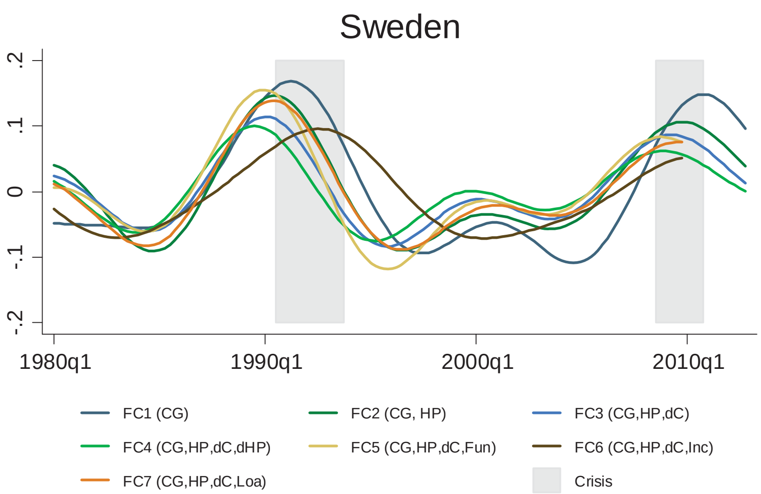
[10] This is applicable, since the components are continuous series of comparable units of measurements (Drehmann et al, 2012).

[11] The theoretical maximum number of observations is calculated using the maximum number of 33 years with four quarters each (1980q1 to 2012q4) multiplied by 11 countries.

observations. We are able to include for FC measure 4–7 only 1019, 1076 and 1076 observations, respectively. Based on this coverage restriction, it would be advisable to employ one of the former four financial cycle measures to ensure a wider data coverage. However, we assess and compare all different financial cycle measures in our analysis.

Figure 2 illustrates the seven potential synthetic financial cycle measures for Sweden. It allows the behaviour of different financial cycle measures to be compared. The graphs for the remaining countries are provided in Figure A2 in the Appendix but they do support the interpretation and conclusion for Sweden. Turning points occur at different points in time and the amplitudes of cycle measures tend to differ. All of the seven financial cycle measures share similar characteristics and patterns. This similarity is explained by the fact that the measures share some common ingredients. The peaks of the cycle measures seem to be related to periods of financial distress although not every peak is associated with a financial crisis. However, by combining the FC1 measure with additional financial indicators the turning points of the time series are shifted and also the amplitudes vary. Figure 2 also confirms the limitation of the data, since not every financial cycle measure is available at every point in time (e.g. FC5–7 from 2010 onwards).

Figure 2: Financial Cycle Measures



The graphical investigation of financial cycle measures does not provide a conclusive indication as to which financial cycle measure to choose, but it provides some intuition that banking sector variables do not seem to be essential to model the financial cycles. Nonetheless, we continue the search for the best synthetic financial cycle measures by employing statistical methods to evaluate the different measures.

5 Assessment/Evaluation

The previous section focused on the graphical investigation in order to identify the best financial cycle measure. In this section we extend the analysis by employing statistical methods to assess the various measures and to determine the best financial cycle measure. On the one hand, we analyse the concordance of the financial cycle measures and their ingredients. On the other hand, we explore the fitting of the financial cycle measures by investigating the development of synthetic cycle measures with regard to the outbreak of financial crises.

In the first step, we investigate the synchronicity between the cyclical characteristics of financial cycle ingredients and the aggregated financial cycle measures. For this purpose we use a bivariate index of synchronisation, called the concordance index. This statistical measure was developed by Harding and Pagan (2002). Basically, it expresses the time periods in which two time series are in the same phase in relation to all periods. If both time series are expanding or contracting, the index will be at 100% (positively concorded). In cases when the series are in different phases, the concordance measure is zero (negatively concorded).

Table 2: Concordance Measures for Medium-term Cycles

Cycle Measure	FC1	FC2	FC3	FC4	FC5	FC6	FC7
Concordance	100%	79%	76%	73%	74%	67%	72%

Table 2 exhibits the concordance measures for the ingredients of the financial cycle and its synthetic financial cycle measure. Each number reflects the average of the underlying concordance measures of the synthetic financial cycle measure and its corresponding time series. More specifically, it represents the fraction of time in which the individual underlying time series components and the corresponding financial cycle share a common phase. The financial cycle measures FC2 and FC3 show very distinctive values in the concordance index indicating a close co-movement of the financial cycle ingredients and that the synchronicity of the individual ingredients with the synthetic financial cycles is high. Other cycle measures tend to be less harmonised. Moreover, it is worth noting that the credit-to-GDP ratio seems to be in comparison to other ingredients less concorded with the financial cycle. Typically, the concordance is around 50 - 60% for the credit-to-GDP ratio, whereas the concordance index of other indicators is considerably higher.[12]

In the next step, we explore the relationship between financial cycles and financial crises. In detail, we study the coincidence and timing of a financial cycle's peak and the outbreak of a

[12] This finding may also deliver some insight that cyclical movements can be grouped into leading and lagging parameters. As noted in Section 4, the growth rates of credit and house prices seem to act as leading indicators in our sample. The credit-to-GDP-ratio seems to act rather as a lagging indicator.

financial crisis. It is important to stress that we do not attempt to forecast crises as in early warning literature. Therefore, we restrain from employing usefulness measures or specifying any policy loss function which is typically used in this type of literature to gauge the model's predictive ability (e.g. Alessi and Detken (2011), Detken et al. (2014)). Rather, we are interested in evaluating the goodness of fit properties of financial cycle measures in an early warning framework.

In the spirit of Bush et al. (2014), we utilise the well-established statistical measure "Area Under the Receiver Operating Characteristic" (AUROC) to assess the goodness of fit of each financial cycle specification (e.g. Detken et al. (2014), Drehmann and Juselius (2014), Drehmann and Tsatsaronis (2014), Giese et al. (2014)). This technique does not require any assumption on possible threshold values and weights of the signal ratio against the noise ratio. The AUROC summary statistics are bounded between 0 and 1, whereas higher AUROC values reflect more informative models. A value of 1 would represent a perfect fit, whereas a value below 0.5 corresponds with an uninformative specification.

In line with the dominating strand of the macro-prudential literature, we employ a simplistic univariate standard panel logistic model approach.[13]

$$Crisis_{i,t} = C + FC_{i,t}.$$

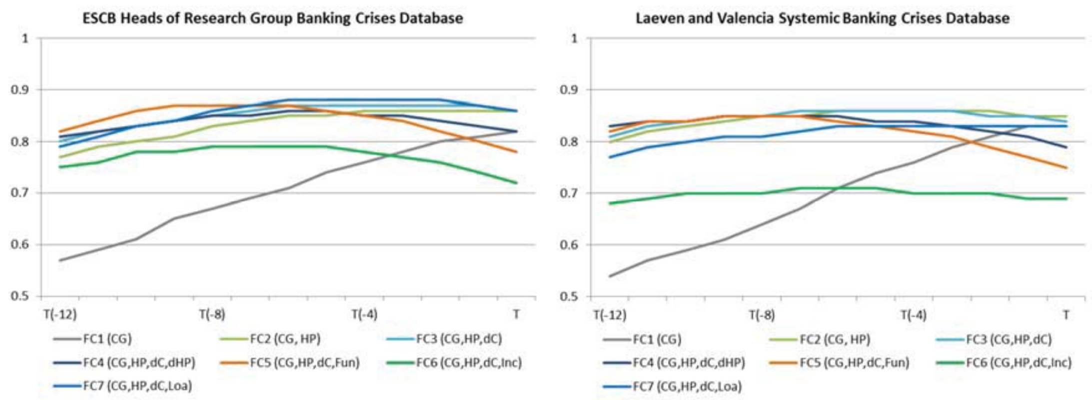
In turn, we incorporate two financial crisis variables *Heads of Research Group Banking Crises Database* by the ESCB and *Systemic Banking Crises Database* by Laeven and Valencia as the dependent *Crisis* variable. As independent variables we include a constant term *C* and one synthetic financial cycle measure *FC* at a time. Our estimation procedure involves multiple steps. To determine the power of each financial cycle measure in explaining crisis events, we estimate the specification for each financial cycle measure separately. Furthermore, we consider 13 consecutive time horizons. We specify for each synthetic financial cycle measure a separate model, lagging the independent variable up to 3 years (12 quarters). In total, we estimate 12 regressions for each financial cycle measure. For each specification, we determine the AUROC which allows us to judge the model's adequacy and the goodness of fit. We repeat this estimation procedure for both measures.[14]

In Figure 3 we plot the AUROC paths of the various synthetic financial cycle measures with the corresponding time period for both crisis measures. All seven synthetic financial cycle measures are informative using both crisis indicators and tend to give reliable signals ahead of crises indicated by AUROC values higher than 0.5. Thus, all specifications are equipped

[13] The framework is similar to a majority of the macro-prudential literature. For example, Behn et al. (2013), and Bush et al. (2014) employ the logit estimation technique. For more information see Dekten et al. (2014).
[14] For information on the area under the receiver operating curve (AUROC) measure see Bush et al. (2014), Dekten et al. (2014) and Giese et al. (2014)

with well-behaving characteristics and are well-determined. In particular, the higher the AUROC curve, the better is the performance of the model.

Figure 3: AUROC of Financial Cycle Measures Over Time



Both panels in Figure 3 show similar patterns. In both panels, the measures tend to behave quite similarly (except for FC1 and FC6) and it is challenging to distinguish between the various cycle measures as well as to identity the best-performing measure. Nonetheless, the figure reveals that specific financial cycles tend to be more informative than others. In the left panel (Heads of Research Group Banking Crises Database) the FC3 and FC7 measures have the highest AUROC values and can be described as the best-performing models. In the right panel (Systemic Banking Crises Database) the FC2 and FC3 measures provide the highest AUROC values. For both financial crisis measures, indicator FC3 is in the top ranks over all horizons and the value starts to decline slightly six quarters before the crisis. In comparison, AUROC values of the FC1 measure which is the sole credit-to-GDP ratio decline steadily with each further lag. In addition to that, it is observable that the explanatory power of the financial cycle measures in terms of the AUROC value can be improved by adding further variables to the credit-to-GDP ratio. For example, in the left panel the AUROC value of the FC1 measure is much lower during the period of T(-12) until T(-3) than for the other cycle measures.

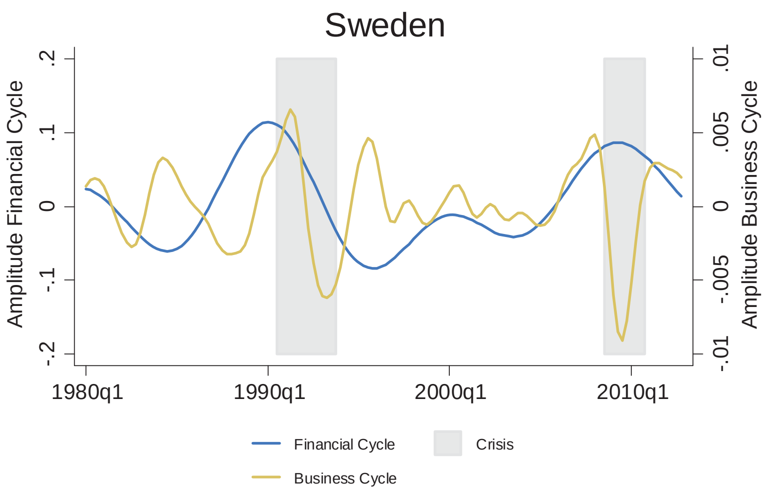
Taking the graphical and statistical examinations as well as the data availability concerns into account, we conclude that the FC3 measure consisting of the credit-to-GDP ratio, credit growth and house-prices-to-income ratio seems to be the best choice for a synthetic financial cycle measure. In comparison with other measures, this indicator is constantly ranked among the top in different graphical and statistical investigations.

6 Applications of the Financial Cycle Measure

After deriving the best-fitting financial cycle indicator, we turn to some possible applications of the financial cycle measure. The synthetic financial cycle could be of help for various policy purposes such as early warning indicators for detecting exuberance or distress within the financial system. In this section we briefly highlight three applications for policy purposes that may provide insights for policy makers. First, we compare financial and business cycles and assess similarities and differences. Second, we explore the synchronicity of financial cycles across the 11 countries. Last, we highlight the impact of banking sector characteristics on the financial cycle measure. In this part, we employ the financial cycle with the best-fit - FC3 measure - and refer to it as the financial cycle.

In the first application, we compare financial and business cycles by employing filtered times series for the financial and the business cycle over time. As in the previous section, Figure 4 exemplarily exhibits the cycles for Sweden. Other charts are provided in Figure A3 in the Appendix but suggest a similar conclusion. Beside the synthetic financial cycle measure, we also employ a band-pass filtered nominal GDP series as the business cycle measure using the recommend settings to retrieve the cyclical pattern of business cycles (Harding and Pagan, 2002, 2006).

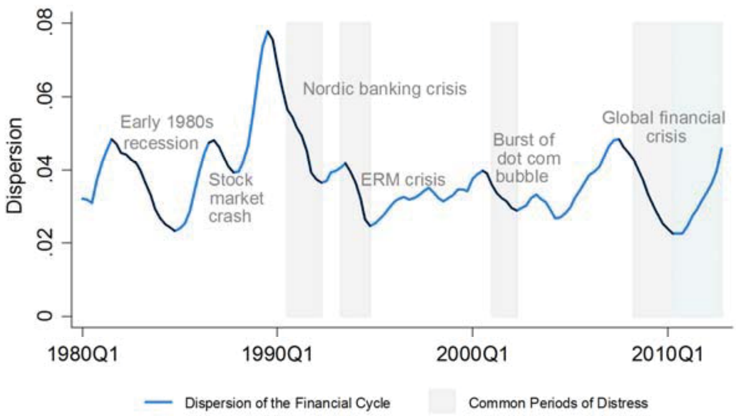
Figure 4: Comparison of Business and Financial Cycles



Previous literature has investigated the long-established relationship between credit and business cycles for more than 130 years across countries (e.g., Aikman et al. (2010, 2014)). Although our time span is considerably shorter, we spot similar cyclical patterns. We are able to confirm their findings for a wider range of European countries and spot similar divergences. For example, the average duration of financial cycles in Figure 4 seems to be longer than that of business cycles. Furthermore, business cycles seem to be more volatile and have a higher order of variance. This finding also offers insights into the appropriate design of macro-prudential policy: Peaks of financial cycles are more associated with the onset of financial crises than with business cycles. Haldane (2014) underpins this strong empirical link between macroeconomic destabilisation and cycle peaks. In addition, Drehmann et al. (2012) also emphasise that in the aftermath of a financial cycle peak, a serious weakening in economic activity is more likely. These findings also support the intuition that dampening the financial cycle is an important element of policy measures aiming at enhancing financial and macroeconomic stability as well.

In a second application, we analyse the synchronicity of financial cycles across the 11 European countries. We define the cycle dispersion or synchronicity as the one-year cross-country standard deviation of filtered time series.[15] This dispersion measure can be used to evaluate whether cycles converge or diverge over time. A lower dispersion measure represents a higher synchronicity and, vice versa, a lower synchronicity constitutes a higher dispersion.

<u>Figure 5: Synchronicity of Cycles</u>



The cycle dispersion metric is calculated each quarter as the one-year cross-country standard deviation of the filtered time series for the 11 European countries.

Note: The global financial crisis is divided in two sub-periods: 2007-2009, when all EU countries were hitby the crisis and 2010-2012, when some EU countries recovered, while others continued to be impacted by the sovereign crisis.

Figure 5 offers an important insight: In awakening of cross-border financial stress events (darker shaded line and labelled as “Early 1980s recession”, “1987 stock market crash”, “Nordic banking crisis”, “European exchange rate mechanism crisis”, “Burst of the dotcom bubble”, “Global financial crisis”) the financial cycle dispersion tends to decrease and financial synchronicity tends to increase.[16] Or to put it the other way around, financial cycles are less synchronised in good times.[17] This divergence of financial cycles calls for differentiated and well-targeted policy responses that take into account the cyclical position of individual Member States.

In a third and last step, we shed light on the potential drivers of the financial cycle amplitude and its importance for macro-prudential policy purposes. Based on the newly

[15] There are multiple options to analyse and model the synchronicity of cycles. For a detailed review on different synchronisation measures see Gächter et al. (2012, 2013).
[16] The different shading during the Global financial crisis refers to the European Debit Crisis.
[17] Straetmans (2014) also finds that cross-asset crisis spill-overs – co-movement of stocks, bonds and commodities prices – become more pronounced and thus diversifying portfolio risks becomes more difficult during recessions. Straetmans (2014) defines recessions in relation to the business cycle.

available instruments within the Capital Requirements Regulation and Directive (CRR/CRD IV) framework in Europe, designated macro-prudential authorities obtain the power to implement and calibrate certain capital buffers. The financial sectors feature different cyclical and structural characteristics across Member States, suggesting that capital buffers should be calibrated and implemented differently. Moreover, the timing of introducing macro-prudential measures in the financial cycle appears to be a key question to minimise unintended economic costs. From a financial stability perspective, awareness of the drivers of the financial cycle as well as its current state is essential to determine the adequate policy actions. For instance, our synthetic financial cycle measure could be employed as an indicator in the early warning system to assess countries' financial sectors.

A detailed analysis of the relationship between certain structural features of the banking sector and the financial cycle is undertaken by Stremmel and Zsámboki (2015). The authors identify bank concentration, the market share of foreign banks as well as the share of foreign currency loans in total loans which explain a significant part of the variation of the financial cycle amplitude. In addition, they also argue that macro-prudential measures addressing cyclical movements and structural characteristics of the banking system could be considered in combination.

7 Conclusion

In this paper we identify key ingredients for the financial cycle in Europe. We review construction techniques and contrast different financial indicators such as credit aggregates, asset prices and banking sector variables and create various synthetic financial cycle measures to guide our choice. Employing various graphical and statistical assessments, we identify the most appropriate financial cycle measures. Our results suggest that the best-fitted synthetic financial cycle measure contains the credit-to-GDP ratio, credit growth and house-prices-to-income ratio.

Moreover, our paper elaborates on different potential applications of the financial cycle measure, contributing to the on-going discussion on macro-prudential policy. Awareness of the drivers of the financial cycle as well as its current state is essential to take the correct policy actions. We investigate the synchronicity of financial cycles in Europe. Our results suggest that financial cycles are highly correlated during stress times and diverge in boom periods that should be taken into account in policy actions.

Further, we provide examples for potential application of the financial cycle measure. This paper paves the way for further avenues of research. From a research perspective it may be interesting to further elaborate on the decomposition of financial cycles and whether the relative influence of individual components varies over time. In addition, our study provides also the foundation to employ the financial cycle measures in other econometric frameworks. A possible application could involve using the financial cycle measures in VAR models to conduct impact studies. Another interesting application is related to early warning systems. This financial cycle metric could be employed in the early warning framework to assess the cyclical position of financial systems in countries and to issue signals if emerging vulnerabilities are detected.

References

AIKMAN, D., A.G. HALDANE and B. NELSON (2010): “Curbing the Credit Cycle”, Speech given at the Columbia University Center on Capitalism and Society Annual Conference, New York, November.

AIKMAN, D., A.G. HALDANE and B. NELSON (2014): “Curbing the Credit Cycle”, The Economic Journal, forthcoming.

AIZENMAN, J., B. PINTO and S. VLADYSLAV (2013): "Financial Sector Ups and Downs and the Real Sector in the Open Economy: Up by the Stairs, Down by the Parachute", Emerging Markets Review, 16(C), 1–30.

ALESSI, L. and C. DETKEN, (2011): “Real Time Early Warning Indicators for Costly Asset Price Boom/Bust Cycles: A Role for Global Liquidity”, European Journal of Political Economy, 27(3), 520–33.

BASEL COMMITTEE ON BANKING SUPERVISION (BCBS) (2010): “Guidance for National Authorities Operating the Countercyclical Capital Buffer”, Available at http://www.bis.org/publ/bcbs187.pdf.

BASEL COMMITTEE ON BANKING SUPERVISION (BCBS) (2011): “Basel III: A Global Regulatory Framework for more Resilient Banks and Banking Systems”, Available at http://www.bis.org/publ/bcbs189.pdf.

BEHN, M., C. DETKEN, T. PELTONEN, and W. SCHUDEL (2013): “Setting Countercyclical Capital Buffers Based on Early Warning Models: Would it Work?”, ECB Working Paper, No 1604.

BORIO, C. and P. LOWE (2002): “Assessing the Risk of Banking Crises”, BIS Quarterly Review, December 2002, 43–54.

BORIO, C. and P. LOWE (2004): “Securing Sustainable Price Stability, Should Credit Come back from the Wilderness?”, BIS Working Paper, No 157.

BORIO, C. and M. DREHMANN (2009): “Assessing the Risk of Banking Crises – Revisited”, BIS Quarterly Review, March 2009, 29–46.

BORIO, C. (2012): “The Financial Cycle and Macroeconomics: What Have We Learnt?“, BIS Working Paper, No 395.

BORIO, C. (2013): “Macroprudential Policy and the Financial Cycle: Some Stylized Facts and Policy Suggestions”, Speech given at the “Rethinking Macro Policy II: First Steps and Early Lessons” hosted by the IMF in Washington, DC.

BORIO, C., P. DISYATAT, and M. JUSELIUS (2013): “Rethinking Potential Output: Embedding Information about the Financial Cycle”, BIS Working Paper, No 404.

BRACKE, P. (2013): "How Long Do Housing Cycles Last? A Duration Analysis for 19 OECD Countries", Journal of Housing Economics, 22, 213–30.

BRY, G. and C. BOSCHAN (1971): “Cyclical Analysis of Time Series: Selected Procedures and Computer Programs”, NBER Technical Paper, No 20.

BURNS, A. F., and W. C. MITCHELL (1946): “Measuring Business Cycles”, Columbia Univ. Press.

BUSCH, U. (2012): “Credit Cycles and Business Cycles in Germany: A Comovement Analysis”, Manuscript.

BUSH, O., R. GUIMARAES and H. STREMMEL (2014): “Beyond the Credit Gap: Quantity and Price of Risk Indicators for Macro–Prudential Policy”, Bank of England, Manuscript.

BUSSIÈRE, M. and M. FRATZSCHER (2006): “Towards a New Early Warning System of Financial Crisis”, Journal of International Money and Finance 25(6), 953–73.

CHRISTIANO, L. and T. FITZERALD (2003): “The Band–Pass Filter”, International Economic Review, 44(2), 435–65.

CLAESSENS, S., M. KOSE and M. TERRONES (2011a): “Financial Cycles: What? How? When?”, IMF Working Paper, No WP/11/76.

CLAESSENS, S., M. KOSE and M. TERRONES (2011b): “How Do Business and Financial Cycles Interact?”, IMF Working Paper, No WP/11/88.

COMIN, D. and M. GERTLER (2006): “Medium–Term Business Cycles”, American Economic Review, 96(3), 523–51.

DETKEN, C. and F. SMETS (2004): "Asset Price Booms and Monetary Policy", ECB Working Paper, No 364.

DETKEN, C., O. WEEKEN, L. ALESSI, D. BONFIM, M. M. BOUCINHA, C. CASTRO, S. FRONTCZAK, G. GIORDANA, J. GIESE, N. JAHN, J. KAKES, B. KLAUS, J. H. LANG, N. PUZANOVA and P. WELZ (2014): “Operationalizing the Countercyclical Capital Buffer: Indicator Selection, Threshold Identification and Calibration Options”, ESRB Occasional Paper, 5.

DREHMANN, M., C. BORIO and K. TSATSARONIS (2011): “Anchoring Countercyclical Capital Buffers: The Role of Credit Aggregates”, International Journal of Central Banking, 7(4), 189–240.

DREHMANN, M., C. BORIO and K. TSATSARONIS (2012): “Characterising the Financial Cycle: Don't Lose Sight of The Medium Term!”, BIS Working Paper, No 380.

DREHMANN, M. and K. TSATSARONIS (2014): “The Credit–to–GDP Gap and Countercyclical Capital Buffers: Questions and Answers”, BIS Quarterly Review, March 2014.

DREHMANN, M. and M. JUSELIUS (2014): “Evaluating Early Warning Indicators of Banking Crises: Satisfying Policy Requirements“, International Journal of Forecasting, 30(3), 759-780.

ENGLISH, W, K. TSATSARONIS and E. ZOLI (2005): "Assessing the Predictive Power of Measures of Financial Conditions for Macroeconomic Variables", BIS Papers, No 22.

EUROPEAN SYSTEMIC RISK BOARD (ESRB) (2014): Macro-prudential policy actions, https://www.esrb.europa.eu/mppa/html/index.en.html.

GÄCHTER, M., RIEDL, A. and D. RITZBERGER–GRÜNWALD (2012): "Business Cycle Synchronization in the Euro Area and the Impact of the Financial Crisis", Monetary Policy & the Economy, Oesterreichische Nationalbank (Austrian Central Bank), 2, 33–60.

GÄCHTER, M., RIEDL, A. and D. RITZBERGER–GRÜNWALD (2013):"Business Cycle Convergence or Decoupling?", BOFIT Discussion Paper, No 3/2013.

GERDRUP, K., A. KVINLOG and E. SCHAANNING (2013): “Key Indicators for a Countercyclical Capital Buffer in Norway – Trends and Uncertainty”, Norges Bank Staff Memo, No 13/2013.

GIESE, J., H. ANDERSEN, O. BUSH, C. CASTRO, M. FARAG, and S. KAPADIA (2014), “The credit-to-GDP gap and complementary indicators for macroprudential policy: Evidence from the UK”, International Journal of Finance & Economics, 19(1), 25-47.

GOODHART, C and B HOFMANN (2008): "House Prices, Money, Credit, and the Macroeconomy", Oxford Review of Economic Policy, 24, 180–205.

HALDANE, A. (2014): “Ambidexterity”, Speech given at the 2014 American Economic Association Annual Meeting in Philadelphia.

HANSEN, L. P.: “Challenges in Identifying and Measuring Systemic Risk”, NBER Working Paper, No 18505.

HARDING, D. and A. PAGAN (2002): “Dissecting the Cycle: A Methodological Investigation”, Journal of Monetary Economics, 49(2), 365–81.

HARDING, D. and A. PAGAN (2006): "Synchronization of Cycles", Journal of Econometrics, 132, 59–79.

HIEBERT, P., B. KLAUS, T. PELTONEN, Y. SCHÜLER and P. WELZ (2014): "Capturing the Financial Cycle in Euro Area Countries", ECB Financial Stability Review – November 2014, Special Feature B.

HODRICK, R. and E. PRESCOTT (1981): “Post–war U.S. Business Cycles: An Empirical Investigation”, Working Paper. Reprinted in: Journal of Money, Credit and Banking (1997), 29(1), 1–16.

KINDLEBERGER, C. P. (1978): “Manias, Panics, and Crashes: A History of Financial Crisis”, 1 , Basic Books.

LAEVEN, L. and F. VALENCIA (2008): “Systemic Banking Crises: A New Database”, IM Working Paper, No 08/224.

LAEVEN, L. and F. VALENCIA (2010): “Resolution of Banking Crises: The Good, the Bad, and the Ugly”, IMF Working Paper, No 10/146.

LAEVEN, L. and F. VALENCIA (2012): “Systemic Banking Crises Database: An Update”, IMF Working Paper, No 12/163.

LAEVEN, L. and F. VALENCIA (2013): “Systemic Banking Crises Database”, IMF Economic Review 61 (2), 225-270.

LESER, C. E. V. (1961): “A Simple Method of Trend Construction”, Journal of the Royal Statistical Society, Series B (Methodological), 23, 91–107.

LESER, C. E. V. (1963): “Estimation of Quasi–Linear Trend and Seasonal Variation”, Journal of the American Statistical Association, 58, 1033–43.

MINSKY, HYMAN P. (1972): “Financial Instability Revisited: The Economics of Disaster.” Reappraisal of the Federal Reserve Discount Mechanism, 3, 97–136.

MINSKY, HYMAN P. (1982): “The Financial Instability Hypothesis: Capitalistic Processes and the Behavior of the Economy”, in “Financial Crises: Theory, History, and Policy”, Cambridge University Press, 12–29.

MINSKY, HYMAN P. (1986): “Stabilizing an Unstable Economy”, Yale University Press.

NG, T. (2011): “The Predictive Content of Financial Cycle Measures For Output Fluctuations”, BIS Quarterly Review, June 2011, 53–65.

RAVN, M. O. and H. UHLIG (2002): “On Adjusting the Hodrick–Prescott Filter for the Frequency of Observations”, The Review of Economics and Statistics, 84(2), 371–80.

SCHULARICK, M. and TAYLOR, A. M. (2012): “Credit Booms Gone Bust: Monetary Policy, Leverage Cycles and Financial Crises, 1870–2008”, American Economic Review, 102(2), 1029–1061.

STRAETMANS, S. (2014): “Financial Crisis, Crisis Spillovers and the Business Cycle”, Manuscript.

STREMMEL, H. and B. ZSAMBOKI (2015). “The Relationship between Structural and Cyclical Features of the EU Financial Sector”, ECB Working Paper Series, No 1812.

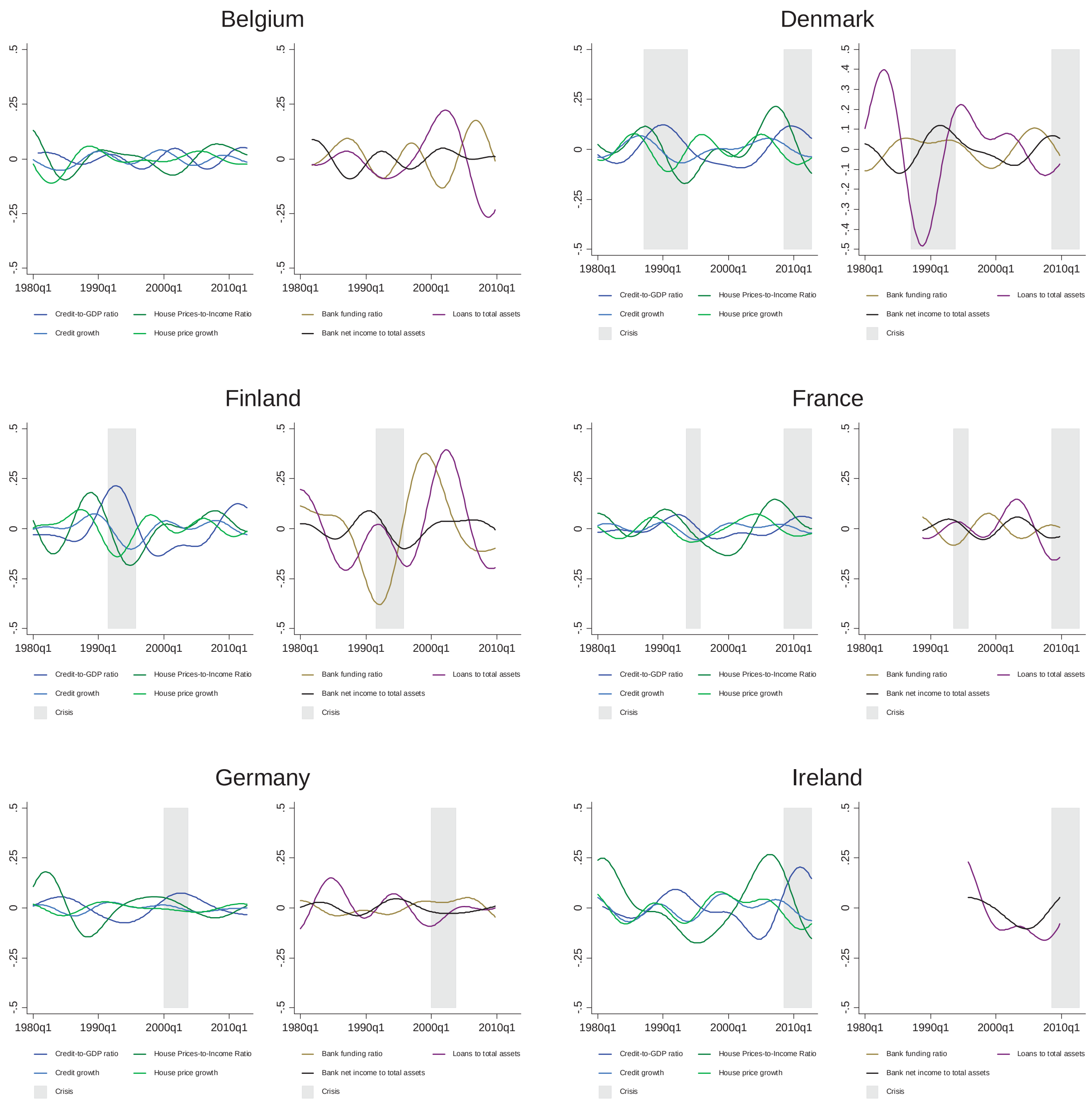
UHDE, A. and U. HEIMESHOFF (2009): "Consolidation in Banking and Financial Stability in Europe: Empirical Evidence", Journal of Banking & Finance, 33(7), 1299–1311.

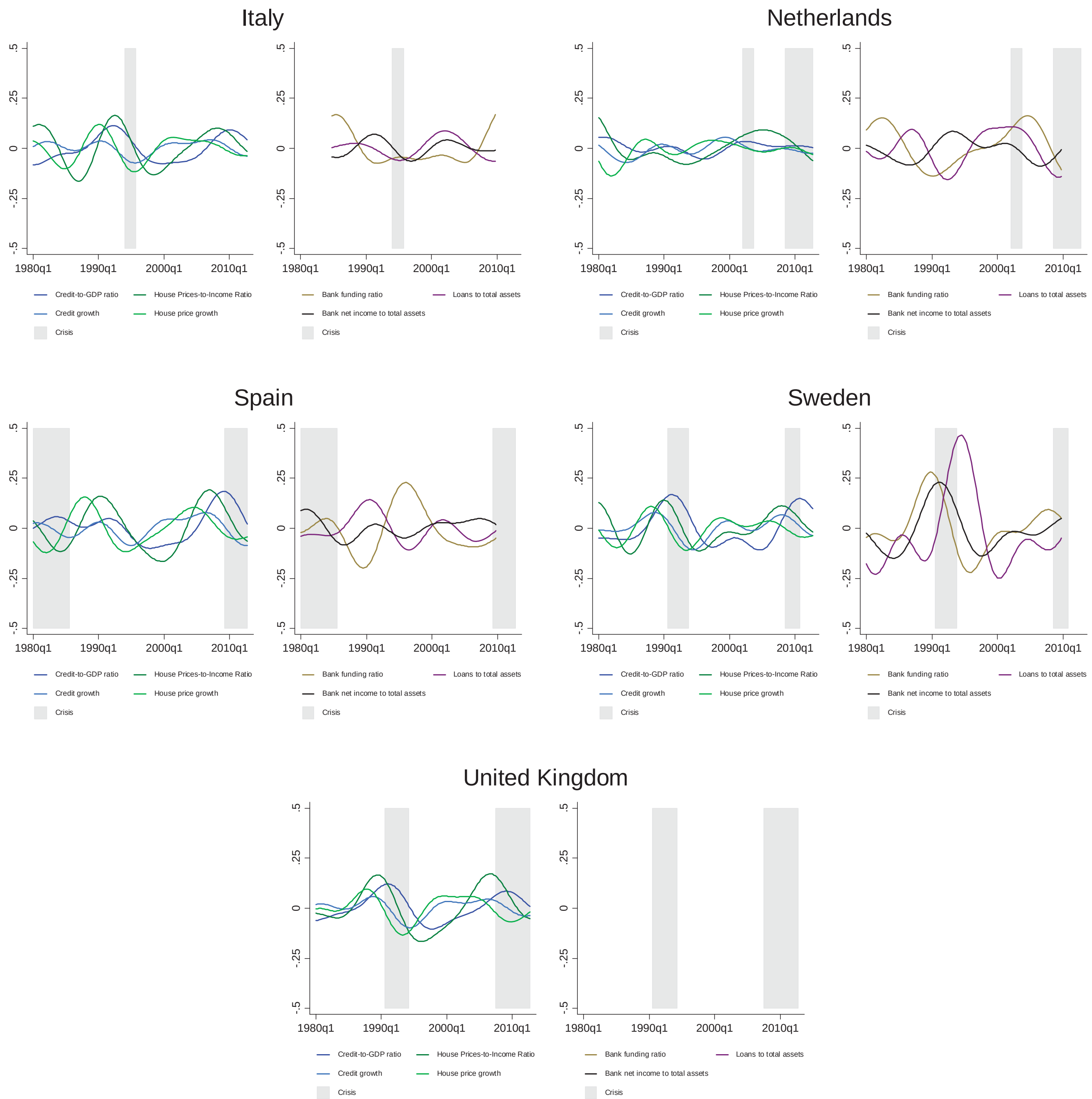
WEZEL, T. (2014): “Rightsizing the Countercyclical Capital Buffer for EU Countries – A Residual Loss Approach”, European Central Bank, Manuscript.

WHITTAKER, E. T. (1923): “On a New Method of Graduation”, Proceedings of the Edinburgh Mathematical Society, 41, 63–75.

Appendix

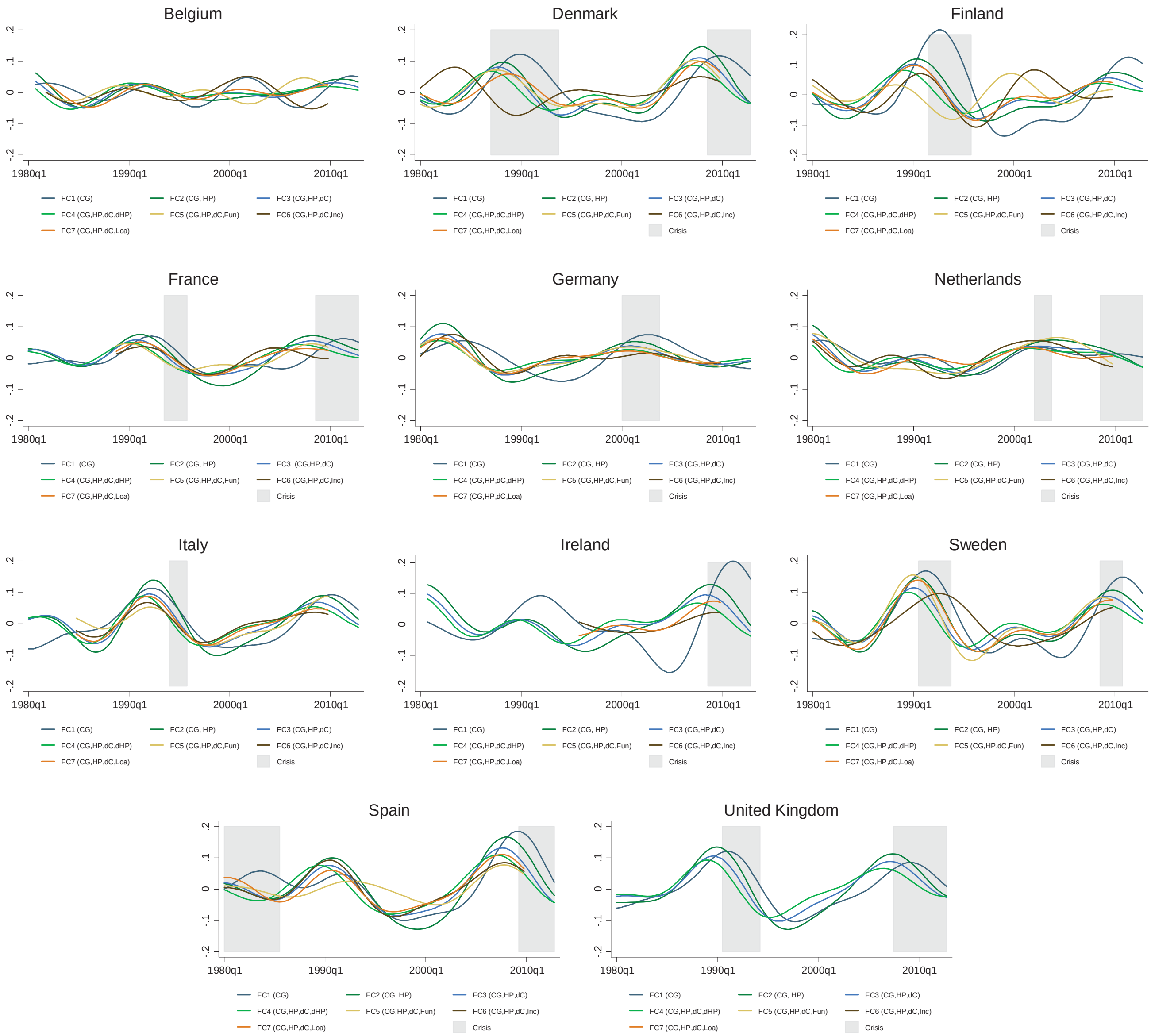
Figure A1: Cyclical Movements of Financial Indicators





Each panel reflects the cyclical movements for seven different financial indicators. The cyclical movements are obtained using the described methodology in Section 3. The left part of each panel, represent the cyclic components of macro-financial variables such as credit-to-GDP ratio, house-prices-to-income ratio, credit growth, whereas the right part of each panel represents the cyclical components of banking balance variables such as bank funding, loans-to-total-assets, and bank-ne-income-to-total-assets ratios. This figure reveals that coverage of the banking sector balance sheet variables differs across the countries. For example, in the Italian case for some periods no data is available, whereas for the United Kingdom no balance sheet data is available at all. Other countries such as Spain have considerable higher data coverage. The grey shaded areas refer to financial crisis periods identified by ESCB Heads of Research Group Banking Crises Database for the corresponding country. For a detailed interpretation, please see Section 4.

Figure A2: Financial Cycle Measures

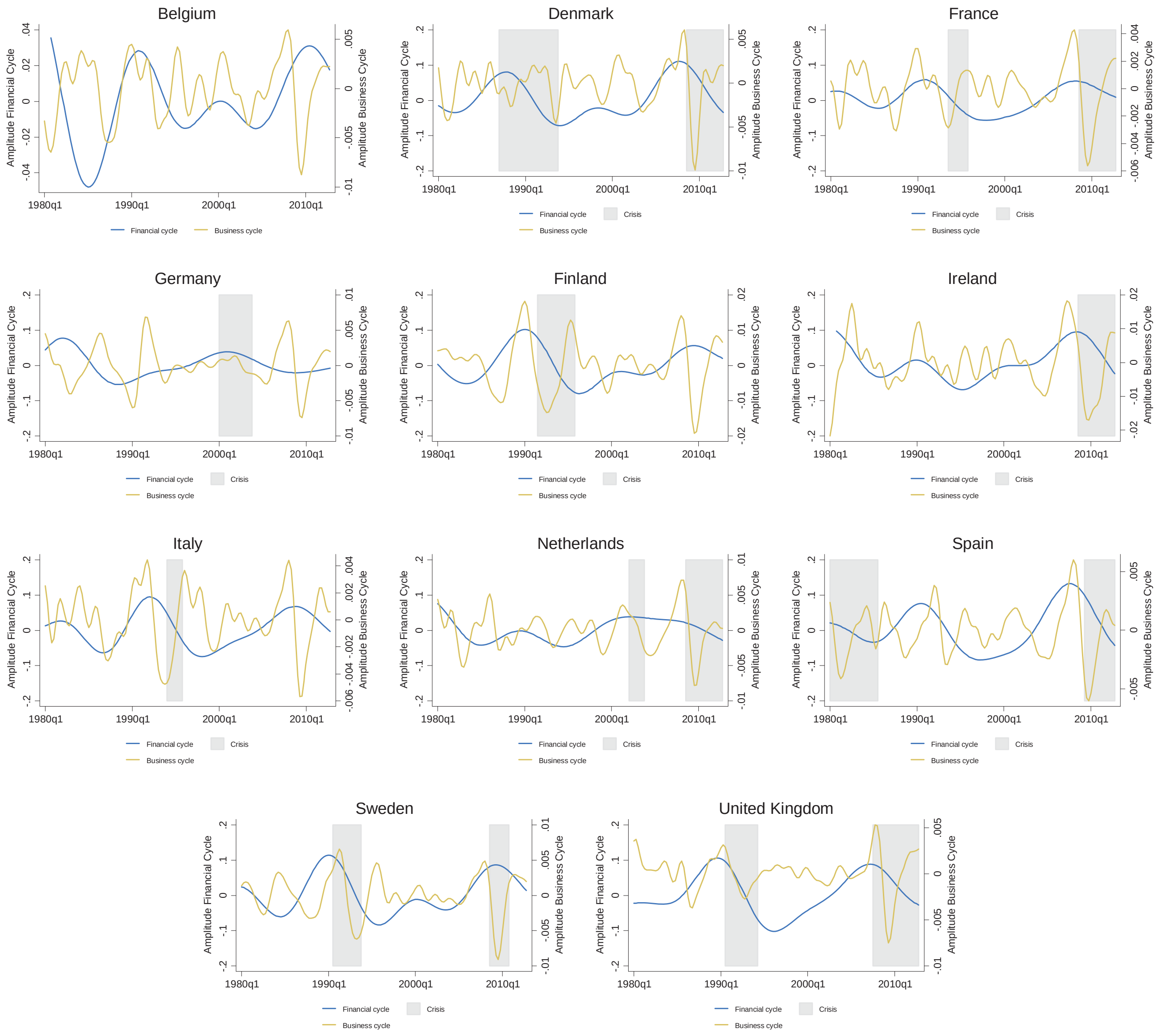


Each country panels reflects seven constructed individual synthetic financial cycle measures. We use the following ingredients:

- FC1: Credit-to-GDP ratio (*CG*).
- FC2: Credit-to-GDP ratio (*CG*), House prices to income ratio (*HP*).
- FC3: Credit-to-GDP ratio (*CG*), House prices to income ratio (*HP*), Credit growth (*dC*).
- FC4: Credit-to-GDP ratio (*CG*), House prices to income ratio (*HP*), Credit growth (*dC*), House price growth (*dHP*).
- FC5: Credit-to-GDP ratio (*CG*), House prices to income ratio (*HP*), Credit growth (*dC*), Bank funding ratio (*Fun*).
- FC6: Credit-to-GDP ratio (*CG*), House prices to income ratio (*HP*), Credit growth (*dC*), Bank net income to total assets (*Inc*).
- FC7: Credit-to-GDP ratio (*CG*), House prices to income ratio (*HP*), Credit growth (*dC*), Loans to total assets (*Loa*).

Grey shaded areas reflect financial crisis periods identified by ESCB Heads of Research Group Banking Crises Database for the corresponding country. In line with Figure A1, for the United Kingdom the financial cycle measures FC5, FC6, and FC7 are not available due to the lack of balance sheet variables. For an interpretation of these country panels please see Section 4.

Figure A3: Comparison of Business and Financial Cycles



In each of the country panels, we plot the financial and the business cycle over the time. For the financial cycle, we employ the financial cycle measure FC3 and for the business cycle we use the band-pass filtered nominal GDP series. In each graph, the grey shaded areas reflect financial crisis periods identified by ESCB Heads of Research Group Banking Crises Database for the corresponding country. For a detailed interpretation of these country panels please see Section 6.

Acknowledgements
A draft version was written during my stay at the European Central Bank. The author thanks the Financial Regulation Division of the Directorate General Macro-prudential Policy and Financial Stability for its hospitality and support. In particular, the author would like to thank his supervisor Balázs Zsámboki for his ideas and support. The author is also very grateful to Luis Gutierrez de Rozas, Benjamin Klaus, Tuomas Peltonen, Willem Schudel, Peter Welz, Bent Vale as well as Benjamin Nelson and Jonathan Frost for their useful comments on an earlier version of this paper. I also thank seminar participants at the European Central Bank (2014), 6th IFABS conference (2014), 46th MMF conference (2014), 11th International Conference - Western Economic Association International (2015) as well as an anonymous referee for valuable comments and suggestions. The views expressed in this paper are those of the author and do not necessarily reflect the views of the ECB or the Eurosystem.

Hanno Stremmel
WHU – Otto Beisheim School of Management;
e-mail: hanno.stremmel@whu.edu

Postal address	60640 Frankfurt am Main, Germany
Telephone	+49 69 1344 0
Internet	www.ecb.europa.eu

ISSN	1725-2806 (online)
ISBN	978-92-899-1624-0
DOI	10.2866/279538
EU catalogue number	QB-AR-15-051-EN-N