DEUTSCHE
BUNDESBANK
EUROSYSTEM

Discussion Paper

Deutsche Bundesbank
No 20/2015

The synchronization of European credit cycles

Barbara Meller
Norbert Metiu

Deutsche Bundesbank, Wilhelm-Epstein-Straße 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 9566-0

Please address all orders in writing to: Deutsche Bundesbank,
Press and Public Relations Division, at the above address or via fax +49 69 9566-3077

Internet http://www.bundesbank.de

ISBN 978–3–95729–165–3 (Printversion)
ISBN 978–3–95729–166–0 (Internetversion)

Non-technical summary

Research Question

We study the synchronization of credit boom and bust episodes among 12 major European economies and, owing to strong financial linkages, the United States. Boom-bust cycles in credit have moved to the forefront of policy attention in the aftermath of the 2007-08 global financial crisis because systemic banking crises are typically preceded by credit booms. Macroprudential policy aim to alleviate the risks from credit booms and ultimately to reduce the probability and cost of systemic banking crisis. We seek to answer the questions whether boom-bust cycles in credit are synchronized across countries, how credit cycle synchronization evolves over time, and what drives synchronization.

Contribution

To the best of our knowledge, we are the first to perform a formal statistical analysis of international credit cycle synchronization. To that end, we propose a straightforward econometric test for cyclical synchronization. Further, we examine different aspects of credit cycle synchronization such as clustering. Finally, we shed light on the effects of macroeconomic and financial interdependence on the synchronization of credit cycles.

Results

We find evidence against the existence of a common credit cycle. Instead, the analyzed countries form two distinct clusters: Austria, Belgium, Germany, Ireland, and the Netherlands on the one hand, and Denmark, Finland, France, Italy, Spain, Sweden, the United Kingdom, and the United States on the other hand. Within each of the two clusters, credit cycle synchronization has a positive time trend indicating convergence, at least since the last decade. Additional regressions indicate that countries with more highly correlated business cycles tend to have more strongly synchronized credit cycles. Moreover, a higher degree of credit market integration between two countries is accompanied by higher credit cycle synchronization.

Nichttechnische Zusammenfassung

Fragestellung

Wir untersuchen die Synchronisation von Boom-Bust Phasen zwischen den Kreditzyklen 12 großer europäischer Volkswirtschaften und, wegen starker finanzieller Verbindungen, der USA. Seit der globalen Finanzkrise von 2007-08 richtet die Politik verstärkt ihren Augenmerk auf exzessive Kreditvergabe da sie typischerweise systemischen Bankenkrisen vorausgeht. Das Ziel der makroprudenziellen Politik ist es daher die Risiken von Kreditbooms einzudämmen und letztendlich die Wahrscheinlichkeit sowie die Folgen einer systemischen Bankenkrise zu reduzieren. Wir untersuchen ob Boom-Bust-Kreditzyklen international synchronisiert sind, ob die Zyklen mancher Länder vorlaufen, wie sich die Kreditzyklussynchronisation über die Zeit entwickelt und was ihre Determinanten sind.

Beitrag

Unserer Kenntnis nach sind wir die ersten, die eine formale statistische Analyse der Synchronisation von internationalen Kreditzyklen durchzuführen. So schlagen wir einen einfachen ökonometrischen Test zur Bestimmung von Synchronisation vor. Des Weiteren untersuchen wir statistisch verschiedene Aspekte der Kreditzyklus Synchronisation wie die Clusterbildung. Schließlich beleuchten wir die Auswirkungen der makroökonomischen und finanziellen Interdependenz auf der Synchronisation von Kreditzyklen.

Ergebnisse

Wir finden keine Hinweise auf die Existenz eines gemeinsamen europäischen Kreditzyklus. Stattdessen bilden die untersuchten Länder zwei unterschiedliche Cluster: Österreich, Belgien, Deutschland, Irland sowie die Niederlande auf der einen Seite, und Dänemark, Finnland, Frankreich, Italien, Spanien, Schweden, das Vereinigte Königreich sowie die USA auf der anderen Seite. Innerhalb der beiden Cluster zeigt die Kreditzyklussynchronisation einen positiven Trend der zumindest seit den letzten zehn Jahren auf eine Konvergenz hindeutet. Zusätzliche Regressionen zeigen, dass die Kreditzyklen von Ländern mit stark korrelierten Konjunkturzyklen in der Regel stärker synchronisiert sind. Darüber hinaus wird ein höherer Grad an Kreditmarktintegration zwischen zwei Ländern auch mit einer höheren Kreditzyklussynchronisation in Zusammenhang gebracht.

Bundesbank Discussion Paper No 20/2015

The synchronization of European credit cycles*

Barbara Meller
Deutsche Bundesbank

Norbert Metiu
Deutsche Bundesbank

Abstract

We study the synchronization of credit booms and busts among 12 major European economies and the United States between 1972-2011. We propose a regression-based procedure to test whether boom-bust phases of credit cycles coincide across countries and to cluster countries with positively synchronized credit cycles. We find strong evidence against the existence of a common credit cycle across all countries. Instead, the credit cycles of Austria, Belgium, Germany, Ireland, and the Netherlands are clustered together, while Denmark, Finland, France, Italy, Spain, Sweden, the UK, and the US belong to another distinct cluster. Overall, the relationship among credit cycles is found to be stable over time. However, within each of the two clusters, credit cycles have been converging at least since the last decade. Using a simultaneous equations model, we find that deeper financial integration and a higher degree of business cycle co-movement are associated with stronger credit cycle synchronization.

Keywords: Business cycles; Credit booms; Financial cycles; Financial integration; Synchronization.

JEL classification: C32; F34; G15.

*Contact addresses: Barbara Meller: Financial Stability Department, Deutsche Bundesbank. Norbert Metiu: Corresponding author. Research Centre, Deutsche Bundesbank, Wilhelm-Epstein-Straße 14, 60431 Frankfurt am Main, Germany. E-mail: norbert.metiu@bundesbank.de. Tel.: +49 69 9566 8513.
We thank Herman van Dijk, Mathias Drehmann, Uwe Hassler, Helmut Lütkepohl, Alexander Schulz, and the participants at the 68th European meeting of the Econometric Society for their helpful comments, and we are grateful to Calebe de Roure for his research assistance. Discussion Papers represent the authors' personal opinions and do not necessarily reflect the views of the Deutsche Bundesbank.

1 Introduction

We study the synchronization of credit boom and bust episodes among 12 major European economies and, owing to strong financial linkages, the United States. More specifically, we seek to answer the question whether boom-bust cycles in credit coincide across countries, how credit cycle synchronization evolves over time, and what drives synchronization. To that end, we outline an econometric approach to test for the cross-country synchronization of credit boom and bust phases. Moreover, we assess time variation in credit cycle synchronization using a Chow-type breakpoint test. Finally, we analyze the relationship between credit cycle synchronization, credit market integration, and business cycle co-movement by means of a simultaneous equations model similar to those used by Imbs (2004, 2006), Inklaar, Jong-A-Pin, and de Haan (2008), and Davis (2014).

We propose a regression-based test for whether different countries reside simultaneously in the same – boom or bust – phase of the credit cycle. Following Drehmann, Borio, and Tsatsaronis (2012), Arnold, Borio, Ellis, and Moshirian (2012), and Aikman, Haldane, and Nelson (2014), we define the credit cycle in terms of medium-term fluctuations in the volume of real credit. The credit cycle is mapped into a binary variable that distinguishes boom phases (to which we assign a value of 1) from bust phases (coded as -1). The correlation coefficient between two countries' binary variables provides a measure for what we call "phase synchronization". For each pair of countries, we test the hypothesis that this correlation is non-positive, implying that the credit cycles of two countries fail to exhibit positive phase synchronization. Using the corresponding test-statistic and p-values, we develop a clustering algorithm which sorts countries that are significantly positively synchronized with each other.

We find evidence against the existence of a common credit cycle across all countries. Instead, the analyzed countries form two distinct clusters. Austria, Belgium, Germany, Ireland, and the Netherlands belong to the first cluster, while the second cluster comprises Denmark, Finland, France, Italy, Spain, Sweden, the United Kingdom, and the United States. Within each of the two clusters, credit cycle synchronization has a positive time trend indicating convergence, at least since the last decade. Our regressions show that countries with more highly correlated business cycles tend to have more strongly synchronized credit cycles. Moreover, a higher degree of credit market integration between two countries is accompanied by higher credit cycle synchronization both directly as well as indirectly, through the amplifying effect of credit market integration on business cycle co-movement.

Boom-bust cycles in credit have moved to the forefront of attention in the aftermath of the 2007-08 global financial crisis. The international evidence shows that systemic banking crises are typically preceded by credit booms (see, for example, Mendoza and Terrones, 2008; Reinhart and Rogoff, 2009; Gourinchas and Obstfeld, 2012; Laeven and Valencia, 2013; Schularick and Taylor, 2012; Aikman et al., 2014). Economic activity is disrupted during the credit bust that accompanies a financial crisis; recessions that coincide with financial crises are therefore more severe (see, for example, Hutchinson and Noy, 2005; Reinhart and Rogoff, 2009; Jorda, Schularick, and Taylor, 2011; Claessens, Kose, and Terrones, 2012; Schularick and Taylor, 2012). The intertwined nature of credit and financial crises raises the question of whether, and to what extent, credit cycles are synchronized across countries. We address precisely this question. The stylized facts on credit cycle synchronization documented in this paper may be useful for building theoretical models to analyze international financial crises, similar to the models proposed by, for example, Mendoza (2010), Mendoza and Quadrini (2010), and Benigno, Chen, Otrok, Rebucci, and Young (2013).

Whether credit booms and busts occur simultaneously across countries constitutes an important question, particularly for macroprudential policy makers. Macroprudential policy can moderate the build-up of excessive leverage and its rapid unwinding in the financial sector, as shown by Lorenzoni (2008) and Bianchi (2011).[1] However, macroprudential measures implemented at the national level – say, time-varying loan-to-value ratios and counter-cyclical capital buffers – may have international repercussions in a financially integrated world (see, for example, Jeanne, 2014; Beirne and Friedrich, 2014; Banque de France, 2014).[2] Thus, the synchronization of credit cycles has provoked a lively policy debate in Europe, which is the motivation for our focus on credit cycle synchronization primarily among major European economies.

The issue of a common European credit cycle is key when discussing the feasibility of a common macroprudential policy, just as a common business cycle constitutes a prerequisite for a common monetary policy. A centralized macroprudential policy might be optimal if different countries reside simultaneously in the same phase of the credit cycle. However, if credit cycles are not synchronized, macroprudential policies should be coordinated across countries, as is currently being discussed by the European Systemic Risk Board and various national authorities. Our findings may facilitate the design of macroprudential policies in an environment prone to interdependence across economies. The credit cycle heterogeneity documented in this paper implies that macroprudential policy should remain at the national level, while at the same time also stressing the importance of supranational policy coordination.

To the best of our knowledge, we are the first to perform a formal statistical analysis of international credit cycle synchronization. Earlier studies that deal with this issue include Drehmann et al. (2012) and Aikman et al. (2014), but these are descriptive in nature. Our contribution to the literature is threefold. First, we propose a straightforward econometric test for cyclical synchronization. Second, we examine different aspects of credit cycle synchronization: clustering, lead and lag relations, and the evolution of synchronization over time. Finally, we shed light on the effects of macroeconomic and financial interdependence on the synchronization of credit cycles, complementing a broad literature on the relationship between the financial sector and aggregate economic conditions.[3]

The remainder of the paper is organized as follows. In section 2, we introduce our novel synchronization test. We describe the data used in the analysis in section 3, and present the main empirical results in section 4. Finally, in section 5 we conclude with discussions of the implications of our findings for the design of macroprudential policies.

2 Econometric Methodology

In this section, we define the credit cycle and its boom and bust phases using two alternative definitions. Furthermore, we define two types of phase synchronization, designated as "swing synchronization" and "gap synchronization". Finally, an econometric approach to test for phase synchronization between a pair of credit cycles is presented.

[1] More generally, macroprudential policy aims to reduce systemic risk. We address the time-varying dimension of systemic risk. The latter also has a cross-sectional dimension that stems from the interconnectedness of financial institutions, which is beyond the scope of this paper.

[2] Evidence suggests that credit supply shocks can propagate across borders, which lends empirical support to this viewpoint (see, for example, Eickmeier and Ng, 2011; Helbling, Huidrom, Kose, and Otrok, 2011). For example, globally active banks may serve as a potential transmission channel of credit supply shocks. In response to an unexpected decline of liquidity, global banks tend to rebalance their lending in favor of domestic borrowers, which can lead to cross-border loan supply contraction, as shown by Cetorelli and Goldberg (2011, 2012) and Giannetti and Laeven (2012).

[3] The links between credit and the macroeconomy have been studied by, for example, Balke (2000), Bordo and Haubrich (2010), Jorda et al. (2011), Schularick and Taylor (2012), and Claessens et al. (2012).

We measure credit cycles as transitory fluctuations in the volume of real credit around its long-run trend level. This approach is consistent with a widespread view on cyclical fluctuations in macroeconomic time series, which is often referred to as the "growth cycle".[4] Recently, Aikman et al. (2014) have shown in a theoretical model that financial frictions give rise to credit cycles characterized by longer duration and larger amplitude than the traditional business cycle which typically spans 1.5-8 years. Focusing on fluctuations at lower frequencies is supported from an empirical perspective by the observation that the occurrence of financial crises is well-aligned with medium-frequency movements in credit, as shown by Drehmann et al. (2012) and Arnold et al. (2012). Furthermore, the international evidence shows that systemic banking crises are typically preceded by secular credit booms; see Mendoza and Terrones (2008), Reinhart and Rogoff (2009), Gourinchas and Obstfeld (2012), Laeven and Valencia (2013), and Schularick and Taylor (2012). In line with this strand of the literature, we focus on fluctuations in credit associated with medium-term frequencies that lie between 8-30 years, conform to the concept of the "medium-term cycle" introduced by Comin and Gertler (2006).

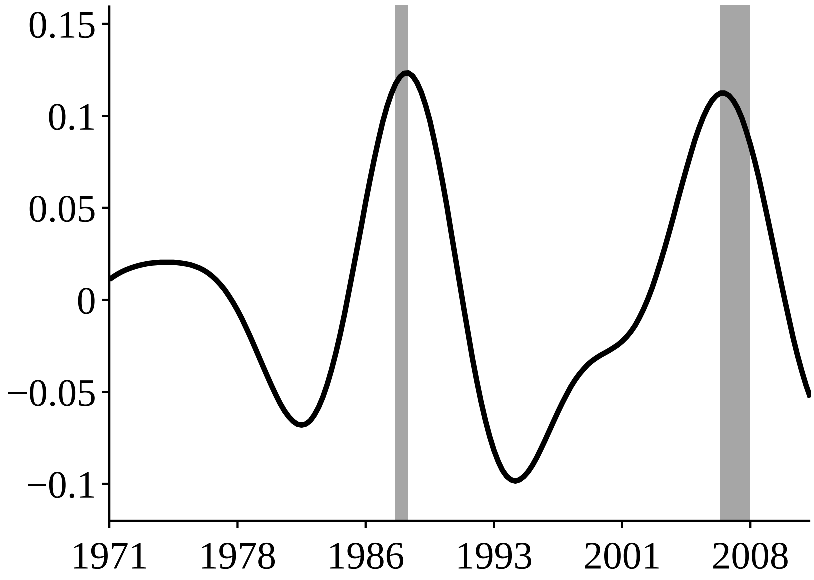
We apply the band-pass filter proposed by Christiano and Fitzgerald (2003) (denoted CF filter) to extract the medium-frequency cyclical component $c_{i,t}$ of logarithmic real credit $x_{i,t}$ observed for country $i = 1, \dots, N$ at quarter $t = 1, \dots, T$.[5] An important advantage of the CF filter compared to e.g. the popular Hodrick and Prescott (1997) filter is that it isolates periodic components in the data that lie in a particular frequency range, while the fluctuations at all other frequencies are removed. This enables us to focus exclusively on the medium-frequency movements in credit. Moreover, since the CF filter is asymmetric, it does not suffer from the endpoint problem of other commonly used filters, including the ones proposed by Hodrick and Prescott (1997) and Baxter and King (1999). As an example, Figure 1 illustrates the medium-term credit cycle of the United States together with systemic banking crisis episodes dated by Laeven and Valencia (2013). The figure reveals that systemic financial crises typically ensue at the height of a secular credit boom, which underlines our focus on medium-term fluctuations.

We map the credit cycle $c_{i,t}$ into a binary variable $B_{i,t}$ to which we assign a value of 1 if the credit cycle is in a boom phase, while it equals -1 if the credit cycle is in a bust phase. We propose two alternative definitions for $B_{i,t}$. First, we define $B_{i,t}$ such that it reflects upswings (from trough to peak) and downswings (from peak to trough) of the credit cycle. Second, we define $B_{i,t}$ in terms of the deviation from the long-run trend level of credit, i.e., as a "credit gap". More formally, according to our first definition, we distinguish between upswings and

[4]Business cycle researchers who analyze the growth cycle include, for example, Hodrick and Prescott (1997), Baxter and King (1999), Stock and Watson (1999), Christiano and Fitzgerald (2003), and Morley and Piger (2012). Another concept of the cycle put forward by NBER researchers corresponds to an alternation between persistent periods of expansion and contraction observed in the level of the time series. This is typically referred to as the "classical cycle" (see, for example, Burns and Mitchell, 1946; Bry and Boschan, 1971; Harding and Pagan, 2002, 2006, 2011; Candelon, Metiu, and Straetmans, 2013).

[5]The CF filter provides an optimal finite sample linear approximation to the ideal band-pass filter without knowledge of the true time series representation of $x_{i,t}$. Instead, the series is assumed to follow a pure random walk process, $x_{i,t} = x_{i,t-1} + u_{i,t}$. The data is drift-adjusted prior to applying the CF filter by computing: $x_{i,t} = y_{i,t} - (t-1)(y_{i,T} - y_{i,1})/(T-1)$, where $y_{i,t}$ denotes the raw real credit series prior to drift-adjustment. In practice, the CF filter produces an asymmetric two-sided moving average of $x_{i,t}$. The cyclical component of real credit, $c_{i,t}$, with period of oscillation between $p_u = 32$ quarters (8 years) and $p_l = 120$ quarters (30 years) (where $2 \leq p_u < p_l < \infty$) is obtained as $c_{i,t} = B_0 x_{i,t} + B_1 x_{i,t+1} + \dots + B_{T-1-t} x_{i,T-1} + B_{T-t} x_{i,T} + B_1 x_{i,t-1} + \dots + B_{t-2} x_{i,2} + \tilde{B}_{t-1} x_{i,1}$, where for $k > 1$, $B_k = (\sin(kb) - \sin(ka))/\pi k$ and $\tilde{B}_q = -1/2 B_0 - \sum_{k=1}^{q-1} B_k$, with $B_0 = (b-a)/\pi$, $a = 2\pi/p_u$ and $b = 2\pi/p_l$.

Figure 1: The medium-term US credit cycle



Note: Cyclical fluctuations in US real credit at medium-term frequencies between eight and 30 years extracted with the Christiano and Fitzgerald (2003) band-pass filter. The gray shaded areas denote systemic banking crisis periods dated by Laeven and Valencia (2013).

downswings or, equivalently, periods of positive and negative growth in the credit cycle:

$$B_{i,t}^{swing} = \frac{\Delta c_{i,t}}{|\Delta c_{i,t}|} = \begin{cases} 1 & \text{if credit in country } i \text{ in upswing at time } t \\ -1 & \text{if credit in country } i \text{ in downswing at time } t, \end{cases} \tag{1}$$

where $\Delta c_{i,t} = c_{i,t} - c_{i,t-1}$ is the first-difference of the credit cycle. Macroprudential instruments, such as the capital conservation buffer and the counter-cyclical capital buffer, might be elevated during an upswing and reduced during a downswing. Alternatively, macroprudential instruments, such as loan-to-value-ratios, might be designed to bind whenever the credit gap is positive. In our second definition, we therefore distinguish between a positive and a negative credit gap:

$$B_{i,t}^{gap} = \frac{c_{i,t}}{|c_{i,t}|} = \begin{cases} 1 & \text{if credit in country } i \text{ is above long-run trend at time } t \\ -1 & \text{if credit in country } i \text{ is below long-run trend at time } t. \end{cases} \tag{2}$$

Let us now define three concepts of phase synchronization. First, perfect positive phase synchronization (PPS) between two countries i and j can be defined as

$$\text{PPS}: \; P(B_{i,t} = 1, B_{j,t} = 1) + P(B_{i,t} = -1, B_{j,t} = -1) = 1.$$

Second, perfect negative phase synchronization (PNS) can be defined as

$$\text{PNS}: \; P(B_{i,t} = 1, B_{j,t} = -1) + P(B_{i,t} = -1, B_{j,t} = 1) = 1.$$

Third, non-synchronization (NonS) occurs if the two cycles are equally likely to be in the same phase or in the opposite phase. That is the case if either NonS a) or b) holds, where one implies the other

$$\begin{aligned}
\text{NonS a):}\ & P(B_{i,t}=1, B_{j,t}=1) + P(B_{i,t}=-1, B_{j,t}=-1) = 1/2, \\
\text{NonS b):}\ & P(B_{i,t}=1, B_{j,t}=-1) + P(B_{i,t}=-1, B_{j,t}=1) = 1/2.
\end{aligned}$$

We measure phase synchronization between the cycles of two countries i and j by the product:

$$S_t^{ij} = B_{i,t}B_{j,t} = \begin{cases} 1 & \text{if cycles } i \text{ and } j \text{ are in the same phase at time } t \\ -1 & \text{if cycles } i \text{ and } j \text{ are not in same phase at time } t. \end{cases}$$

Thus, we define swing synchronization as $S_t^{ij,swing} = B_{i,t}^{swing}B_{j,t}^{swing}$, and gap synchronization is given by $S_t^{ij,gap} = B_{i,t}^{gap}B_{j,t}^{gap}$. The expected value of S_t^{ij} is[6]

$$\begin{aligned}
E[S_t^{ij}] = E[B_{i,t}B_{j,t}] = & \ 1\ \ (P(B_{i,t}=1, B_{j,t}=1) + P(B_{i,t}=-1, B_{j,t}=-1)) \\
& -1\ \ (P(B_{i,t}=1, B_{j,t}=-1) + P(B_{i,t}=-1, B_{j,t}=1)).
\end{aligned}$$

Rewriting the phase synchronization definitions in terms of the expected value $E[S_t^{ij}]$ gives

$$PPS:\ E[S_t^{ij}] = 1 \tag{3}$$

$$PNS:\ E[S_t^{ij}] = -1 \tag{4}$$

$$NonS:\ E[S_t^{ij}] = 0 \tag{5}$$

We seek to answer the question whether boom-bust cycles in credit are positively – but not necessarily perfectly – synchronized across two countries. We are therefore interested in the following null hypothesis:

$$H_0 : \mu_{S^{ij}} := E[S_t^{ij}] \leq 0, \tag{6}$$

that is, we test whether credit cycles are not synchronized or whether they are negatively synchronized against the one-sided alternative of positive synchronization:

$$H_1 : \mu_{S^{ij}} > 0.$$

A rejection of the null hypothesis is interpreted as evidence for positive phase synchronization.[7] To test the null, we run the following OLS regression:

$$S_t^{ij} = \mu_{S^{ij}} + \varepsilon_t, \tag{7}$$

[6]Note that $Corr(B_i, B_j) = Cov(B_{i,t}B_{j,t}) = E[B_{i,t}B_{j,t}] = E[S_t^{ij}]$, where the first equality holds because $\text{var}(B_{i,t}) = 1^2\text{Pr}(B_{i,t}=1) + (-1)^2\text{Pr}(B_{i,t}=-1) = \text{Var}(B_{j,t}) = 1$, and the second equality follows from the symmetry property of $\Delta c_{i,t}$ so that $\text{E}[B_{i,t}] = 1\text{Pr}(B_{i,t}=1) + (-1)\text{Pr}(B_{i,t}=-1) = 1\text{Pr}(\Delta c_t > 0) + (-1)\text{Pr}(\Delta c_t < 0) = 1/2 - 1/2 = \text{E}[B_{j,t}] = 0$. The symmetry property of $\Delta c_{i,t}$ follows by construction of the CF filter, since this filter is designed to produce a stationary, zero-mean cyclical component $c_{i,t}$ under the assumption that the underlying time series $x_{i,t}$ follows a pure random walk. Phase synchronization may therefore be interpreted as phase correlation.

[7]Alternatively, we could also test for PPS. However, the rejection of this hypothesis does not allow us to discriminate between the alternatives of positive (but not perfect) synchronization, non-synchronization and negative synchronization. While positive synchronization would mean that macroprudential policies in the two countries may reinforce each other, non-synchronization and negative synchronization may indicate risks for adverse policy spillovers.

and we perform a one-sided t-test for the null hypothesis $\mu_{S^{ij}} \leq 0$. The OLS estimate of $\mu_{S^{ij}}$ is the sample mean of phase synchronization: $\hat{\mu}_S^{ij} = \frac{1}{T}\sum_{t=1}^{T} S_t^{ij}$. The synchronization variable S_t^{ij} and therefore ε_t may be prone to serial correlation, as they inherit their serial dependence structure from the underlying time series. Therefore, we use Newey and West (1987) standard errors for inference, which have also been used by Harding and Pagan (2006, 2011) as a remedy in the context of binary variable regressions. In Appendix A we outline an alternative approach based on a bootstrap approximation of the test statistic's asymptotic distribution, similar to the one applied by Mink, Jacobs, and De Haan (2012). We opt for an OLS regression-based approach, as this enhances the applicability of the test, and it is useful when studying the evolution of synchronization over time.[8] In the box below, we briefly summarize the testing procedure.

Our framework can be generalized to analyze synchronization between two credit cycles, of which one potentially leads the other. To that aim, we may extend our synchronization measure as follows:

$$S_{t,l}^{ij} = B_{i,t}B_{j,t+l} \tag{8}$$

where $l \in \mathcal{Z}$ is the number of periods by which the credit cycle phase of country j potentially leads (or lags) that of country i. If a country i at time t and a country j at time $t+l$ are in the same credit cycle phase, then $S_{t,l}^{ij} = 1$; otherwise $S_{t,l}^{ij} = -1$.

Harding and Pagan (2002, 2006) use a similar approach to our swing synchronization. They define synchronization between a pair of cycles by the "degree of concordance", "[...] quantified by the fraction of time both series are simultaneously in the same state of expansion or contraction" (Harding and Pagan, 2002, page 370). However, their definition of cycles pertains to a pattern of expansions and contractions in the level of the time series $x_{i,t}$ (i.e. the classical cycle), while we focus on band-pass filtered cycles. Moreover, our definition of the binary variable S_t^{ij} as well as the values it can take differs from their approach. Most importantly, the properties of our variable are different from theirs, allowing for a more straightforward test procedure. We use the same definition for credit gap synchronization as the measure of business cycle "synchronicity" proposed by Mink et al. (2012). We add to their concept a regression-based test procedure.

Summary: Testing for phase synchronization

1. Extract medium-term cycle $c_{i,t}$ using CF.
2. Compute credit cycle phase using either $B_{i,t}^{swing} = \frac{\Delta c_{i,t}}{|\Delta c_{i,t}|}$ or $B_{i,t}^{gap} = \frac{c_{i,t}}{|c_{i,t}|}$.
3. Compute the synchronization variable $S_t^{ij} = B_{i,t}B_{j,t}$.
4. Take the average of the synchronization variable to obtain phase synchronization: $\hat{\mu}_S^{ij} = \frac{1}{T}\sum_{t=1}^{T} S_t^{ij}$ (Or equivalently, run OLS regression using Newey and West (1987) standard errors on: $S_t^{ij} = \mu_{S^{ij}} + \varepsilon_t$).
5. If $\hat{\mu}_S^{ij} \leq 0$ is rejected using a one-sided t-test, there is evidence that the credit cycle phases are positively synchronized.

[8] A robustness exercise conducted with the bootstrap-based test has led to results which are nearly identical to these obtained from the OLS approach.

3 Data description

We use data from the BIS on total (outstanding) credit to the private non-financial sector expressed in billions of national currency for Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Spain, Sweden, the United Kingdom, and the United States. We include the US due to its central role in the international financial system and its strong trade and financial ties to European economies. The credit data reflect lending relationships for a broad group of borrowers and lenders. The borrowers are non-financial corporations (both privately and publicly owned), households, and non-profit institutions serving households as defined in the System of National Accounts 2008. The lenders include non-financial corporations, financial corporations (including central banks), the general government, households, non-profit institutions serving households, and internationally active banks. The instruments covered are debt securities (bonds and short-term paper) and loans. We use quarterly (end-of-period) observations between 1972Q1 and 2011Q4 adjusted for breaks by the BIS, and the credit series are deflated with the national consumer price indices to obtain real values. Dembiermont, Drehmann, and Muksakunratana (2013) provide a comprehensive description of the data and its statistical treatment, and they argue that the data displays a high degree of consistency and comparability across countries.

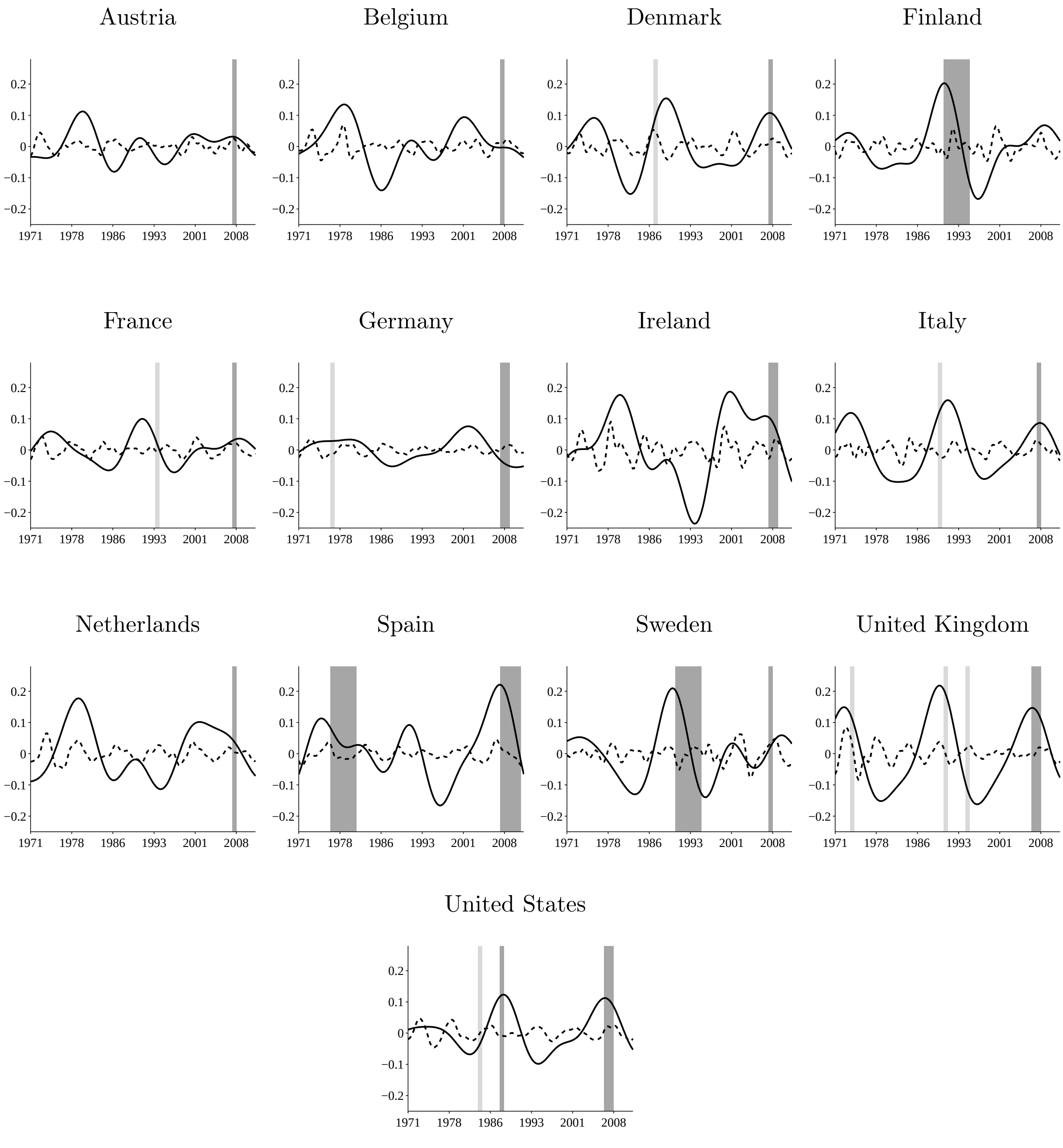
Figure 2 illustrates for each country the short-term variation in real credit between 1.5-8 years (dotted line) and the medium-frequency component between 8-30 years (solid line). Areas shaded in dark gray denote systemic banking crises dated by Laeven and Valencia (2013). These include the 2008 global financial crisis, the 1977-81 Spanish crisis, and the 1991-95 Finnish and Swedish crises. Areas shaded in light gray denote other banking crises dated by Reinhart and Rogoff (2008), which represent events of a lesser magnitude, e.g., the 1984 savings and loan crisis in the US and the 1995 Barings investment bank crisis in the UK.

At a first glance, three main patterns stand out from Figure 2. First, the medium-term component exhibits substantially larger volatility than the short-term component, with the exception of Austria, France and Germany, that have relatively subdued medium-term cycles compared to others. Second, the figure already provides some casual evidence that countries display distinct boom-bust patterns in credit. For instance, the United Kingdom and the United States seem to have similar cycles that stand in contrast to the cycles of, for example, Ireland or the Netherlands. Third, the figure reveals that systemic banking crises tend to occur around the peaks of the medium-term cycle.

Further conclusions can be drawn from the contemporaneous sample correlations reported in Table 1. The entries in the upper triangular of the table correspond to the sample correlations between the medium-term components, while the entries in the lower triangular correspond to the sample correlations between the short-term components of the credit series (shaded in gray). The highest short-term correlations are observed among Belgium, France, the UK, and the US, and among Denmark, Germany, and the Netherlands. In contrast, the highest medium-term correlations are observed, on the one hand, among Austria, Belgium, Ireland, and the Netherlands, and, on the other hand, among Denmark, Finland, Italy, Sweden, UK, and US.

In several instances – in the case of France and Germany or Italy and the Netherlands, for instance – the correlations of the short-term components and the correlations of medium-term components have the opposite sign. Thus, it is possible to reach markedly different conclusions regarding cyclical co-movement, depending on the cyclical component under study. In particular, focusing solely on the short-term component may be misleading if interest centers on synchronization among large and persistent credit boom and bust episodes. In this article, we follow Drehmann et al. (2012), Arnold et al. (2012), and Aikman et al. (2014) and focus on the medium-term component of the credit cycle. Moreover, we are interested in the correlation of

Figure 2: Short-term and medium-term credit cycles



Note: The short-term component of the credit cycle (dotted line) includes frequencies between six and 32 quarters (1.5 and eight years), while the medium-term component (solid line) includes frequencies between 32 and 120 quarters (eight and 30 years). Areas shaded in dark gray denote systemic banking crises dated by Laeven and Valencia (2013). Areas shaded in light gray denote other banking crises dated by Reinhart and Rogoff (2008).

boom/bust phases rather than the correlation of credit cycles. Even though Pearson's correlation coefficient is a good starting point for our analysis, it does not properly take into account the coincidence of cyclical phases, as already argued by Mink et al. (2012). In what follows, we therefore study the phase correlation of the credit cycle.

4 Empirical results

In this section we analyze the international synchronization of credit boom and bust phases. First, for each country pair we present the test results for swing synchronization and for gap synchronization. Second, we perform a cluster analysis in order to determine whether there is a single European credit cycle. Third, we study the evolution of phase synchronization over time. Finally, we examine the macroeconomic and financial drivers of credit cycle synchronization.

4.1 Synchronization of credit cycle phases

To study the synchronization of credit cycle phases, for each pair of countries we run the OLS regression in equation (7). Table 2 presents the degree of swing synchronization between the medium-term components of each country pair obtained from this regression. Asterisks denote significantly positive synchronization at the 5% level, and Newey-West heteroscedasticity and autocorrelation consistent (HAC) standard errors are given in parentheses. From this table we can make several observations. Specifically, the Dutch and Belgian cycles display overall the strongest swing synchronization ($\hat{\mu}_{Sij}^{swing} = 0.84$), while the largest negative swing synchronization is observed between Italy and Germany ($\hat{\mu}_{Sij}^{swing} = -0.42$). Indeed, swing synchronization is negative between the German cycle and most other cycles, including the Danish, Finnish, French, Swedish, Spanish, UK and US cycles, while the German cycle is most closely related to the Dutch and Belgian cycles. Perhaps not surprisingly, the US cycle is most closely synchronized with the UK cycle, followed by the Danish cycle. Analogously, Table 3 shows the degrees of gap synchronization. Even though the two measures capture somewhat different aspects of cyclical phases, a relatively consistent picture emerges from both synchronization measures. In Appendix B, we extend our analysis beyond contemporaneous synchronization in order to investigate whether credit cycles potentially exhibit leading or lagging properties.

In order to illustrate the relative synchronization between countries, we present the information of Table 2 and 3 in the form of a multidimensional scaling map. To that end, we transform the bilateral synchronization measures, $\hat{\mu}_{S^{ij}}$, which indicate the similarity between a pair of credit cycles, into measures of dissimilarity by taking $D_{i,j} = 1 - \hat{\mu}_{S^{ij}}$. Let $\mathbf{D}_{NxN} = [D_{i,j}]$ denote the matrix that contains the dissimilarities between every possible pair of countries. We project the dissimilarity matrix $\mathbf{D}_{NxN}$ onto a two-dimensional plane using the multidimensional scaling method also known as principal coordinates analysis. An eigen-decomposition of the dissimilarity matrix is used to identify the main axes or "principal coordinates" (see Torgerson, 1952). Similar methods have been applied in the business cycle literature by Croux, Forni, and Reichlin (2001) and Camacho, Perez-Quiros, and Saiz (2006).

The resulting maps for swing synchronization and gap synchronization are shown in Figure 3. The relative distances between countries reflect the extent of synchronization of their credit cycle phases: countries whose cycles are more synchronized are closer to each other on this two-dimensional plane. Thus, the scaling map helps in detecting potential clusters and outliers. The maps suggest that Denmark, Finland, France, Italy, Spain, Sweden, the UK, and the US are clustered on one side, while Austria, Belgium, Germany, Ireland, and the Netherlands are on the other side of the plane.

Table 1: Credit cycle correlations

	AUT	BEL	DEN	FIN	FRA	GER	IRE	ITA	NED	ESP	SWE	UK	US
AUT	1.00	0.74	-0.26	-0.03	0.12	0.42	0.67	-0.27	0.86	0.29	-0.05	-0.25	-0.12
BEL	0.40	1.00	-0.20	-0.15	0.21	0.70	0.62	-0.10	0.81	0.20	0.00	-0.39	-0.28
DEN	0.58	0.26	1.00	0.71	0.67	-0.59	-0.21	0.74	-0.22	0.55	0.79	0.75	0.81
FIN	0.60	0.34	0.40	1.00	0.89	-0.50	-0.26	0.84	-0.24	0.63	0.89	0.88	0.56
FRA	0.56	0.59	0.39	0.51	1.00	-0.31	-0.19	0.89	-0.06	0.68	0.84	0.66	0.36
GER	0.57	0.55	0.70	0.33	0.42	1.00	0.62	-0.49	0.66	-0.19	-0.39	-0.53	-0.40
IRE	0.39	0.39	0.46	0.49	0.27	0.53	1.00	-0.47	0.87	0.28	-0.16	-0.23	0.15
ITA	0.57	0.18	0.51	0.44	0.47	0.43	0.44	1.00	-0.42	0.55	0.77	0.76	0.38
NED	0.55	0.55	0.57	0.62	0.47	0.73	0.63	0.39	1.00	0.29	-0.18	-0.35	0.01
ESP	0.02	0.04	0.02	0.24	0.29	-0.20	0.00	0.21	0.00	1.00	0.43	0.58	0.58
SWE	0.18	0.47	0.38	0.14	0.47	0.38	0.02	0.16	0.37	0.26	1.00	0.76	0.57
UK	0.31	0.73	0.00	0.22	0.67	0.37	0.26	0.00	0.36	0.14	0.38	1.00	0.77
US	0.65	0.79	0.46	0.45	0.68	0.71	0.58	0.44	0.69	0.03	0.37	0.68	1.00

Note: The entries in the upper triangular correspond to the sample correlations between medium-term cycles (8-30 years). The entries in the lower triangular shaded in gray correspond to the sample correlations between the short-term cycles (1.5-8 years).

Table 2: swing synchronization

	BEL	DEN	FIN	FRA	GER	IRE	ITA	NED	ESP	SWE	UK	US
AUT	0.61*	0.04	0.12	0.25*	0.26*	0.65*	-0.01	0.55*	0.30*	0.21	0.07	0.03
	(0.12)	(0.15)	(0.15)	(0.15)	(0.15)	(0.11)	(0.16)	(0.12)	(0.15)	(0.15)	(0.15)	(0.15)
BEL	1.00	0.06	0.01	0.31*	0.52*	0.61*	0.06	0.84*	0.28*	0.25*	-0.12	-0.01
		(0.16)	(0.15)	(0.15)	(0.13)	(0.11)	(0.16)	(0.07)	(0.15)	(0.15)	(0.16)	(0.16)
DEN		1.00	0.27*	0.37*	-0.35	0.09	0.52*	0.09	0.37*	0.33*	0.35*	0.54*
			(0.14)	(0.13)	(0.14)	(0.15)	(0.13)	(0.15)	(0.14)	(0.14)	(0.14)	(0.13)
FIN			1.00	0.67*	-0.32	-0.03	0.57*	-0.03	0.60*	0.53*	0.60*	0.31*
				(0.10)	(0.14)	(0.14)	(0.12)	(0.15)	(0.11)	(0.12)	(0.11)	(0.14)
FRA				1.00	-0.09	0.12	0.62*	0.22	0.62*	0.61*	0.27*	0.26*
					(0.15)	(0.15)	(0.11)	(0.15)	(0.11)	(0.10)	(0.15)	(0.15)
GER					1.00	0.41*	-0.35	0.53*	-0.04	-0.23	-0.42	-0.33
						(0.14)	(0.15)	(0.13)	(0.16)	(0.15)	(0.14)	(0.15)
IRE						1.00	-0.16	0.72*	0.22	0.16	-0.06	0.06
							(0.15)	(0.09)	(0.15)	(0.15)	(0.16)	(0.16)
ITA							1.00	-0.06	0.52*	0.48*	0.52*	0.51*
								(0.16)	(0.13)	(0.13)	(0.13)	(0.13)
NED								1.00	0.19	0.21	-0.03	0.11
									(0.16)	(0.15)	(0.16)	(0.16)
ESP									1.00	0.28*	0.47*	0.28*
										(0.14)	(0.13)	(0.15)
SWE										1.00	0.28*	0.35*
											(0.15)	(0.14)
UK											1.00	0.64*
												(0.12)

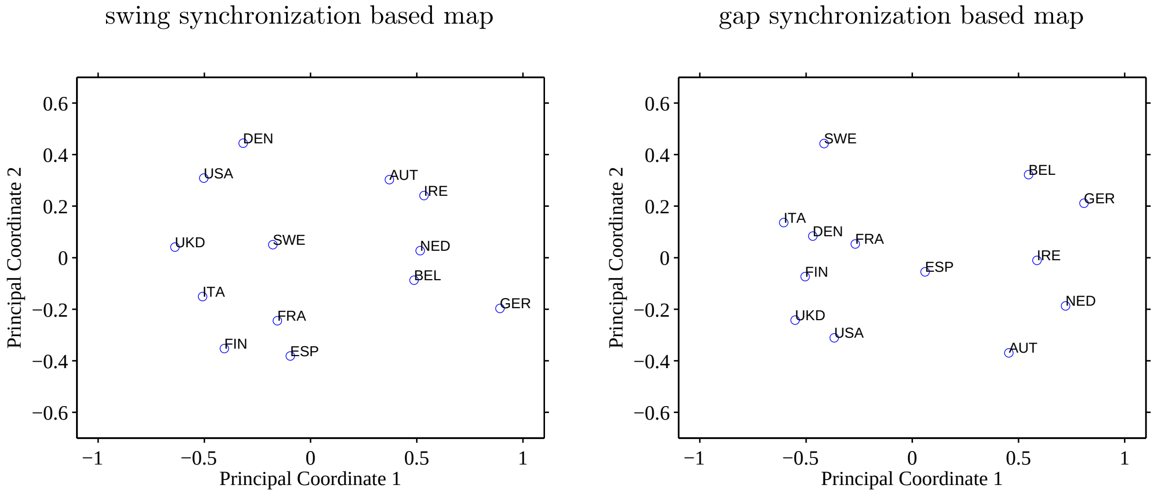
Note: The table entries show the bilateral degree of swing synchronization between two countries. Asterisks denote significantly positive synchronization at the 5% level, and HAC standard errors are given in parentheses.

Table 3: gap synchronization

	BEL	DEN	FIN	FRA	GER	IRE	ITA	NED	ESP	SWE	UK	US
AUT	0.43*	-0.03	0.01	0.14	0.25	0.50*	-0.14	0.67*	0.47*	-0.09	0.03	-0.01
	(0.13)	(0.16)	(0.16)	(0.16)	(0.15)	(0.13)	(0.16)	(0.11)	(0.14)	(0.15)	(0.16)	(0.16)
BEL	1.00	-0.09	-0.11	0.11	0.66*	0.51*	-0.18	0.51*	0.33*	-0.01	-0.16	-0.09
		(0.16)	(0.16)	(0.16)	(0.11)	(0.14)	(0.15)	(0.13)	(0.15)	(0.15)	(0.15)	(0.15)
DEN		1.00	0.64*	0.67*	-0.31	-0.06	0.71*	-0.21	0.45*	0.54*	0.64*	0.67*
			(0.12)	(0.11)	(0.15)	(0.16)	(0.11)	(0.16)	(0.14)	(0.13)	(0.12)	(0.11)
FIN			1.00	0.76*	-0.35	-0.09	0.72*	-0.25	0.46*	0.55*	0.77*	0.61*
				(0.10)	(0.15)	(0.16)	(0.10)	(0.16)	(0.14)	(0.13)	(0.08)	(0.12)
FRA				1.00	-0.13	0.12	0.71*	-0.03	0.65*	0.48*	0.53*	0.55*
					(0.16)	(0.16)	(0.11)	(0.16)	(0.11)	(0.13)	(0.13)	(0.13)
GER					1.00	0.72*	-0.42	0.57*	0.19	-0.22	-0.40	-0.18
						(0.11)	(0.14)	(0.13)	(0.16)	(0.15)	(0.14)	(0.16)
IRE						1.00	-0.17	0.72*	0.45*	-0.12	-0.14	0.07
							(0.16)	(0.10)	(0.14)	(0.16)	(0.16)	(0.16)
ITA							1.00	-0.32	0.38*	0.55*	0.57*	0.48*
								(0.15)	(0.14)	(0.13)	(0.12)	(0.14)
NED								1.00	0.30*	-0.27	-0.30	-0.08
									(0.15)	(0.15)	(0.15)	(0.16)
ESP									1.00	0.21*	0.33*	0.37*
										(0.15)	(0.15)	(0.14)
SWE										1.00	0.40*	0.36*
											(0.15)	(0.14)
UK											1.00	0.71*
												(0.10)

Note: The table entries show the bilateral degree of gap synchronization between two countries. Asterisks denote significantly positive synchronization at the 5% level, and HAC standard errors are given in parentheses.

Figure 3: Two-dimensional scaling map



Note: The two-dimensional scaling map illustrates the dissimilarity of credit cycle phases, defined as $D_{i,j} = 1 - \hat{S}_{i,j}$. Subfigure (a): scaling map based on swing synchronization. Subfigure (b): scaling map based on gap synchronization. Countries whose cycles phases are more synchronized are closer to each other on this two-dimensional plane. The scaling map is based on an eigen decomposition that identifies the principal coordinates through the dissimilarity matrix $\mathbf{D}_{NxN} = [D_{i,j}]$ (see Torgerson, 1952).

4.2 Is there a single European credit cycle?

Are the credit cycles synchronized strongly enough across countries to imply that all countries share a single European credit cycle? We answer this question by performing a cluster analysis. In particular, we combine the hierarchical clustering algorithm of Timm (2002) with the regression p-values from equation (7) in order to group countries such that all country pairs within a cluster exhibit significantly positive phase synchronization. Countries that belong to the same cluster are considered to share a common credit cycle.

The upper panel of Figure 4 shows the hierarchical clustering tree also known as dendrogram, obtained by applying the clustering algorithm to the dissimilarity matrix $\mathbf{D}_{NxN}$. The dendrogram visualizes groups of countries clustered based on their level of credit cycle dissimilarity. The dendrogram's heights measured on the vertical axis represent the level of dissimilarity at which countries or country groups are merged to form a new group. To construct the dendrogram, we begin with N clusters, each containing a single country. We then select the most similar pairs from the dissimilarity matrix $\mathbf{D}_{NxN}$ and combine these into new clusters. Subsequently, we recompute the dissimilarities between the clusters based on the largest dissimilarity between two clusters' elements (countries), and the most similar pairs are again combined into new clusters. This cluster-forming criterion is known as the farthest-neighbor method. We keep merging clusters based on this principle until we reach a certain cut-off value.

The criterion for choosing the cut-off at which the clustering is stopped is the most important and usually most arbitrary step in the clustering procedure, as this determines the number of clusters and thus the number of distinct credit cycles. The cut-off is often chosen according to some rule of thumb which is *ad hoc* and highly controversial. In contrast, we propose a statistical criterion for choosing the cut-off value using the p-values from the OLS regressions in equation (7). Larger p-values indicate a higher probability that the null of non-positive synchronization is true, in which case the two countries do not share a common cycle. Consequently, we repeat the hierarchical clustering procedure using as input instead of $\mathbf{D}_{NxN}$ the p-values for each country pair obtained from the regressions in equation (7). We stop the clustering procedure as soon as the p-values that determine the distance between two clusters exceed the 5% significance level. The farthest-neighbor method ensures that the null hypothesis is rejected for each pair of countries within a cluster, which implies that all bilateral pairs exhibit significantly positive synchronization within each cluster. The lower panel of Figure 4 shows the dendrograms obtained by applying the clustering algorithm to the regression p-values and the dashed line represents the cut-off point at the 5% significance level. According to this cut-off, the analyzed countries form two distinct clusters, which provides evidence against the existence of a common credit cycle across all countries.

The dendrograms in Figure 4 confirm the grouping suggested by the two-dimensional maps shown in Figure 3. Focusing on swing synchronization, we observe two major clusters with the cycles of Belgium and the Netherlands being the most similar to each other, as we have seen in Table 2. Austria, Belgium, Germany, Ireland, and the Netherlands are sorted into one cluster (depicted by the red dashed links), while Denmark, Finland, France, Italy, Spain, Sweden, the United Kingdom, and the United States form a separate cluster (depicted by the blue links). Upon inspecting the dendrogram based on gap synchronization, we consistently find the same two clusters. However, Austria and Spain seem to have a rather idiosyncratic credit gap and we can not assign these two countries to any of the two clusters.

While we have not found evidence for a common European cycle, we determined two groups of countries which can be said to share a common cycle. In order to construct such common cycles, we take the cross-section mean of all real credit series within a cluster and we apply the CF filter to this pseudo time series. This approach delivers a cluster-specific cycle that lies close to the credit cycles of all individual countries within the cluster. Figure 5 shows the common cycles obtained via this procedure together with the country-specific cycles within each group. We also plot the two cluster-specific cycles separately in the third subfigure.

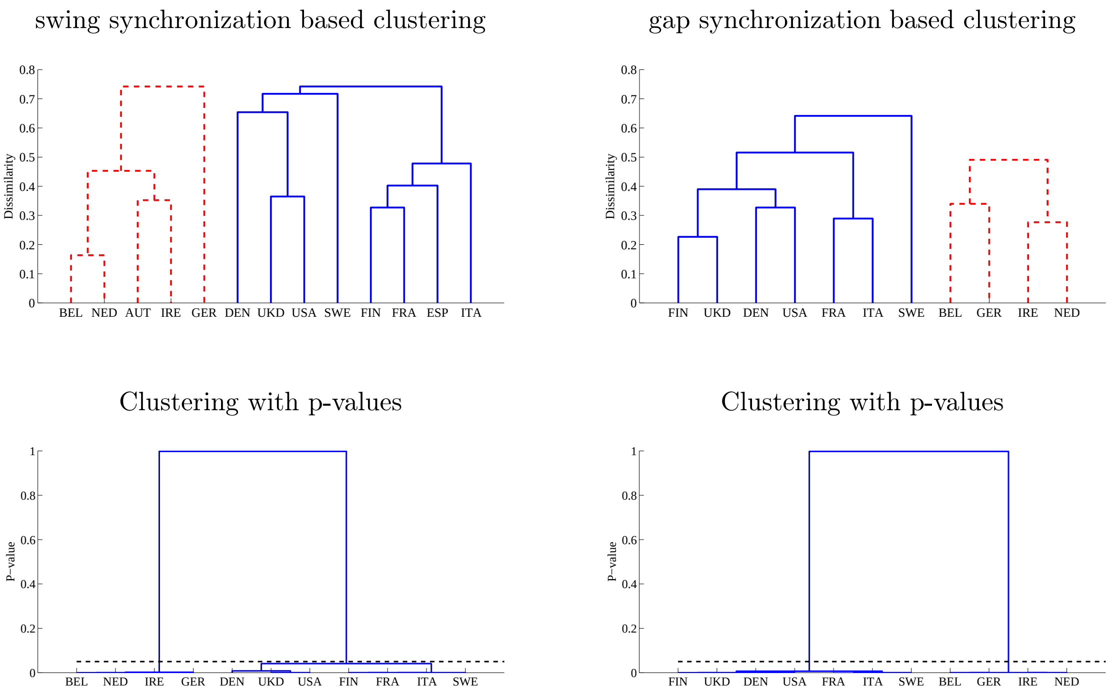
We observe credit cycle co-movement within each cluster. The common cycle of the first group exhibits a boom-bust episode between the mid-1970s and the mid-1980s. It also displays another boom from the mid-1990s till the economic recession in 2001. Subsequently, the cycle undergoes a gradual decline during the 2000s that becomes more pronounced following the 2007-08 crisis. Meanwhile, the second cycle displays a long decline starting from the first oil crisis in the early 1970s that lasts until the mid-1980s. The second half of the 1980s marks a large boom that turns into a bust from 1990 onward. Similar to the first group, credit picks up again in the mid-1990s. However, unlike in the first group, this cycle undergoes a large secular boom that outlasts the 2001 recession, and it culminates in the credit crunch of 2007-2008. We run the OLS regression on swing synchronization between the two cluster-specific cycles, which gives a value of $\hat{\mu}_{Sij}^{swing}$=0.098 with a t-statistic of 0.61. On the basis of the t-test we cannot reject the null hypothesis that the two groups have non-synchronized credit cycles at the 5% significance level (p-value = 0.27).

4.3 Evolution of synchronization

Having clustered countries by their credit cycle synchronization, we now investigate whether the overall degree of synchronization as well as the synchronization within these clusters has changed over time. This will provide information on whether credit cycles in Europe and the US converge. If this is the case, a more harmonized macroprudential policy might be beneficial and less coordination would be needed in the future.

We start by taking the cross-sectional average of the bilateral synchronization measure of all

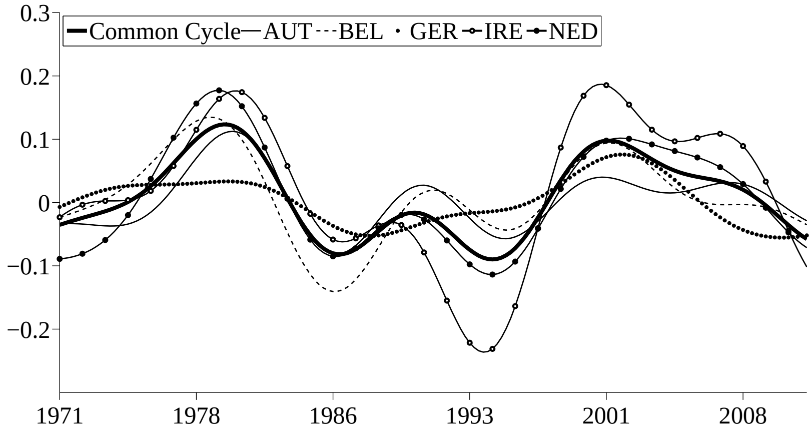
Figure 4: Hierarchical clustering tree



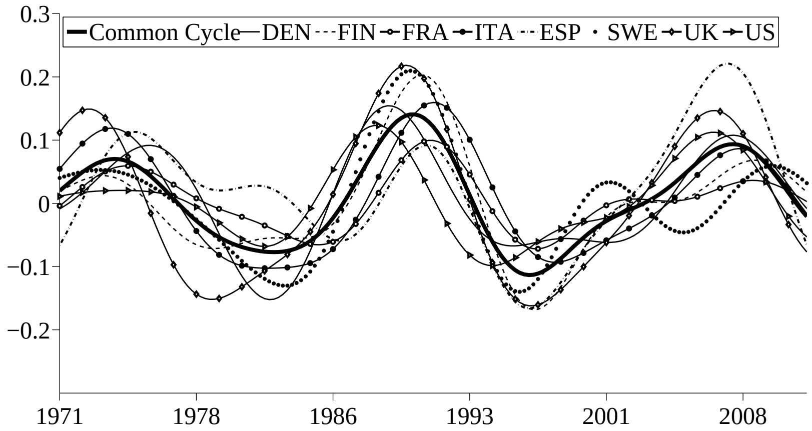
Note: Dendrograms obtained by applying the agglomerative hierarchical clustering algorithm of Timm (2002) to the dissimilarity matrix $\mathbf{D}_{NxN}$. Subfigure (a): dendrogram based on swing synchronization. Subfigure (b): dendrogram based on gap synchronization. Subfigure (c): dendrogram based on correlation. To construct the dendrogram, we begin with N clusters, each containing a single country. We then select the most similar pairs from the dissimilarity matrix $\mathbf{D}_{NxN}$ and combine these into new clusters. Subsequently, we recompute the dissimilarities between the clusters and the most similar pairs are again combined into new clusters, and so on. The dissimilarity between two clusters is set equal to the largest dissimilarity between two clusters' elements (farthest neighbor method). The dendrogram's heights measured on the vertical axis represent the level of dissimilarity at which countries or country groups are merged to form a new group.

Figure 5: Cluster-specific cycles

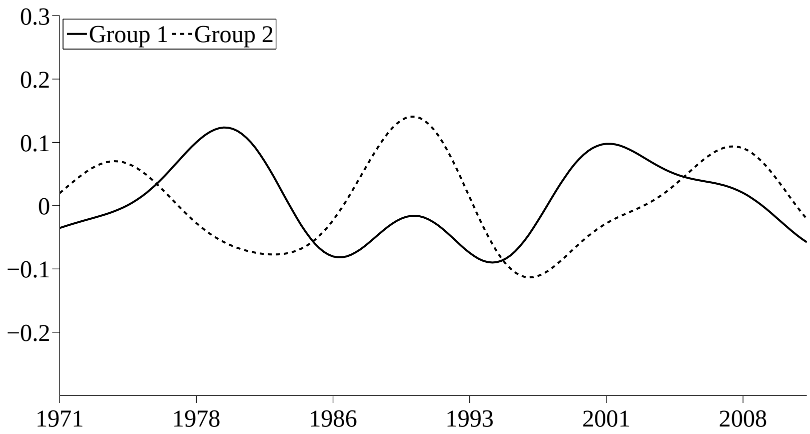
Group 1



Group 2



Common cycles



Note: Cluster-specific credit cycles are extracted with the CF filter as the medium-term component of the average log real credit series within each cluster.

countries within a cluster with each other:

$$S_t^c = \frac{1}{N_c(N_c-1)/2} \sum_i \sum_{j>i} S_t^{ij}$$

for all countries i, j within some cluster c containing N_c countries. Using the resulting time series, we then test against a trend – towards convergence or divergence – and a break in synchronization.[9] Specifically, we run the following OLS regression with Newey-West standard errors:

$$S_t^c = \mu + \beta_1 dum_t(\lambda) + \beta_2 t + \epsilon_t, \tag{9}$$

where t is a time trend and $dum_t(\lambda)$ is a step dummy variable equal to zero before a certain break point, λT, and equal to one thereafter. For each value of $\lambda = \{0.15, 0.16, \ldots, 0.85\}$, we compute the t-statistic of $dum_t(\lambda)$ and define λ_{max}=$\arg\max_\lambda tstat^2_{dum_t(\lambda)}$. The potential break in synchronization then takes place at $\lambda_{max}T$. We test whether this potential break is significant by comparing the squared t-statistic of $dum_t(\lambda_{max})$ with the critical values calculated by Andrews (1993).[10]

We find that the overall degree of synchronization between all 13 countries has not changed significantly over time. The average amount of synchronization is significantly positive and amounts to 0.25 in case of swing synchronization and 0.21 in case of gap synchronization, with a t-statistic of 1.70 and 2.42 respectively. In both cases, neither the potential break point nor the trend were significant at the 10% significance level.

The findings are different for synchronization within the two clusters which we identified in the previous subsection.[11] Independently of the group and the type of synchronization measure, we find a trend towards convergence. However, with one exception, we also find a negative mean shift which tends to qualify this conclusion. In none of the cases did we find evidence for a second break using a sequential break test procedure and using critical values tabulated by Bai and Perron (2003). Figure 6 illustrates our results for all countries and for each of the two clusters, depicting the five-year moving average of S_t^c as well as the estimated trend and/or break in mean if significant at the 10% level. In Figure 7 in Appendix C, we also present the five-year moving average of the cross-sectional average of each country's synchronization with respect to all other countries in the cluster. This figure is useful in depicting the effect of single countries on the overall synchronization.

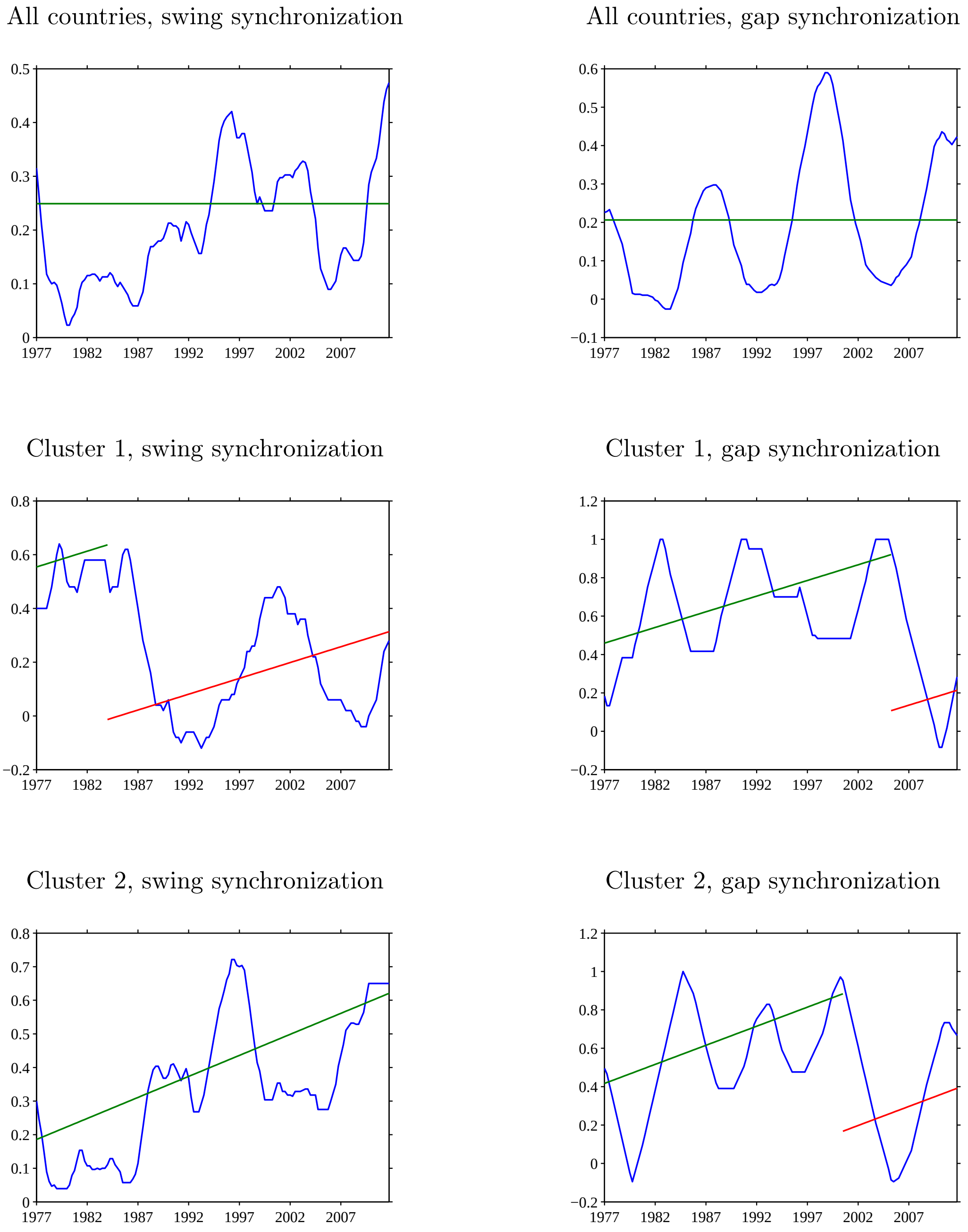
Considering swing synchronization, we find that group 1 was highly synchronized at the start but experienced a strong downward shift in 1984Q1. Since then, group 1 has been converging again with an average speed of $\hat{\beta}_2$=0.003 per quarter. The break in synchronization was due to a decrease in bilateral synchronization among almost all country pairs, with Germany having the most pronounced drop in synchronization towards the other group members. In contrast, group 2 started with a rather low degree of swing synchronization but did not experience a break in mean. Notwithstanding, the credit swing phases of Ireland were least synchronized with the other countries before 1990, while this holds for Denmark thereafter. Group 2 has an upwards

[9]Instead of analyzing the cross-sectional averages of the bilateral synchronization measure, we also used the cross-sectional averages of the synchronization between each country and the group-specific reference cycle. Regardless of the definition of the dependent variable, we drew the same conclusions.

[10]In our case, these critical values are 7.17 for 10% significance level, 8.85 for 5% significance level and 12.35 for 1% significance level.

[11]In accordance with the previous subsection, group 1 consists of Austria, Belgium, Germany, Ireland, and the Netherlands while group 2 consists of Denmark, Finland, France, Italy, Spain, Sweden, the United Kingdom, and the United States in the case of swing synchronization. In the case of gap synchronization, Austria and Spain are excluded from group 1 and 2, respectively.

Figure 6: Credit cycle synchronization over time – clusters



Note: This Figure depicts the five-year moving average of S_t^c as well as the estimated trend and/or break in mean if significant at the 10% level in regression 9. S_t^c is the cross-sectional average of the bilateral synchronization measure of all countries within a cluster with each other, $S_t^c = \frac{1}{N_c(N_c-1)/2}\sum_i \sum_{j>i} S_t^{ij}$ for all countries i, j within some cluster c containing N_c countries.

trend of 0.007. The break in mean of group 1 is significant at the 5% significance level, the trends of group 1 and group 2 have a t-statistic of 1.80 and 2.71, respectively.

Considering gap synchronization, for both groups we find a similar positive trend of 0.004 and 0.005, with t-statistics of 2.24 and 1.96, respectively. Both groups experience a negative shift in mean in the 2000s; group 1 in 2005Q2 and group 2 in 2000Q3. This shift to less synchronization was driven by a decoupling of the German credit cycle in group 1 and a decoupling of the UK, US, and the Swedish credit cycles in group 2.

We conclude from this analysis that credit cycle phases seem to converge in both groups, with group 2 having reached a higher degree of convergence than group 1. However, the recent occurrence of substantial negative mean shifts in gap synchronization within both clusters cautions against concluding that less macroprudential policy coordination would be needed in the future.

4.4 Credit cycle synchronization, financial integration, and business cycle co-movement

In this section, we seek to understand the macroeconomic and financial drivers of credit cycle synchronization. Economic globalization has been on the rise since the 1970s, and this process has likely played a role in shaping credit cycle synchronization. This process is also reflected in the trend towards credit cycle convergence documented in the previous section. Thus, our main explanatory variables are two measures of credit market integration and business cycle correlation. Empirical evidence suggests that causality between financial market integration and business cycle co-movement may go both ways (see, for example, Imbs, 2004, 2006; Inklaar et al., 2008; Davis, 2014). Thus, to explore the influence of these variables on credit cycle synchronization, we estimate a simultaneous equations model similar to the ones employed in the related literature. In this model, credit cycle synchronization, credit market integration, and business cycle correlation are all determined endogenously. We can thus shed light on the direct effects of financial integration and output correlation on credit cycle synchronization, as well as on the indirect effects coming from the interdependence between financial integration and business cycle co-movement.

We estimate the following system of equations simultaneously:

$$\begin{aligned} \mu_{S^{ij}} &= \alpha_0 + \alpha_1 CM_{i,j} + \alpha_2 BC_{i,j} + \varepsilon^{\rho}_{i,j}, \\ CM_{i,j} &= \beta_0 + \beta_1 BC_{i,j} + \beta_2 I^{CM}_{i,j} + \varepsilon^{CM}_{i,j}, \\ BC_{i,j} &= \gamma_0 + \gamma_1 CM_{i,j} + \gamma_2 I^{BC}_{i,j} + \varepsilon^{BC}_{i,j}, \end{aligned} \tag{10}$$

where i and j index country pairs, $\mu_{S^{ij}}$ is bilateral credit cycle synchronization (measured by swing synchronization and gap synchronization), $CM_{i,j}$ is an index of bilateral credit market integration, and $BC_{i,j}$ is the bilateral correlation of medium-term business cycles. All variables represent time averages over the period 1972-2011. Any direct effect of $CM_{i,j}$ on credit cycles is captured by α_1, while $\gamma_1\alpha_2$ captures the indirect effect working via business cycles. Similarly, α_2 reflects the direct impact of $BC_{i,j}$ on credit cycles, while $\beta_1\alpha_1$ captures the indirect effect via credit market integration. The vectors I^{CM} and I^{BC} contain exogenous instrumental variables that help to explain bilateral credit market integration and bilateral business cycle correlation. Identification of the system requires that these two instrument sets differ. The model is estimated using a three-stage least squares (3SLS) procedure.

We measure credit market integration $CM_{i,j}$ by an index proposed by Imbs (2004) and Davis (2014). Data from Lane and Milesi-Ferretti (2007) is used to construct $CM_{i,j} = |(NFDA_i/GDP_i) - (NFDA_j/GDP_j)|$, where $NFDA_i$ denotes the net foreign debt asset position in country i, equal to its external debt market assets minus its external debt market liabilities. $CM_{i,j}$ will take higher values for pairs of countries with diverging external positions, as these countries are more likely to lend and borrow from each other than pairs of countries with similar external positions.[12] Our measure of business cycle co-movement $BC_{i,j}$ is the pairwise correlation coefficient between medium-term output fluctuations, obtained by applying the CF filter to real GDP. We focus on medium-term output fluctuations that lie between 8-30 years – i.e., medium-term business cycles introduced by Comin and Gertler (2006) – in order to match the frequency of the credit cycle.

We have chosen instruments I^{CM} and I^{BC} frequently used in the existing literature. The vector $I^{CM}_{i,j}$ contains the exogenous variables used to instrument bilateral credit market integration. This vector contains six elements which come from La Porta, Lopez-de Silanes, and Shleifer (1998), and they are indices that reflect the quality of the legal and institutional framework of the financial system in each country. The indices reflect creditor rights; government corruption; the efficiency of the judicial system; accounting standards; the risk of a modification in a contract taking the form of a repudiation, postponement, or scaling down by the government due to e.g. budget cutbacks; and the risk of expropriation (outright confiscation or forced nationalization). These variables can help explain financial market integration, as shown by e.g. Imbs (2006), Waelti (2011), Fidrmuc, Ikeda, and Iwatsubo (2012), and Davis (2014). We construct bilateral measures by taking the mean of the indices for each country pair, following Davis (2014).

The vector $I^{BC}_{i,j}$ contains seven exogenous variables that describe bilateral business cycle co-movement. The first four are indices that capture the economic, political, and social aspects of globalization constructed by Dreher (2006) and the KOF institute at ETH Zurich. The indices measure economic liberalization as captured by hidden import barriers, the mean tariff rate, taxes on international trade, and capital account restrictions; political globalization as captured by the number of embassies in a country, membership in international organizations, participation in U.N. Security Council missions, and the number of international treaties ratified; information flows measured by the number of internet users (per 1,000 persons), television sets (per 1,000 persons), trade in newspapers (as a percentage of GDP); and personal contact captured by international telephone traffic, transfers of goods and services (as a percentage of GDP), international tourism, foreign population (as a percentage of total population), and the number of international letters (per capita). Bilateral measures are again obtained by taking the mean of the variables for each country pair. The last three variables come from the gravity literature (see, for example, Baxter and Kouparitsas, 2005), and are dummies for common language and common border, as well as the distance (in km) between capital cities.

The estimates of the 3SLS regressions are presented in Table 4. The left panel of the table provides the results for swing synchronization, while the right-hand panel presents the estimates for gap synchronization. The estimation results from the two synchronization measures are qualitatively identical. The instrumental variables have the expected signs in the regressions.[13] Two

[12]Ideally, one would use a bilateral measure of credit market integration, however, existing bilateral data starts only in 1999 (publicly available from the BIS).

[13]Stronger credit market integration between two countries is associated with a more efficient judicial system in those countries on average, while a higher risk of contract repudiation or expropriation by the government tend to be accompanied by less integrated credit markets. We find a significant positive relation between business cycle co-movement and factors that facilitate the dispersion of news across countries. These empirical findings are consistent with theoretical models on news-driven business cycles, which hypothesize that information markets amplify business cycle co-movement. For example, Beaudry, Dupaigne, and Portier (2011) show that news shocks can generate robust positive output co-movement across countries in a two-country general equilibrium model. Similarly, Veldkamp and Wolfers (2007) demonstrate that economies with common, aggregate information at their disposal make highly correlated production choices.

Table 4: Credit cycle synchronization, financial integration, and business cycle co-movement

	swing synchronization			**gap synchronization**		
	$\rho_{i,j}$	$CM_{i,j}$	$BC_{i,j}$	$\rho_{i,j}$	$CM_{i,j}$	$BC_{i,j}$
$CM_{i,j}$	0.39*		0.58*	0.54*		0.55*
	(0.176)		(0.296)	(0.235)		(0.296)
$BC_{i,j}$	0.71**	-0.30		0.54*	-0.30	
	(0.171)	(0.170)		(0.227)	(0.170)	
Creditor rights		-0.03			-0.03	
		(0.018)			(0.018)	
Corruption		0.00			0.01	
		(0.013)			(0.013)	
Effic. of judicial system		0.12**			0.11**	
		(0.040)			(0.040)	
Accounting standards		-0.01			-0.01	
		(0.004)			(0.004)	
Risk of contract repudiation		-0.31*			-0.31*	
		(0.132)			(0.133)	
Risk of expropriation		-0.61**			-0.54*	
		(0.214)			(0.215)	
Economic liberalization			-0.28			-0.24
			(0.179)			(0.179)
Political globalization			-0.19			-0.19
			(0.130)			(0.129)
Information flows			0.37**			0.39**
			(0.122)			(0.122)
Personal contact			0.38			0.30
			(0.285)			(0.284)
Common language			0.24*			0.22*
			(0.122)			(0.122)
Common border			0.10			0.11
			(0.093)			(0.093)
Distance			0.00			0.00
			(0.000)			(0.000)
Constant	-0.23*	8.67**	-0.10	-0.18	8.07**	-0.10
	(0.105)	(2.639)	(0.227)	(0.139)	(2.654)	(0.227)
Adj. R-squared	0.208	0.111	0.048	0.079	0.108	0.061

Note: 3SLS estimates of the simultaneous equations model. The left panel of the table provides the results for credit cycle concordance, the middle panel presents the estimates for synchronicity, and the findings for correlation are given in the right-hand panel of the table. All regressions are estimated with 78 cross-sectional observations. HAC standard errors are in parentheses, and asterisks * and ** denote significance at the 5% and 1% level, respectively.

main findings emerge from our analysis. First, we find a strong positive association between medium-term business cycles and credit cycles. Countries with more highly correlated business cycles tend to have more strongly synchronized credit cycles. This relationship is significant across all model specifications. Second, the results also suggest that countries with stronger credit market integration tend to display significantly higher synchronization among their credit cycles. Besides this direct effect, credit market integration also impacts credit cycle synchronization indirectly, through its effect on business cycle co-movement. Countries with more deeply integrated credit markets tend to display stronger co-movement in their medium-term business cycles, which, in turn, leads to stronger credit cycle synchronization. Again, this indirect channel is present for both synchronization measures.

5 Conclusion

A variety of macroprudential policy tools have been devised in order to increase the resilience of the financial sector and reduce its pro-cyclicality. Examples for such measures include counter-cyclical capital buffers and risk weights, as well as time-varying loan-to-value ratios, debt-to-income ratios, and margin requirements. There is compelling empirical evidence that credit supply shocks propagate across countries. Therefore, in a financially integrated world, national macroprudential policy shocks may have international repercussions. Consider, for instance, a country that is about to introduce counter-cyclical policies in order to prevent an excessive credit boom. Such policies may reduce the level of over-borrowing across several countries, given that they are simultaneously experiencing a credit expansion. However, the same policy actions may provoke a credit crunch in countries that are undergoing a credit contraction.

Understanding whether credit cycles are synchronized across countries therefore constitutes a central question. Thus, in this paper we study the synchronization of credit booms and busts among 12 major European economies and the United States between 1972-2011. Our empirical results may be useful for constructing theoretical models that analyze international macroeconomic fluctuations and in particular financial crises. Our findings may also have implications for the design of macroprudential policies in an environment prone to interdependence across economies.

We find strong evidence against the existence of a common credit cycle across all countries. Instead, the credit cycles of Austria, Belgium, Germany, Ireland, and the Netherlands are clustered together, while Denmark, Finland, France, Italy, Spain, Sweden, the UK, and the US belong to another distinct cluster. The absence of a single European credit cycle underlines the importance of macroprudential policy coordination among national authorities as currently fostered by the European Systemic Risk Board. Policy coordination seems especially important between the macroprudential authorities of the two clusters. Even within the clusters, occasional drops in synchronization may render policy coordination beneficial. We find that credit cycle phases seem to converge in both groups, with group 2 having reached a higher degree of convergence than group 1. From this we might conclude that less macroprudential policy coordination within the two clusters will be needed in the near future. However, the recent occurrence of substantial negative mean shifts in synchronization within both clusters cautions against this conclusion.

If policymakers strive for a macroprudential policy union and therefore wish to foster credit cycle synchronization, they should aim at improving credit market integration and increasing business cycle co-movement across countries. In particular, our findings suggest that countries with more highly correlated business cycles tend to have more strongly synchronized credit cycles. Moreover, a higher degree of credit market integration between two countries is accompanied by higher credit cycle synchronization both directly as well as indirectly, through the amplifying effect of credit market integration on business cycle co-movement.

To summarize, the credit cycle heterogeneity documented in this paper implies that macro-prudential policy should remain at the national level, while at the same time also stressing the importance of supranational policy coordination.

Appendix A: Bootstrap-based concordance test

The null hypothesis H_0^{POS} can be tested by means of the following statistic:

$$\tau_{i,j} = \frac{\hat{\mu}_{S^{ij}}}{s_{i,j}/\sqrt{T}}, \tag{11}$$

where the sample standard deviation is $s_{i,j} = \sqrt{T^{-1}\sum_{t=1}^{T}(S_t^{ij} - \hat{\mu}_{S^{ij}})^2}$. The synchronization variable, S_t^{ij}, is not independently distributed, as it may inherit the serial dependence structure of the underlying cycles (see Harding and Pagan, 2011).

The asymptotic distribution of the test statistic can be approximated using a simple bootstrap procedure. For each country $i = 1, ..., N$, we draw with replacement $b = 1, \ldots, B$ random samples of size T from the first-differenced series $u_{i,t} = x_{i,t} - x_{i,t-1}$ for $t = 2, 3, \ldots, T$. For each draw, the bootstrapped time series $x_{b,i,t}^*$ is obtained by setting $x_{b,i,1}^* = u_{b,i,1}^*$ and then cumulating $x_{b,i,t}^* = x_{b,i,t-1}^* + u_{b,i,t}^*$ for $t = 2, \ldots, T$. Subsequently, the cyclical component $c_{b,i,t}^*$ of the bootstrap series $x_{b,i,t}^*$ is extracted with the CF filter. Having obtained the bootstrap cyclical component $c_{b,i,t}^*$ for each country $i = 1, ..., N$, we compute for any pair of countries i and j with $i \neq j$, the bootstrap statistic $\hat{\mu}_{S^{ij},b}^* = T^{-1}\sum_{t=1}^{T} S_{t,b}^{ij*}$. We then obtain the bootstrap test statistic as

$$\tau_{b,i,j}^* = \frac{\hat{\mu}_{S^{i,j,b}}^*}{s_{b,i,j}^*/\sqrt{T}}, \tag{12}$$

where $s_{b,i,j}^* = \sqrt{T^{-1}\sum_{t=1}^{T}(Con_{b,i,j,t}^* - \rho_{b,i,j}^*)^2}$.

Bootstrap re-sampling is repeated $B = 10,000$ times. The null hypothesis 6, that $\mu_{S^{ij}} \leq 0$, is rejected at a significance level α, if $Pval_{i,j}^*(\tau_{i,j}) = B^{-1}\sum_{b=1}^{B} I(\tau_{b,i,j}^* > \tau_{i,j}) \leq \alpha$, where $I(.)$ is an indicator function. The re-sampling is performed under the hypothesis that the two cycles are uncorrelated.

Appendix B: swing synchronization and lead/lag relationships

We compute the degree of swing synchronization for each quarter within a three-year window using equation (8), where $l \in [-12; 12]$ quarters, and we select the highest value ($\max_l \hat{\mu}^{swing}_{S^{ij},l}$) for each pair of countries. The lead-lag relationships between credit cycles are shown in Table 5. The entries in the lower triangular part of Table 5 show the highest degree of swing synchronization within the three-year window. The gray shaded entries in the upper triangular part of the table represent the leads/lags l at which the corresponding degree of swing synchronization attains its highest value. A positive entry indicates that the row country (i) *lags* the column country (j), while a negative entry indicates that the row country *leads* the column country.

The Austrian credit cycle, for example, leads the Belgian cycle by two quarters, and the degree of swing synchronization at this lag equals $\hat{\mu}^{swing}_{S^{ij}} = 0.61$, which reflects a relatively strong positive association between these two cycles. In addition, these two countries are also highly synchronized with Ireland and the Netherlands. Again, the Dutch and Belgian cycles seem to display a very strong medium-frequency co-movement, with the Dutch cycle leading by one quarter. However, the highest degree of lagged swing synchronization is observed between Italy and the United Kingdom – the Italian cycle phase lags the British one by five quarters with $\hat{\mu}^{swing}_{S^{ij}} = 0.86$. Again, the overall largest negative synchronization is found between Germany and Italy at the one-year horizon. The German cycle also seems to be unrelated to the majority of countries, with the exception of Austria, Belgium, Ireland, and the Netherlands. Meanwhile, the US credit cycle leads all European cycles (except for the German cycle), and it is synchronized contemporaneously with the British cycle. Results with the gap synchronization measure are nearly identical.

Appendix C: Bilateral credit cycle synchronization over time – all countries

Figure 7 shows the five-year moving average of $S^c_{i,t}$ as well as the estimated trend and/or break in mean if significant at the 10% level in regression 9. $S^c_{i,t}$ is the cross-sectional average of country i's bilateral synchronization with all other countries within a cluster, $S^c_{i,t} = \frac{1}{N_c-1}\sum_j S^{ij}_t$ for all countries $j \neq i$ within some cluster c containing N_c countries. $S^c_{i,t}$ is abbreviated by 'average' in the Figure.

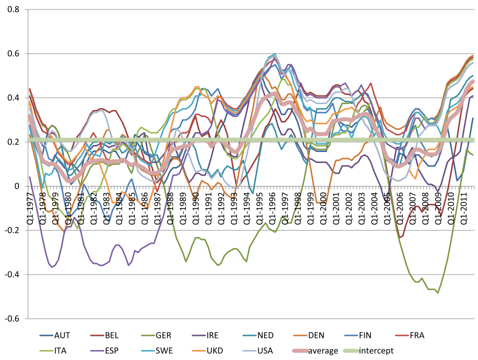
Table 5: swing synchronization and lead-lag relationships

	AUT	BEL	DEN	FIN	FRA	GER	IRE	ITA	NED	ESP	SWE	UK	US
AUT		-2	8	-6	-1	-5	0	-2	3	-1	-3	-4	10
BEL	0.61* (0.11)		10	2	1	-4	5	0	-1	-5	5	6	12
DEN	0.41* (0.13)	0.41* (0.13)		-5	-9	-12	-8	-1	-12	-4	-5	4	4
FIN	0.30* (0.14)	0.05 (0.15)	0.40* (0.13)		-1	-12	9	-2	5	-1	3	3	9
FRA	0.32* (0.14)	0.41* (0.13)	0.52* (0.12)	0.64* (0.11)		-12	7	3	3	0	4	8	10
GER	0.32* (0.14)	0.62* (0.11)	0.02 (0.15)	-0.16 (0.14)	0.17 (0.15)		5	12	2	-6	12	-12	-12
IRE	0.66* (0.10)	0.60* (0.11)	0.22 (0.14)	0.20 (0.15)	0.24* (0.15)	0.47* (0.13)		-5	-2	-4	-2	-3	3
ITA	0.07 (0.16)	0.12 (0.16)	0.53* (0.13)	0.66* (0.10)	0.64* (0.11)	-0.16 (0.15)	-0.08 (0.15)		6	1	2	5	5
NED	0.59* (0.12)	0.80* (0.08)	0.22* (0.14)	0.08 (0.15)	0.29* (0.15)	0.62* (0.12)	0.74* (0.09)	0.00 (0.16)		-8	2	-9	6
ESP	0.36* (0.14)	0.27* (0.14)	0.40* (0.13)	0.58* (0.11)	0.65* (0.11)	0.11 (0.15)	0.35* (0.14)	0.54* (0.13)	0.40* (0.14)		4	3	8
SWE	0.25* (0.15)	0.30* (0.14)	0.46* (0.13)	0.54* (0.12)	0.70* (0.10)	0.12 (0.15)	0.17 (0.15)	0.50* (0.13)	0.20 (0.15)	0.34* (0.14)		3	6
UK	0.09 (0.15)	-0.01 (0.15)	0.43* (0.13)	0.74* (0.08)	0.52* (0.12)	-0.05 (0.15)	0.03 (0.15)	0.86* (0.07)	0.08 (0.16)	0.58* (0.12)	0.41* (0.14)		0
US	0.33* (0.14)	0.30* (0.14)	0.78* (0.08)	0.52* (0.13)	0.67* (0.10)	0.01 (0.15)	0.24 (0.15)	0.63* (0.11)	0.26* (0.15)	0.57* (0.11)	0.51* (0.13)	0.57* (0.13)	

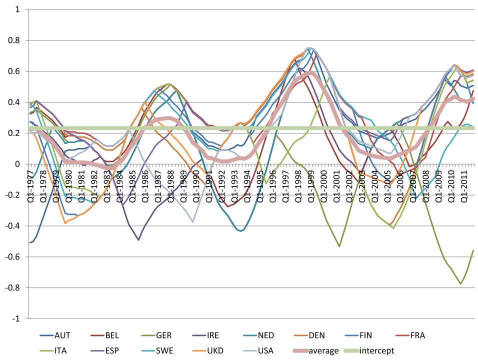
Note: The gray shaded entries in the upper triangular represent the leads/lags l^{max} (in quarters) at which the degree of synchronization $\bar{S}_{ij,t,l} = \frac{1}{T}\sum_{t=1}^{T} B_{i,t}B_{j,t+l}$ are highest (we consider a three-year window $l \in [-12;12]$). A positive entry indicates that the row country lags the column country, while a negative entry indicates that the row country leads the column country. The entries in the lower triangular show the highest degree of synchronization within the three-year window, $\overset{\max}{l}(\bar{S}_{ij,l}^{swing})$. Asterisks denote significantly positive synchronization at the 5% level. HAC standard errors are given in parentheses.

Figure 7: Bilateral credit cycle synchronization over time – all countries

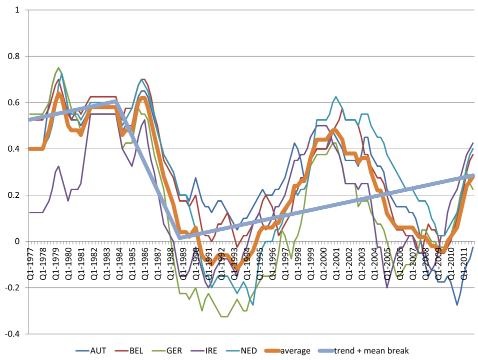
All countries, swing synchronization



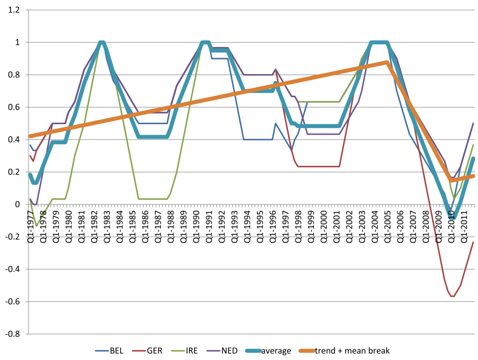
All countries, gap synchronization



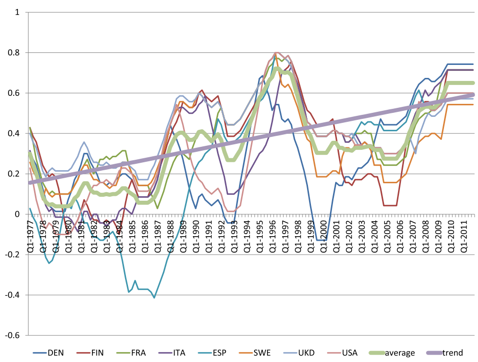
Cluster 1, swing synchronization



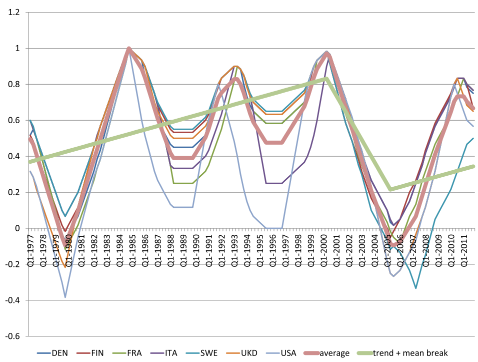
Cluster 1, gap synchronization



Cluster 2, swing synchronization



Cluster 2, gap synchronization



Note: This Figure depicts the five-year moving average of $S^c_{i,t}$ as well as the estimated trend and/or break in mean if significant at the 10% level in regression 9. $S^c_{i,t}$ is the cross-sectional average of country i's bilateral synchronization with all other countries within a cluster, $S^c_{i,t} = \frac{1}{N_c-1}\sum_j S^{ij}_t$ for all countries $j \neq i$ within some cluster c containing N_c countries. $S^c_{i,t}$ is abbreviated by 'average' in the Figure.

References

Aikman, D., A. Haldane, and B. Nelson (2014). Curbing the credit cycle. *Economic Journal*, DOI: 10.1111/ecoj.12113.

Andrews, D. W. K. (1993). Tests for parameter instability and structural change with unknown change point. *Econometrica 61*, 821–56.

Arnold, B., C. Borio, L. Ellis, and F. Moshirian (2012). Systemic risk, macroprudential policy frameworks, monitoring financial systems and the evolution of capital adequacy. *Journal of Banking and Finance 36*(12), 3125–3132.

Bai, J. and P. Perron (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics 18*, 1–22.

Balke, N. (2000). Credit and economic activity: Credit regimes and nonlinear propagation of shocks. *Review of Economics and Statistics 82*(2), 344–349.

Banque de France (2014). Macroprudential policies – Implementation and interactions. Financial Stability Review April 2014.

Baxter, M. and R. G. King (1999). Measuring business cycles: Approximate band-pass filters for economic time series. *Review of Economics and Statistics 81*, 575–593.

Baxter, M. and M. A. Kouparitsas (2005). Determinants of business cycle comovement: A robust analysis. *Journal of Monetary Economics 52*, 113–157.

Beaudry, P., M. Dupaigne, and F. Portier (2011). Modeling news-driven international business cycles. *Review of Economic Dynamics 14*, 72–91.

Beirne, J. and C. Friedrich (2014). Capital flows and macroprudential policies – A multilateral assessment of effectiveness and externalities. ECB Working Paper No. 1721.

Benigno, G., H. Chen, C. Otrok, A. Rebucci, and E. Young (2013). Financial crises and macroprudential policies. *Journal of International Economics 89*(2), 453–470.

Bianchi, J. (2011). Overborrowing and systemic externalities in the business cycle. *American Economic Review 101*, 3400–3426.

Bordo, M. and J. Haubrich (2010). Credit crises, money and contractions: An historical view. *Journal of Monetary Economics 57*, 1–18.

Bry, G. and C. Boschan (1971). *Cyclical Analysis of Time Series: Selected Procedures and Computer Programs.* NBER, New York.

Burns, A. F. and W. C. Mitchell (1946). *Measuring Business Cycles.* NBER, New York.

Camacho, M., G. Perez-Quiros, and L. Saiz (2006). Are European business cycles close enough to be just one? *Journal of Economic Dynamics and Control 30*, 1687–1706.

Candelon, B., N. Metiu, and S. Straetmans (2013). Disentangling economic recessions and depressions. Deutsche Bundesbank Discussion Paper No. 43/2013.

Cetorelli, N. and L. Goldberg (2011). Global banks and international shock transmission: Evidence from the crisis. *IMF Economic Review 59*(1), 41–76.

Cetorelli, N. and L. Goldberg (2012). Liquidity management of U.S. global banks: Internal capital markets in the great recession. *Journal of International Economics 88*, 299–311.

Christiano, L. and T. Fitzgerald (2003). The band pass filter. *International Economic Review 44*(2), 435–465.

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

Comin, D. and M. Gertler (2006). Medium-term business cycles. *American Economic Review 96*(3), 523–551.

Croux, C., M. Forni, and L. Reichlin (2001). A measure of comovement for economic variables: Theory and empirics. *Review of Economics and Statistics 83*(2), 232–241.

Davis, J. S. (2014). Financial integration and international business cycle co-movement. *Journal of Monetary Economics 64*, 99–111.

Dembiermont, C., M. Drehmann, and S. Muksakunratana (2013). How much does the private sector really borrow? A new database of total credit to the private non-financial sector. *BIS Quarterly Review*, 65–81.

Dreher, A. (2006). Does globalization affect growth? Evidence from a new index of globalization. *Applied Economics 38*, 1091–1110.

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

Eickmeier, S. and T. Ng (2011). How do credit supply shocks propagate internationally? A GVAR approach. Bundesbank Discussion Paper No. 27/2011.

Fidrmuc, J., T. Ikeda, and K. Iwatsubo (2012). International transmission of business cycles: Evidence from dynamic correlations. *Economics Letters 114*(3), 252 – 255.

Giannetti, M. and L. Laeven (2012). The flight home effect: Evidence from the syndicated loan market during financial crises. *Journal of International Economics 108*, 23–43.

Gourinchas, P. and M. Obstfeld (2012). Stories of the twentieth century for the twenty-first. *American Economic Journal: Macroeconomics 4*(1), 226–265.

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

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

Harding, D. and A. Pagan (2011). An econometric analysis of some models for constructed binary time series. *Journal of Business and Economic Statistics 29*(1), 86–95.

Helbling, T., R. Huidrom, M. A. Kose, and C. Otrok (2011). Do credit shocks matter? A global perspective. *European Economic Review 55*, 340–353.

Hodrick, R. J. and E. C. Prescott (1997). Postwar U.S. business cycles: An empirical investigation. *Journal of Money, Credit and Banking 29*, 1–16.

Hutchinson, M. and I. Noy (2005). How bad are twins? Output costs of currency and banking crises. *Journal of Money, Credit and Banking 37*(4), 725–752.

Imbs, J. (2004). Trade, finance, specialization, and synchronization. *Review of Economics and Statistics 86*(3), 723–734.

Imbs, J. (2006). The real effects of financial integration. *Journal of International Economics 68*, 296–324.

Inklaar, R., R. Jong-A-Pin, and J. de Haan (2008). Trade and business cycle synchronization in OECD countries – A re-examination. *European Economic Review 52*, 646–666.

Jeanne, O. (2014). Macroprudential policies in a global perspective. NBER Working Paper No. 19967.

Jorda, O., M. Schularick, and A. Taylor (2011). Financial crises, credit booms, and external imbalances: 140 years of lessons. *IMF Economic Review 59*, 340–378.

La Porta, R., F. Lopez-de Silanes, and A. Shleifer (1998). Law and finance. *Journal of Political Economy 106*(6), 1113–1154.

Laeven, L. and F. Valencia (2013). Systemic banking crises database. *IMF Economic Review 61*(2), 225–270.

Lane, P. and G. Milesi-Ferretti (2007). The external wealth of nations mark II: Revised and extended estimates of foreign assets and liabilities, 1970-2004. *Journal of International Economics 73*, 223–250.

Lorenzoni, G. (2008). Inefficient credit booms. *Review of Economic Studies 75*, 809–833.

Mendoza, E. (2010). Sudden stops, financial crises, and leverage. *American Economic Review 100*(5), 1941–1966.

Mendoza, E. and V. Quadrini (2010). Financial globalization, financial crises and contagion. *Journal of Monetary Economics, Carnegie-Rochester Conference Series on Public Policy: Credit Market Turmoil: Implications for Policy 57*(1), 24–39.

Mendoza, E. G. and M. E. Terrones (2008). An anatomy of credit booms: Evidence from macro aggregates and micro data. NBER Working Paper No. 14049.

Mink, M., J. Jacobs, and J. De Haan (2012). Measuring coherence of output gaps with an application to the euro area. *Oxford Economic Papers 64*(2), 1–20.

Morley, J. and J. Piger (2012). The asymmetric business cycle. *Review of Economics and Statistics 94*(1), 208–221.

Newey, W. K. and K. D. West (1987). A simple positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica 55*(3), 703–708.

Reinhart, C. and K. Rogoff (2008). Is the 2007 US sub-prime financial crisis so different? An international historical comparison. *American Economic Review: Papers and Proceedings 98*, 339–344.

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

Schularick, M. and A. Taylor (2012). Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008. *American Economic Review 102*(2), 1029–1061.

Stock, J. H. and M. W. Watson (1999). Business cycle fluctuations in US macroeconomic time series. In M. Woodford and J. B. Taylor (Eds.), *Handbook of Macroeconomics*, Volume 9, Chapter 1, pp. 3–64. Amsterdam: North-Holland.

Timm, N. (2002). Applied multivariate analysis. *Springer Texts in Statistics. Springer, Berlin.*

Torgerson, W. (1952). Multidimensional scaling: I. Theory and method. *Psychometrika 17*(4), 401–419.

Veldkamp, L. and J. Wolfers (2007). Aggregate shocks or aggregate information? Costly information and business cycle comovement. *Journal of Monetary Economics 54*, 37–55.

Waelti, S. (2011). Stock market synchronization and monetary integration. *Journal of International Money and Finance 30*(1), 96 – 110.