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Monetary Policy and Business Cycle Synchronization in Europe

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Abstract

In this paper, we investigate the role of the monetary policy adopted by the European Central Bank (ECB) in business cycle synchronization in Europe between 2000 and 2018. To this aim, we employ wavelets to compute the pairwise business cycle correlations (BCC) at different frequencies and use Generalized Method of Moments (GMM) dynamic estimators in panel to explain their variations. Our results show that monetary policy has a long-term impact on the synchronization of business cycles in Europe. More specifically, we find that the adopted unconventional monetary policies impact positively the synchronization. Finally, we show that fiscal policies can be used as tools to fix country-specific movements of business cycles.

Keywords— Business cycle synchronization, Monetary policy, EMU, Europe
JEL— E52,E58,E37, C01

1. Introduction

There have been numerous policy recommendations and initiatives to face the financial and economic consequences of the Covid-19 crisis. This diversity of responses reflects the unequal ways in which European countries were hit. Indeed, at a country-level, or even at a region-level, European economies have reacted very differently, depending on their productive structure (Prades Illanes and Tello (2020)) and, as a consequence, are likely to require specific policy responses. In addition, this crisis challenges the relevance of challenges the relevance of already existing policies and institutions, especially common ones such as the euro currency. The pandemic indirectly revives the debate on the efficiency and relevance of the euro and, by extension, on what constitutes an optimal currency area (OCA) and its features, a concept introduced by Mundell (1961), McKinnon (1963) and Kenen

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(1969).

The European integration and the emerging idea of a common and single currency area in the 1990s have increased the number of works and discussions on the feasibility of a European Monetary Union (EMU).[1] A strand of this research has focused on the synchronization of business cycles among European countries. Following Mundell (1961), business cycle synchronization (BCS) is one of the main prior conditions for a successful currency union[2] and contributes to more efficient monetary policies and fiscal coordination. Conversely, business cycle *de*-synchronization can threaten the viability of a currency union (Ahmed et al. (2018)). For these reasons, BCS is of significant importance for both researchers and policymakers in Europe.

Several works have studied the relationship between monetary policy and BCS, focusing on the impacts the former may have on the latter. So far, there have been numerous works on the impact of the adoption of the euro as a common and single currency (Christodoulopoulou (2014); Antonakakis and Tondl (2014); Belke et al. (2017)), but few on the impact of the common and single European monetary policy for all member countries over time. Yet monetary policy can have a strong effect on output.[3] This effect is not homogeneous among European countries and can depend on the joint effect of country-specific financial and economic context (Ouerk et al. (2020)), financial characteristics (Elbourne et al. (2018)) or spillovers (Burriel and Galesi (2018)). Beyond the individual dimension, the effect of the monetary policy is also depending on the transmission channel used,[4] which can vary across temporally (Gutiérrez (2006)). Finally, monetary policy can affect macroeconomic variables in very different ways when adopting a frequency approach (Crowley and Hudgins (2017)).[5] The objectives of central banks can differ depending of the timescale adopted: monetary authorities can, for example, react very quickly (i.e. in the short run) to inflation news while the price level is mostly determined by the money supply in the long run, but also by the (slow) evolution of institutions and the replacement of policymakers (Aguiar-Conraria et al. (2008)). It is then important to adopt a frequency approach to the study of monetary policy impact. Our

[1]Especially since the Maastricht Treaty in 1992.

[2]Other prior conditions include: a high trade integration, fiscal coordination and transfers, and a high degree of labor mobility (Mundell (1961))

[3]Including *à la* Mundell-Fleming models (Jordà et al. (2020)) where, originally, the monetary policy efficiency is very limited.

[4]Beyer et al. (2017) counts 9 transmission channels: the *interest rate* channel, the *monetary* channel, the *exchange rate* channel, the *asset price and wealth* channels, the *balance sheet and profitability* channel, the *bank funding and lending* channel, the *bank capital* channel, the *risk-taking* channel and the *expectations* channel

[5]More generally, The need for a frequency-time approach of macroeconomics relationship has been shown in Ramsey et al. (1998).

idea can be formulated as follows: the "one-size-fits-all" policy lead by the ECB, when applied to a diverse set of countries, give place to country-specific reactions which, in turn, result in different BCS processes at different terms. Our paper aims at measuring this correlation and, if it exists, to determine the path of the monetary policy that achieves the greatest BCS.

Several factors have been investigated to explain the BCS of European countries. Frankel and Rose (1998), who were among the first to investigate this topic in Europe, use a single equation model with instrumental variable estimations to study the impact of trade between countries on their business cycle synchronization. They find a positive and strong relationship between bilateral trade intensity and BCS, but highlight the endogenous nature of the OCA. Specifically, the EMU could positively impact trade intensity between its members, fulfilling one of the conditions of its sustainability. This empirical observation is consistent with the one obtained by Otto et al. (2001). The latter, following Frankel and Rose (1998), rely on a single-equation model with instrumental variable estimations to study the impact of trade on BCS[6], but also include financial links and monetary policy coordination.

A broad strand of the literature has investigated the impact of trade and its forms on BCS. Imbs (2004), who extends the set of independent variables to include country specialization, uses a system of simultaneous equations to tackle the endogeneity issue. He refines conclusions on the impact of trade by showing that intra-industry trade has a significant role in BCS, as does financial integration.Similar results are found by Abbott et al. (2008), who estimate a model with fixed and random effects to take into account potentially unobservable factors; Alimi (2015), who uses the Generalized Method of Moments (GMM) for a dynamic panel; and Duval et al. (2014), with an instrumental variable regression. The simultaneous equation strategy is also adopted by Pentecôte et al. (2015), who study the impact of trade exchange composition (i.e., changes in intensive or extensive margin) on BCS in the European Monetary Union. While they find that trade intensity has a significantly positive impact on BCS, new trade flows are shown to have a negative effect on output convergence, similar to the effect of specialization (Krugman (1993)). Beck (2019), with Bayesian Model Averaging (BMA), also supports the positive role of bilateral trade on BCS, but questions the possible role of a free trade area. Beyond its positive impact, trade intensity can also induce leading and lagging behaviors in BCS (Magrini et al. (2008)).

Another branch of the literature considers the impact of financial variables on BCS (Otto et al.

[6]Their sample is broader than the one of Frankel and Rose (1998) as it is composed of 17 OECD countries.

(2001); Imbs (2004)) and finds a positive relationship between financial integration and BCS. Foreign Direct Investments (FDI) may have an ambiguous effect, since they can improve European BCS through its trade enhancing (Antonakakis and Tondl (2014); Jos Jansen and Stokman (2014)), but also negatively impact it as investors seek out to reduce their asset risk, and tend to diversify their portfolio with assets from less correlated economies (García-Herrero and Ruiz (2008)).[7] Eventually, Cerqueira and Martins (2009) and Kalemli-Ozcan et al. (2013) explore the reaction of BCS to financial openness and banking integration, and conclude to a negative effect of them on BCS.

Other factors explaining BCS have been explored, such as country specialization (Siedschlag and Tondl (2011); Dées and Zorell (2012)) or wage differential (Gächter et al. (2017)), with both of which have been found to be negatively correlated to the BCS. Lukmanova and Tondl (2017) employ the simultaneous equations method with the Seemingly Unrelated Regression (SUR) estimator to explore the impact of macroeconomic imbalances. They show that differences in the current account balance between members of the euro area can lead to business cycle divergence.

The effects of policies on BCS, the central topic of our study, account for fewer works in literature. Inklaar et al. (2008), Degiannakis et al. (2016) and Bunyan et al. (2020) explore the impact of fiscal policy on output convergence. Otto et al. (2001) proxy the monetary policy using the volatilities of the spread between real short-term interest rates, and the bilateral exchange rates. While monetary policy coordination, understood as weak bilateral exchange rate volatility, has an impact on BCS (i.e. lower bilateral exchange rate correlated with higher output growth), the interest rate spread seems to have no significant effect on the latter. Altavilla (2004) captures the effect of the EMU employing a MSIH(3)-VAR(2) model[8] and business cycles of seven countries. The results show the business cycles of European countries to be closer to each other than to the cycle of the U.S. since the establishment of the Maastricht Treaty. Partially similar results are reached by Papageorgiou et al. (2010) using a rolling window approach: they notice a peak in European BCS within the 1992-1999 period, while the following 2000-2009 period sees a decreasing correlation of cycles. Conversely, Gächter and Riedl (2014) and Degiannakis et al. (2014) observe a positive effect of the adoption of the single currency on European BCS, with a feasible system GMM estimator and a scalar-BEKK model, respectively. Altough monetary union has allowed a greater cross-country spillover effect of country-specific shocks (and thus an increase in co-movement within its members), it has also

[7] This assumption corresponds to the conclusion of the standard international real business cycle model

[8] Markov Switching model with three-regime shifting the Intercept of the VAR(2) and regime-dependent Heteroscedasticity.

lead to more heterogeneous responses to common variations of the economic environment (Enders et al. (2013)). Other works have included a core-periphery dichotomy to refine the study of BCS in Europe. Konstantakopoulou and Tsionas (2011) and Belke et al. (2017) show that different regimes of synchronization are occurring in Europe: a core group characterized by a BCS, and peripheral countries failing to do so. This dichotomy may have been promoted by the implementation of the euro (Lehwald (2013)).

Falling into this strand of the literature, we investigate the role of monetary policy in explaining BCS in Europe between 2000 and 2018. To this end, we combine the wavelet analysis and a system General Method of Moments (GMM) panel dynamic estimator. To our knowledge, the wavelet method has been seldom used yet to study the relationship between monetary policy and business cycle synchronization. It will help us define the correlation of business cycles at different frequencies. With this output, we estimate a model with a system GMM panel dynamic estimator. Our results show that the effect of monetary policy is twofold: it is negative on the very-short-term and the long-term, but positive in the short- and medium-terms. The range of its effects surely reveals the relevance of a frequency approach as economic variables react differently following the adopted term. The impact that the set of unconventional monetary policies had on maintaining a coherent economic and monetary union is twofold: the reverse relationship between the SSR and the BCS at short and long-term indicates that uncommon monetary policy, or at least expansionary one, can be an efficient emergency response to face cyclical downturn as well as a long-term tools for economic convergence. In contrast, the fiscal policy tend to sustain business cycle synchronization by correcting the country-specific characteristics at medium-term, while short-term and long-term fiscal divergence appears to have a harmful impact on the BCS.

The rest of the paper is organized as follows: Section 2 introduces the methods adopted and the data used. Section 3 presents the results we obtain. Finally, Section 4 concludes.

2. Data and Methodology

2.1. Data

We rely on a set of 10 European countries, namely Austria, Belgium, Finland, France, Germany, Ireland, Italy, Netherlands, Portugal and Spain, over the period 2000Q1-2018Q3. All of the above-mentioned countries are members of the euro area, and in consequence subject to the monetary policy adopted by the ECB. We focus on pairwise synchronization between countries. In that respect, we have 45 country pairs and, consequently, 3375 country pair-quarter observations.[9]

2.1.1. *Dependent variable*

We first extract the business cycles by filtering GDP data series with a Beveridge-Nelson (BN) filter (Kamber et al. (2018)). The Beveridge-Nelson filter presents a number of advantages, such as large amplitudes or persistent estimates of the output gap. Cycles estimated by the BN filter are less subject to revisions than the ones estimated with the Hodrick-Prescott (HP) filter or the Christiano-Fitzgerald (CF) one, for example. From the cycle we obtained, we compute our dependent variable - business cycle synchronization - between countries i and j at each time and frequency with continuous wavelets.[10] The wavelets are used as an adaptative filter as opposed to traditional tools requiring low or high bandpass filters to extract or decompose a series. On this basis, the wavelets allow to study and extract multiple cycles with different periods generally hidden in the time domain (Drago and Boxall (2002)) or requiring many methods to extract them separately. In addition, wavelet transforms have the ability to preserve the time information of frequency components of a time series, unlike the Fourier transform or Adaptative Spectrum analysis (Adamowski et al. (2009); Quiroz et al. (2011)). This property allows to analyze the cycles' evolution across time.

Applying to GDP data, we can extract a wide range of business cycles from one time series and analyze their volatility or time evolution, highlighting changes or breaks due to events localized in a particular time. Yogo (2008) uses wavelet decomposition to describe the gross domestic product of the USA and extract various business cycles. The author indicates that this approach is similar to the Baxter-King filter in their objectives, but more useful as it allows both time and frequency representation of all (sub-) cycles in the initial GDP series. By decomposing the GDP with wavelets, he presents the different cycles obtained, indicating that before the 1960s the dominant business cycle has a period of 8-16 quarters while after 1970 a great part of variations is due to low-frequency cycles of 16-32 quarters.

The wavelet approach is also useful in a multivariate case, as we can catch the time-dynamic correlation between two series through wavelets coherence-phases. The analysis of series linkages is then put into a time-frequency space providing a multidimensional view of correlation and co-movements between two series.

The wavelet decompositions are useful to analyze and describe all components of a univariate

[9] Table 1 presents the variables used, the transformations we performed and the sources.
[10] The methodology is presented for the wavelets later in the article.

time series, including trends. However, trends are in this case considered multifrequency components because their effects are divided across all frequencies (Drago and Boxall (2002)). Craigmile and Percival (2014) indicate that trend estimation or detection through wavelets is conditional to the presence of ''noise", which could disturb the extraction of all the different cycles. In addition, they indicate that wavelets are useful to describe cycles and, on the necessity to associate wavelets with other methods to properly study trend through wavelets (as Prokoph et al. (2012) or Pandey et al. (2017) did recently in hydrology). They also discuss the different kinds of wavelet regarding their different objectives: some wavelets are better suitable to model trends, while others are used to estimate cycles, creating a trade-off between the accuracy of cycles and the trend. Nalley et al. (2012) also indicate that trend extraction or estimation by wavelets is possible but it requires the trend extraction frequencies to be defined clearly.

However, in a multivariate case, the wavelet approach is useful to study the time-frequency correlation and co-movement dynamics. Kahraman and Ünal (2016) use wavelets to study the relationships between financial variables, but they model trend and frequency components separately. The cross-decompositions of two trended time series could be affected by a spurious correlation because, by nature, low-frequencies components are correlated when there are trends.

In our paper, on top of using wavelets to describe cycles and trends, we employ this technique to compute the time-varying correlation between business cycles at different periods which can be used as explanatory variables. The wavelets provide intermediary results on correlations and we should limit the potential effects of trends on the extraction of cycles. Then, we remove trend from GDP data in order to properly analyzes the business cycles without the effect of the trend on frequencies considered as a boundary effects, as mentioned by Craigmile and Percival (2014).

2.1.2. Explanatory variables

A conventional approach to embody monetary policy is to take the main refinancing operation (MRO) rate. This indicator is relevant when studying the conventional monetary policy (CMP) led by central banks. For example, Galariotis et al. (2018) use it to assess the impact of CMP on expectations and sentiments. However, in the aftermath of the 2007-08 financial crisis, the MRO appeared to be a limited tool for central bankers as its interest rate (set by the ECB) was approaching the zero lower bound (ZLB). Several central banks implemented then unconventional measures to face this limitation, such as the Long Term Refinancing Operations (LTROs) or the Securities Markets Programme (SMP) for the European Central Bank.

In order to measure the impact of the unconventional monetary policy (UMP), Galariotis et al.

(2018) and Kenourgios et al. (2019) use dummy variables equal to one the date the program is implemented or announced, and zero otherwise. This method faces some limits: it does not take into account the nature of monetary policy (except if the number of dummy variables used is representative of the panel of UMP), nor its magnitude.

Another strategy is to work with the ECB Balance Sheet. Indeed, it incorporates the nature and the amount of the different UMP. This strategy is adopted by Boeckx et al. (2017) and van den End and Pattipeilohy (2017), among others, to study the effect of UMP on economic activity and inflation. Nevertheless, this approach does not take into account the announcement effect. As reminded by Ouerk et al. (2020), agents anticipate the future decisions of Central Banks (as in January 2015 regarding the quantitative easing). To overcome this obstacle, Ouerk et al. (2020) rely on the Shadow Short Rate (SSR). Developed by Black (1995) and popularized by Wu and Xia (2016) and Krippner (2014), it is a "quantitative measure that indicates the overall stance of the monetary policy when the conventional monetary policy instrument (the short-term policy rate) is at the ZLB" (Kuusela and Jari (2017)) and consists of a decomposition of the observed yield curve into a shadow yield curve plus an option. It embodies both aspects of the UMP (announcement and measure effects) and can be positive or negative. We opt for Leo Krippner's SSR as our monetary policy variable in the rest of the paper.

We adopt the most common and relevant control variables to study BCS: the fiscal policy divergence, the export flows, the saving rate difference and the labor cost difference.

We proxy divergence in fiscal policies adopted in countries i and j with the absolute difference of the Cyclically Adjusted net Lending and net Borrowing (CALB) for each country's general government:

$$\text{Diff in CALB}_t = |\text{CALB}_{i,t} - \text{CALB}_{j,t}| \tag{1}$$

This variable is of particular interest since it is the country-based side of economic policy in Europe (the common and shared policy being the monetary one).

Another important variable is the export flow. We do not use the gross flows of exports but rather divide the sum of the bilateral flows by the sum of the respective countries' GDPs. It gives a relative size of trade flows between the two countries:

$$\text{Sum of Exports}_{ij,t} = \frac{\text{Exports}_{i,t} + \text{Exports}_{j,t}}{\text{GDP}_{i,t} + \text{GDP}_{j,t}} \tag{2}$$

The saving rate difference proxies the consumer side of the economy and is calculated as follows:

$$\text{Diff in Savings}_t = \left|\text{Savings}_{i,t} - \text{Savings}_{j,t}\right| \tag{3}$$

Finally, similarly to Lukmanova and Tondl (2017), we use the labor cost as a proxy of the different development of wages:

$$\text{Diff in Labor cost}_{ij,t} = \left|\text{Labor cost}_{\mathrm{i,t}} - \text{Labor cost}_{j,t}\right| \tag{4}$$

Table 1: Variables' description and data sources

Variable	Title	Source	Frequency	Transformation
CALB	Cyclically adjusted net lending (+) or net borrowing (-) of general government: Adjustment based on potential GDP Excessive deficit procedure (UBLGAP) CALB	AMECO Database	Annual	Quadratic match-average
Bilateral Trade Flows	EU trade by HS6	Eurostat	Monthly	Average of 3 months to obtain the quarterly value
Labour Cost	Unit labour costs and labour productivity (employment based), Total economy	OECD	Quarterly	-
Shadow short rate	Month-End SSR series	Leo Krippner's Website	Monthly	-
GDP	Gross Domestic Product	Eurostat	Quarterly	-
Saving Rate	Household saving rate	Eurostat	Annual	Quadratic match-average

2.2. Wavelets

We use the wavelet phase coherence analysis to estimate the synchronization between the business cycles at each time t and frequency f. Then, we create the dependent variable of the model. The wavelets approach, popularized by Grossmann and Morlet (1984a), is a theoretical extension and a methodological improvement of the (co-)spectral analysis and frequency decomposition of a series. It allows a time-based representation of the frequency component of a signal (in our case, time series) and to realize a time-frequency analysis. Although it has been theoretically developed in a continuous form with the Continuous Wavelets Transform (CWT), the required computational power was a major obstacle to its practical implementation. That is why discretized versions have been elaborated: Mallat (1989, 2001, 2009) made the link between multiresolution analysis and wavelets, reducing substantially the computational time on a discrete basis with the Maximal Overlap Discrete Wavelets Transform (MODWT).

In economics, wavelets can be used to extract different types of cycles in economic series depending on the frequencies and the periods. This methodology allows the analysis of the relations between variables in a new time-frequency space. Gençay et al. (2003, 2005) and Mestre and Terraza (2018a,b, 2019) use the discrete wavelet transform to study the Capital Asset Pricing Model (CAPM) considering frequencies as different investment horizons for agents (long-term, middle-term, short-term). Their works show that results in terms of portfolio risks and allocations can be differentiated following the horizon, which implies the presence of frequency dynamics of co-movements between variables. Rua and Nunes (2009) use coherence and phase of CWT to capture long- and short-term co-movements between international financial markets. The authors highlight the importance of relying on wavelet transform to study causality and inter-dependencies between variables. Vacha and Barunik (2012) and Bekiros et al. (2016) also rely on coherence and phase of CWT to study diversification of portfolio through the time-frequency relationship between assets and commodity prices. Analogously, Auth (2013) and Bekiros and Marcellino (2013) focus on hedge funds and the dynamic of exchange rates, and show that the intensity of the relationship between variables depends on the different cycle frequencies adopted.

Continuous Wavelets Transform (CWT)

The time-frequency analysis using continuous wavelets represents an improvement of the Fourier approach as it allows a time representation of a series' frequency components. Wavelets theory has been formulated by Grossmann and Morlet (1984b), Meyer et al. (1987) and Meyer (1992), and popularized by Mallat (1989, 2001, 2009) and Daubechies (1992) in signal treatment.

A continuous wavelets transform is based on a *mother wavelet* noted $\psi(t)$, translated by τ and dilated by s to extract the information of a series $x(t)$ on several frequencies. Overall translated-dilated versions of $\psi_{\tau,s}(t)$ form the following *wavelet family* :

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{s}}\psi(\frac{t-\tau}{s}) \tag{5}$$

The CWT consists of projecting $x(t)$ on the family $\psi_{\tau,s}(t)$ to obtain the variations of the series in the neighbourhood of $t \mp \tau$ and of frequency amplitude of s. Varying τ and s, we get the following wavelets coefficients $W(s,\tau)$:

$$W(s,\tau)=\int_{-\infty}^{+\infty}x(t)\frac{1}{\sqrt{s}}\psi^{*}(\frac{t-\tau}{s})dt \tag{6}$$

with $\psi^{*}(\frac{t-\tau}{s})$ being the complex conjugate of $\psi_{\tau,s}(t)$.

We can reconstruct $x(t)$ with the following reverse operation:

$$x(t)=\frac{1}{C_{\psi}}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\psi_{\tau,s}(t)W(s,\tau)\frac{d\tau ds}{s^{2}} \tag{7}$$

The expression highlights the C_{ψ} condition of existence of the wavelets (Calderón (1964)):

$$C_{\psi}=\int_{0}^{+\infty}\frac{\left|\hat{\Psi}(f)\right|^{2}}{f}df<+\infty \qquad (8)^{11}$$

where f denotes the frequency and $\hat{\Psi}(f)$ the Fourier transform of the mother wavelet. This condition is respected if $\psi(t)$ has a zero mean and keeps the same variance when decomposed:

$$\int_{0}^{+\infty}\psi(t)dt=0 \quad \text{and} \quad \int_{0}^{+\infty}\left|\psi(t)\right|^{2}dt=1 \tag{9}$$

There are several mother wavelet families with different features related to their orthogonality, symmetry or compact support (as showed by Farge (1992) and Daubechies (1992)). Here, we will use the (continuous) complex Morlet wavelet $\psi_M(t)$, characterized by an equilibrium between the time and the frequency localization:

$$\psi_{M}(t)=\pi^{-1/4}e^{if_{0}t}e^{-\frac{t^{2}}{2}} \tag{10}$$

where $i^2=-1$ and f_0 is the non-dimensional frequency which, in our case, equals 6 to satisfy the admissibility condition. We realize a frequency sampling for the practical implementation because of limited computational power. Facing obstacles in the use of CWT, Lau and Weng (1995) and Torrence and Compo (1998) define the whole s_j scales of a J maximal order CWT decomposition with a good resolution and reasonable computational time. These formulas are defined from the size of the series N (thus from δ_t, the time step) and the frequency step δ_j:

$$\begin{gathered} s_{j}=S_{0}.2^{j\delta_{j}}, \forall j\in[0,...,J] \\ J=\frac{1}{\delta_{j}}\left\lfloor \log_{2}\left(\frac{N\delta_{t}}{s_{0}}\right)\right\rfloor=\frac{1}{\delta_{j}}\left\lfloor \log_{2}\left(\frac{N}{2}\right)\right\rfloor \end{gathered} \tag{11}$$

[11] f being the frequency and $\hat{\Psi}(f)$ the Fourier transform of the mother wavelet

The smaller δ_j, the bigger the number of intermediary scales and the finer the frequency mesh s_j. The choice of δ_j is also linked to the mother wavelet. In our case, the value must not exceed 0.5. We fix the value of δ_j at 1/8 to obtain a consistent frequency mesh with a reasonable computational time.

The interpretation of the frequency scales s_j can be facilitated by expressing them in Fourier Period, whose unity is similar to the initial series. Meyers et al. (1993) propose a Conversion Factor (CF) proper to the Morlet wavelet used:

$$T_j = s_j * \frac{4\pi}{f_o + \sqrt{2 + f_0^2}} \tag{12}$$

$$CF = \frac{4\pi}{f_o + \sqrt{2 + f_0^2}} = 1.033 \tag{13}$$

Wavelet Phase Coherence

The CWT allows to redefine some statistical notions as correlation in time-frequency space. Notions of coherence and phase are similar, in terms of interpretation, to the determination coefficient (i.e., R^2)(Grinsted et al. (2004)) but transcript statistical information depending on the time (time dynamic) and the frequency (frequency dynamic) we are interested in.

Considering two time functions $x(t)$ and $y(t)$ with similar size N, we can deduce the wavelet coefficients (respectively, $W_x(s,\tau)$ and $W_y(s,\tau)$) via the CWT. The time-frequency co-variance can be obtained by crossing the wavelet coefficients:

$$SW_{xy}(s,\tau) = W_x(s,\tau)W_y^*(s,\tau) \tag{14}$$

where $SW_{xy}(s,\tau)$ is the cross transform, $W_x(s,\tau)$ are the wavelet coefficients from the transform, and $W_y^*(s,\tau)$ is the conjugate complex of $W_y(s,\tau)$.

The wavelet coherence, noted $WQ(s,\tau)$, between two functions is achieved by dividing the wavelets crossed spectrum by the power spectrum of each function:[12]

$$WQ(s,\tau) = \frac{\left|G(s^{-1}.SW_{xy}(s,\tau)\right|^2}{G(s^{-1}.|W_x(s,\tau)|^2).G(s^{-1}.|W_y(s,\tau)|^2)} \tag{15}$$

We can then notice the similarity between the coherence and the coefficient of determination. For each frequency scale s_j defined by δ_j and each time moment, we obtain a value between 0

[12]We use the R-package of Gouhier et al. (2019) based on the program of Torrence and Compo (1998).

and 1. However, in our case, they are complex due to the use of the Morlet wavelets. In its real representation, the coherence is equal to 1 regardless of the value of τ, making its interpretation useless. The use of a time-frequency smoothing, noted $G(.)$, is necessary to get interpretable values in practice. A time-based smoothing $G_{time}(.)$ for a fixed scale s is first made, then come the smoothing of frequency scales for a given moment t, noted $G_{scale}(.)$. The general smoothing operator $G(.)$ is written as follows:

$$G(W(s,\tau)) = G_{scale}(G_{time}(W(s,\tau))) \tag{16}$$

The mathematical expressions of G_{scale} and G_{time} are given by Torrence and Webster (1999):

$$G_{time}(\cdot) = W(s\tau)c_1^{\frac{-t^2}{2s^2}} \tag{17}$$

$$G_{scale}(\cdot) = W(s\tau)c_2\Pi(0.6s) \tag{18}$$

where c_1 and c_2 are the *constants of normalization* and $\Pi(.)$ is the rectangular function that takes the value 1 in the interval $[-0.5; 0.5]$ and 0 otherwise.

The difference in phase between two series (hereafter named "phase difference") is the complementary value needed to get the sign of the relationship as well as the mutual influences between the variables (with the notion of "leader").

The phase function in wavelets, noted $\theta_{xy}(s,\tau)$, is defined as the arc-tangent of the ratio between the imaginary part $\Im$ and the real part $\Re$ of $SW_{xy}(s,\tau)$:

$$\theta_{xy}(s,\tau) = \arctan\left(\frac{\Im(SW_{xy}(s,\tau))}{\Re(SW_{xy}(s,\tau)}\right) \tag{19}$$

The study of the phase value, ranging between $[-\pi, \pi]$, allows us to analyze the sign of the relationship and the mutual influences between the two variables, indicating the "leader" variable.

From equations (15) and (19), we extract a correlation coefficient at each time and frequency representing the BCS between two countries i and j such as:

$$\mathrm{BCS}_{ij,s,\tau} = \vartheta_{s,\tau}.\sqrt{WQ(s,\tau)} \tag{20}$$

where $\vartheta_{s,\tau}$ is a phase parameter indicating the sign of the correlation between the two variables according to the value of the phase function.

$$\vartheta_{s,\tau} = \begin{cases} 1, & \text{if } |\theta_{xy}(s,\tau)| \in [0, \frac{\pi}{2}] \\ -1, & \text{if } |\theta_{xy}(s,\tau)| \in [\frac{\pi}{2}, \pi] \end{cases}$$

2.3. System GMM panel dynamic estimator

An important issue raised from our data is the possible *endogeneity* of our variables. Frankel and Rose (1998), who estimated a robust positive relationship between trade and business cycle synchronization, addressed this problem in the dynamic of the estimated relationship: stronger trade linkages would increase BCS which, in turn, would increase trade flows between countries. In response to that, Imbs (2004) will be the first to rely on a dynamic approach by adopting a system of simultaneous equations. This method deals with the endogeneity of the model by employing external instruments for each explanatory variable. However, if this approach allows us to solve a problem, it creates another one with the selection of the instrumental variables.

The other problem is the possible correlation between the lagged dependent variable and country-specific effects. A solution is to take the model in difference but the source of correlation would simply be the difference of the above-mentioned variables.[13]

To deal with these issues and avoid the selection of non-relevant instruments, we adopt the strategy of Cerqueira and Martins (2009) and Bunyan et al. (2020) with a *system GMM panel dynamic estimator*. First, it corrects the bias due to the correlation between the unobservable fixed effects and the lagged values. Second, it allows us to get from the data their own instruments: the lagged values of the data are relevant instruments since they can be correlated to the variation of the next value without being correlated to the variation of the actual error term. Resorting to the GMM regarding the characteristics of our sample may not appear as the optimal solution. Indeed, the GMM estimator works fine in samples with large N and small T, but become inconsistent as the number of instruments grows quadratically with T. To overcome this issue, we apply the double filter IV and GMM estimator developed by Hayakawa et al. (2019), whose properties lead to an unbiased estimator when both N and T are large.

Our model is:

$$\mathrm{BCS}_{ij,t,f} = \alpha + \beta_1 \mathrm{BCS}_{ij,t-1,f} + \beta_{2,f}\mathrm{SSR}_t + \beta_k X'_{ij,t,f} + \alpha_{ij} + \alpha_t + u_{ij,t,f} \tag{21}$$

with $BCS_{ij,t,f}$ our BCS between a given pair of countries i and j at time t and at frequency f, $BCS_{ij,t-1,f}$ its lagged value, SSR_t the shadow short-rate, $X'_{ij,t}$ the matrix of control variables, $\alpha_i j$ a country pair fixed effect, α_t a time fixed effect and $u_{ij,t}$ the error term. $X'_{ij,t}$ includes the exports variable, the difference in CALB, the difference in saving rates and the difference in labor costs. As

[13] In these both cases of endogeneity, the OLS estimations are biaised.

the estimation method requires to take the model in differences, the country pair fixed effects are eliminated. The coefficient of interest is $\beta_{2,f}$ here. Since it is the link to monetary policy variable, we will be able to measure the sign and the significance of the monetary policy at different frequencies f. We also estimate a model to take into account a possible level effect of the SSR by creating the interaction variables $I_t^{SSR^+}$ and $I_t^{SSR^-}$ as follows:

$$\begin{aligned}\mathrm{BCS}_{ij,t,f} = \quad & \alpha + \beta_1 \mathrm{BCS}_{ij,t-1,f} \\ & + \beta_{2,f}\mathrm{SSR}_t * I_t^{\mathrm{SSR}^-} + \beta_{3,f}\mathrm{SSR}_t * I_t^{\mathrm{SSR}^+} \\ & + \beta_k X'_{ij,t,f} + \alpha_{ij} + \alpha_t + u_{ij,t,f}\end{aligned} \tag{22}$$

$$I_t^{\mathrm{SSR}^-} = \begin{cases} 1, & \text{if } \mathrm{SSR}_t < 0 \\ 0, & \text{otherwise} \end{cases}, I_t^{\mathrm{SSR}^+} = \begin{cases} 1, & \text{if } \mathrm{SSR}_t > 0 \\ 0, & \text{otherwise} \end{cases}$$

Finally, our results are presented along with the Sargan-Hansen test of the overidentifying restrictions[14] and the Arellano-Bond test for autocorrelation of the first-differenced residuals ($AR(1)$ and $AR(2)$).

3. Results

3.1. Wavelet correlations

Figures 1 to 9 present the correlograms for the business cycles of the ten countries selected. The color-coding ranges from blue (low synchronization) to red (high synchronization) and the black lines delineate the strong coherency area. The period (the y-axis) goes from 2 (6 months) to 32 (8 years). Here, the notion of lead is not to be understood as a causal relationship (for example, "the belgium cycle explains the german one"), but more as the observed correlation (when common movements occur, the belgium cycle predates the german one).

In most of the figures presented, we can first notice that the synchronization is "in phase".[15] In other words, we mainly observe a positive correlation of the cycles.[16] Then, we note a peak in the synchronization of cycles between mid-2007 and 2010 for the short/medium-term period (1.5 years to 2.5/3 years), which corresponds to the 2007 subprime crisis period. Since it was a common and

[14] The results of the Sargan-Hansen test of the overidentifying restrictions maybe be questioned since the test can be biaised by data features such as persistence or large time series (Richard et al. (2001)).

[15] In regions of high significance (delimited with a dark line), arrows are pointing right in almost every case.

[16] Otherwise, it would mean that the cycles are significantly in anti-phase. This result would raise a certain number of issues regarding the relevance of the euro area.

global shock, most of the countries' economies reacted similarly: a drastic fall of their outputs. So it is no surprise to us to notice that business cycles of most of European countries were in phase.

Ireland seem to have considerably de-synchronized cycles with the rest of our sample. Our result corroborates those obtained by Aguiar-Conraria and Joana Soares (2011): after 2011, the Irish business cycle does not seem to be synchronized with any of the European business cycles. In the face of this observation, we can rightly wonder if the Irish economy is tailored for the euro area. To a lesser extent, Portugal's business cycles seem independent from those of the other European countries, with the exception of Italy. However, unlike what we can observe for Ireland, Portugal appears to be incrementally synchronized"., notably at medium-term (2 to 4 years cycles). Finally, Spain also presents a limited synchronization of its cycles with the rest of Europe.

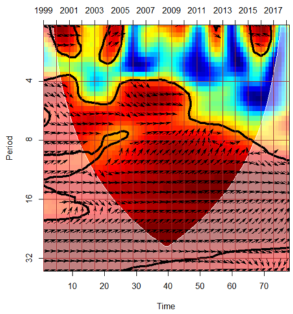
We can identify two countries which are the center of what is usually named the "European core": France and Germany. Both have highly synchronised business cycles with other European countries (Figures 4 and 5). This "cyclic" proximity reveals a geographical one: the European core is mostly composed of northern European countries, with common borders (France, Germany, Belgium, Netherlands, Austria, Finland), while countries such as Portugal, Spain and Ireland have their own business cycle patterns.

Italy has strong cycle synchronizations with most of the countries composing our panel, remarkably strong and deep with Spain and Portugal. This outcome reflects the ambiguous situation of Italy as part of the European core and the European periphery (Ahlborn and Wortmann (2018)).

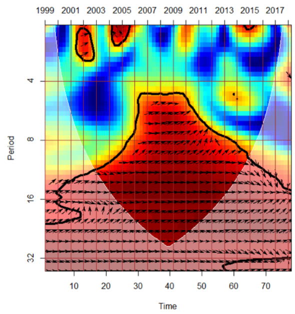
3.2. System GMM estimation

Table 2 shows the results of the model estimations. The Sargan-Hansen test and the Arellano-Bond tests highlight the good statistical properties of our estimates. In this model, all our variables are considered as endogenous variables. The model is estimated with 4 different dependent variables: the correlation at a 6 months frequency ($Corr.\, 6m_t$), at 1 year ($Corr.\, 1y_t$), 2 years ($Corr.\, 2y_t$), and 4 years ($Corr.\, 4y_t$). The variety of frequencies will help us control the effect of monetary policy at different horizons and determine the short-, medium- and long-run determinants of the BCS. The 6 months frequency represents the short-run period, the 1 year and 2 years frequencies the medium-run period, and the 4 years frequency the long-run period. The model with the correlation at 6 months shows the short-term drivers of correlations. In this case, besides the lagged value of the dependent variable ($Corr.\, 6m_{t-1}$ with a significant positive coefficient that equals to 0.832), the exports play a negative role in the synchronization of the business cycles ($-4.86e^{(-10)}$). This result may be surprising since we expect a transmission of business cycle movement to commercial partners

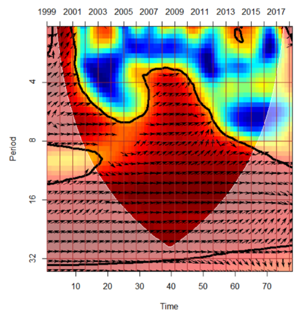
Figure 1: Wavelet correlation with Belgian business cycles.



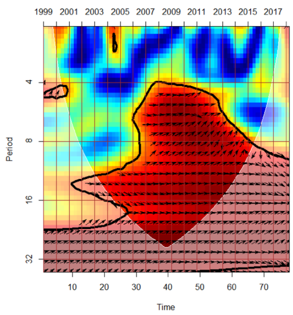
(a) Austria



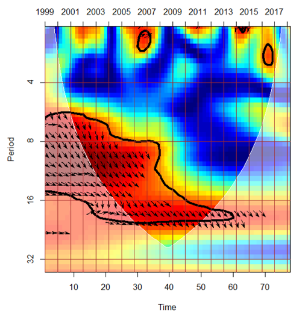
(b) Finland



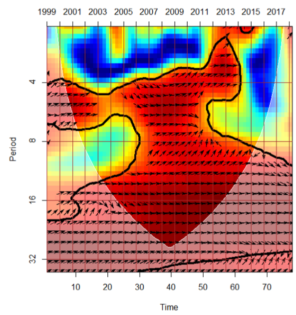
(c) France



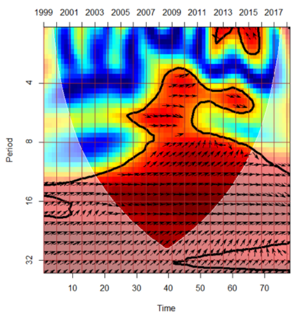
(d) Germany



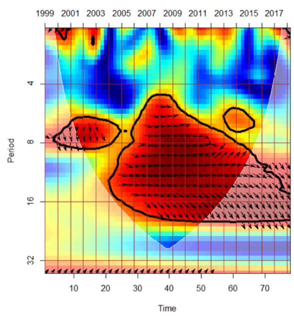
(e) Ireland



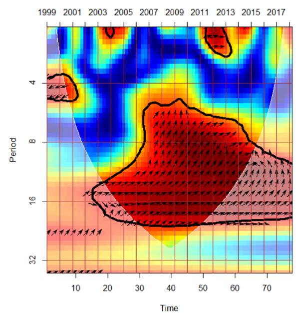
(f) Italy



(g) Netherlands



(h) Portugal

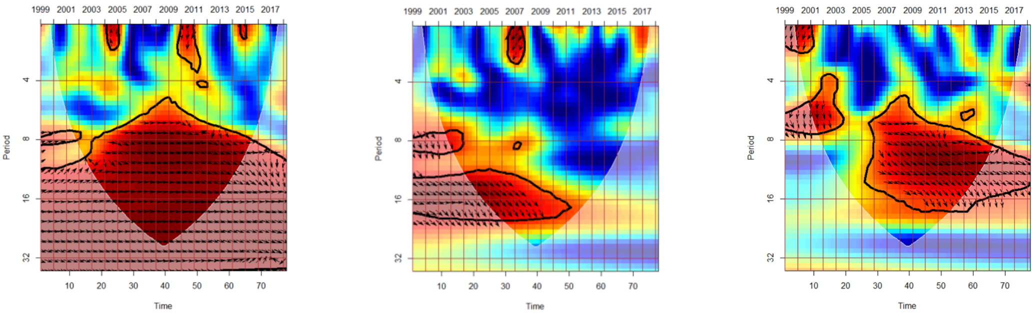


(i) Spain

Note: Morlet mother wavelets, 1/12 frequency step, phase difference plotted with arrows, significance of R^2 at 5% by Monte-Carlo method (300 simulations). If the arrows are pointing right then X (here, Belgium) and Y (here, countries mentioned below the graph) are in phase (positive correlation). If the arrows are pointing left then X and Y are in anti-phase (negative correlation). The phase difference, θ, is useful to analyze "lead-Lag" indicating if X (or Y) leads Y (or X):

- If $\theta \in [\frac{\pi}{2}, \pi]$,then Y lead X in anti-phase: arrow pointing **up-left**.
- If $\theta \in [\frac{-\pi}{2}, 0]$, then Y lead X in phase: arrow pointing **down-right**.
- If $\theta \in [0, \frac{\pi}{2}]$, then X lead Y in phase: arrow pointing **up-right**.
- If $\theta \in [-\pi, \frac{-\pi}{2}]$, then X lead Y in anti-phase: arrow pointing **down-left**.

Figure 2: Wavelet correlation with Austrian business cycles.

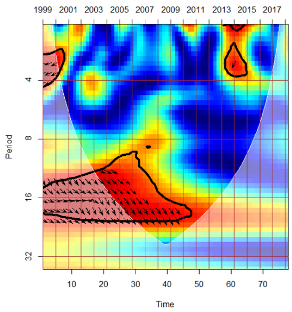


(a) Finland (b) Ireland (c) Portugal

Note: Morlet mother wavelets, 1/12 frequency step, phase difference plotted with arrows, significance of R^2 at 5% by Monte-Carlo method (300 simulations). If the arrows are pointing right then X (here, Austria) and Y (here, countries mentioned below the graph) are in phase (positive correlation). If the arrows are pointing left then X and Y are in anti-phase (negative correlation). The phase difference, θ, is useful to analyze "lead-Lag" indicating if X (or Y) leads Y (or X):

- If $\theta \in [\frac{\pi}{2}, \pi]$,then Y lead X in anti-phase: arrow pointing **up-left**.
- If $\theta \in [\frac{-\pi}{2}, 0]$, then Y lead X in phase: arrow pointing **down-right**.
- If $\theta \in [0, \frac{\pi}{2}]$, then X lead Y in phase: arrow pointing **up-right**.
- If $\theta \in [-\pi, \frac{-\pi}{2}]$, then X lead Y in anti-phase: arrow pointing **down-left**.

Figure 3: Wavelet correlation with Finnish business cycles.

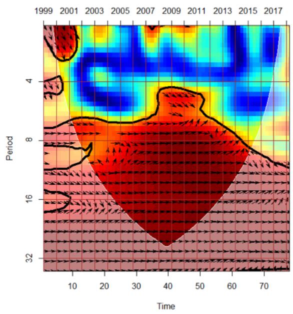


(a) Ireland

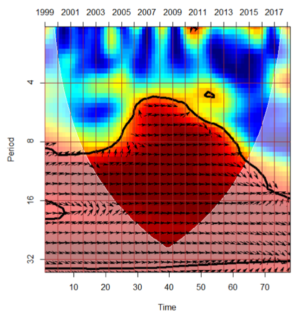
Note: Morlet mother wavelets, 1/12 frequency step, phase difference plotted with arrows, significance of R^2 at 5% by Monte-Carlo method (300 simulations). If the arrows are pointing right then X (here, Finland) and Y (here, countries mentioned below the graph) are in phase (positive correlation). If the arrows are pointing left then X and Y are in anti-phase (negative correlation). The phase difference, θ, is useful to analyze "lead-Lag" indicating if X (or Y) leads Y (or X):

- If $\theta \in [\frac{\pi}{2}, \pi]$,then Y lead X in anti-phase: arrow pointing **up-left**.
- If $\theta \in [\frac{-\pi}{2}, 0]$, then Y lead X in phase: arrow pointing **down-right**.
- If $\theta \in [0, \frac{\pi}{2}]$, then X lead Y in phase: arrow pointing **up-right**.
- If $\theta \in [-\pi, \frac{-\pi}{2}]$, then X lead Y in anti-phase: arrow pointing **down-left**.

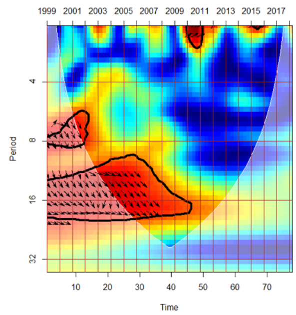
Figure 4: Wavelet correlation with French business cycles.



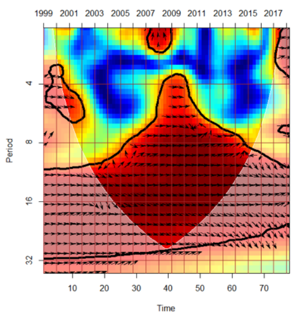
(a) Austria



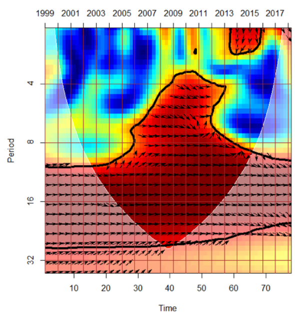
(b) Finland



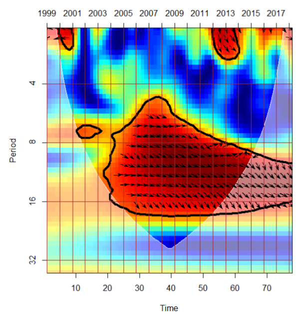
(c) Ireland



(d) Italy



(e) Netherlands

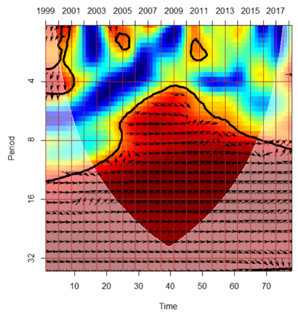


(f) Portugal

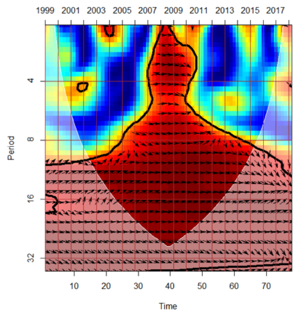
Note: Morlet mother wavelets, 1/12 frequency step, phase difference plotted with arrows, significance of R^2 at 5% by Monte-Carlo method (300 simulations). If the arrows are pointing right then X (here, France) and Y (here, countries mentioned below the graph) are in phase (positive correlation). If the arrows are pointing left then X and Y are in anti-phase (negative correlation). The phase difference, θ, is useful to analyze "lead-Lag" indicating if X (or Y) leads Y (or X):

- If $\theta \in [\frac{\pi}{2}, \pi]$,then Y lead X in anti-phase: arrow pointing **up-left**.
- If $\theta \in [\frac{-\pi}{2}, 0]$, then Y lead X in phase: arrow pointing **down-right**.
- If $\theta \in [0, \frac{\pi}{2}]$, then X lead Y in phase: arrow pointing **up-right**.
- If $\theta \in [-\pi, \frac{-\pi}{2}]$, then X lead Y in anti-phase: arrow pointing **down-left**.

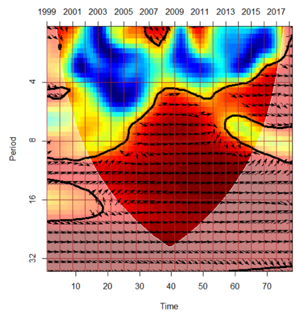
Figure 5: Wavelet correlation with German business cycles.



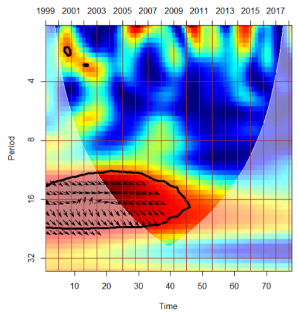
(a) Austria



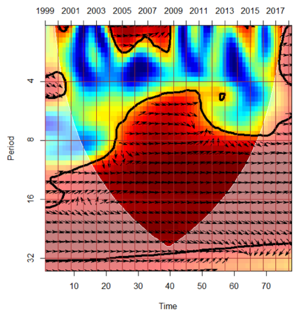
(b) Finland



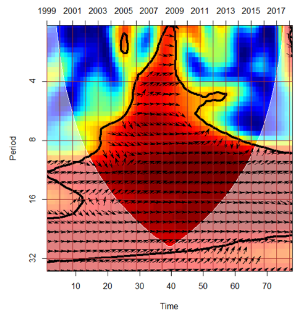
(c) France



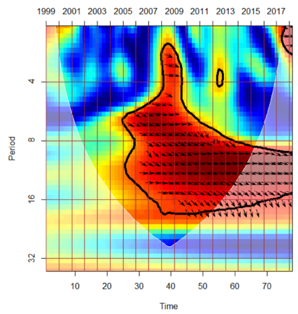
(d) Ireland



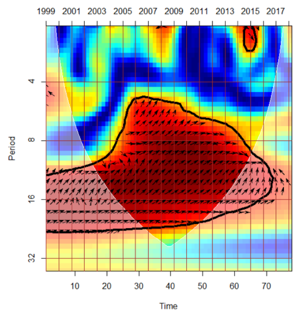
(e) Italy



(f) Netherlands



(g) Portugal

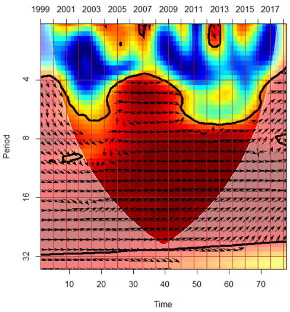


(h) Spain

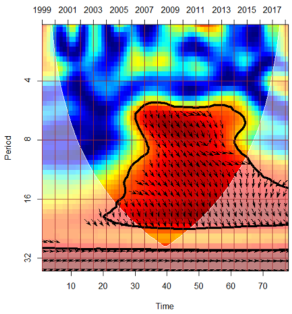
Note: Morlet mother wavelets, 1/12 frequency step, phase difference plotted with arrows, significance of R^2 at 5% by Monte-Carlo method (300 simulations). If the arrows are pointing right then X (here, Germany) and Y (here, countries mentioned below the graph) are in phase (positive correlation). If the arrows are pointing left then X and Y are in anti-phase (negative correlation). The phase difference, θ, is useful to analyze "lead-Lag" indicating if X (or Y) leads Y (or X):

- If $\theta \in [\frac{\pi}{2}, \pi]$,then Y lead X in anti-phase: arrow pointing **up-left**.
- If $\theta \in [\frac{-\pi}{2}, 0]$, then Y lead X in phase: arrow pointing **down-right**.
- If $\theta \in [0, \frac{\pi}{2}]$, then X lead Y in phase: arrow pointing **up-right**.
- If $\theta \in [-\pi, \frac{-\pi}{2}]$, then X lead Y in anti-phase: arrow pointing **down-left**.

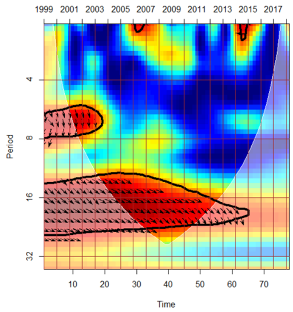
Figure 6: Wavelet correlation with Italian business cycles.



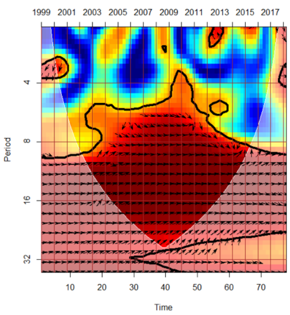
(a) Austria



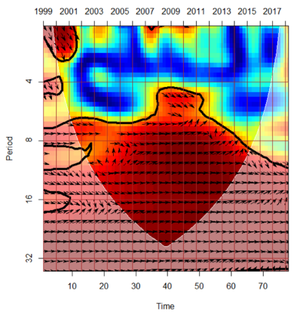
(b) Finland



(c) Ireland



(d) Netherlands

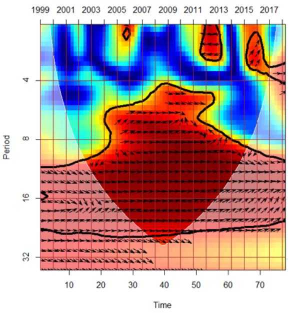


(e) Portugal

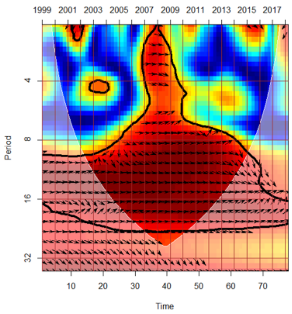
Note: Morlet mother wavelets, 1/12 frequency step, phase difference plotted with arrows, significance of R^2 at 5% by Monte-Carlo method (300 simulations). If the arrows are pointing right then X (here, Italy) and Y (here, countries mentioned below the graph) are in phase (positive correlation). If the arrows are pointing left then X and Y are in anti-phase (negative correlation). The phase difference, θ, is useful to analyze "lead-Lag" indicating if X (or Y) leads Y (or X):

- If $\theta \in [\frac{\pi}{2}, \pi]$,then Y lead X in anti-phase: arrow pointing **up-left**.
- If $\theta \in [\frac{-\pi}{2}, 0]$, then Y lead X in phase: arrow pointing **down-right**.
- If $\theta \in [0, \frac{\pi}{2}]$, then X lead Y in phase: arrow pointing **up-right**.
- If $\theta \in [-\pi, \frac{-\pi}{2}]$, then X lead Y in anti-phase: arrow pointing **down-left**.

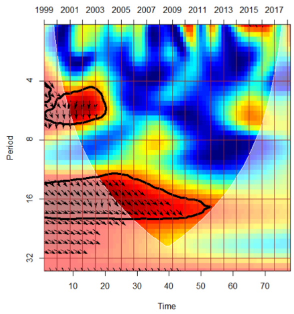
Figure 7: Wavelet correlation with Dutch business cycles.



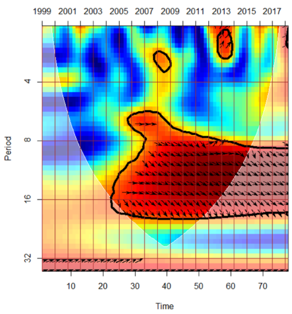
(a) Austria



(b) Finland



(c) Ireland

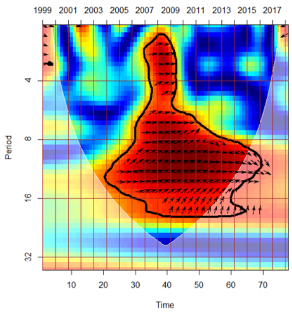


(d) Portugal

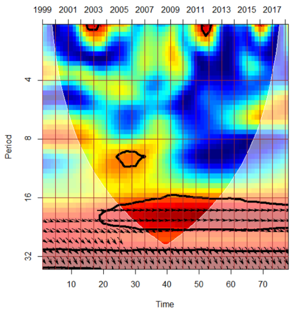
Note: Morlet mother wavelets, 1/12 frequency step, phase difference plotted with arrows, significance of R^2 at 5% by Monte-Carlo method (300 simulations). If the arrows are pointing right then X (here, Netherlands) and Y (here, countries mentioned below the graph) are in phase (positive correlation). If the arrows are pointing left then X and Y are in anti-phase (negative correlation). The phase difference, θ, is useful to analyze "lead-Lag" indicating if X (or Y) leads Y (or X):

- If $\theta \in [\frac{\pi}{2}, \pi]$,then Y lead X in anti-phase: arrow pointing **up-left**.
- If $\theta \in [\frac{-\pi}{2}, 0]$, then Y lead X in phase: arrow pointing **down-right**.
- If $\theta \in [0, \frac{\pi}{2}]$, then X lead Y in phase: arrow pointing **up-right**.
- If $\theta \in [-\pi, \frac{-\pi}{2}]$, then X lead Y in anti-phase: arrow pointing **down-left**.

Figure 8: Wavelet correlation with Portuguese business cycles.



(a) Finland

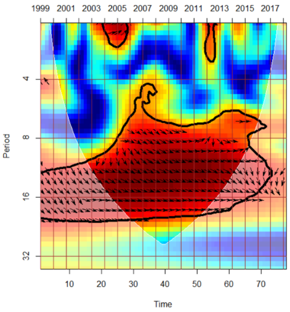


(b) Ireland

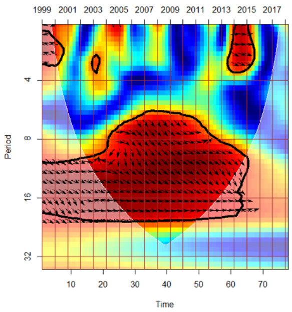
Note: Morlet mother wavelets, 1/12 frequency step, phase difference plotted with arrows, significance of R^2 at 5% by Monte-Carlo method (300 simulations). If the arrows are pointing right then X (here, Portugal) and Y (here, countries mentioned below the graph) are in phase (positive correlation). If the arrows are pointing left then X and Y are in anti-phase (negative correlation). The phase difference, θ, is useful to analyze "lead-Lag" indicating if X (or Y) leads Y (or X):

- If $\theta \in [\frac{\pi}{2}, \pi]$,then Y lead X in anti-phase: arrow pointing **up-left**.
- If $\theta \in [\frac{-\pi}{2}, 0]$, then Y lead X in phase: arrow pointing **down-right**.
- If $\theta \in [0, \frac{\pi}{2}]$, then X lead Y in phase: arrow pointing **up-right**.
- If $\theta \in [-\pi, \frac{-\pi}{2}]$, then X lead Y in anti-phase: arrow pointing **down-left**.

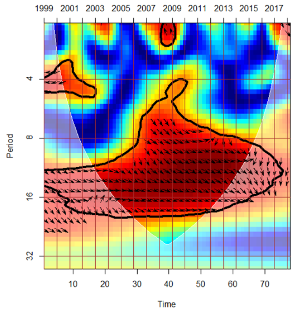
Figure 9: Wavelet correlation with Spanish business cycles.



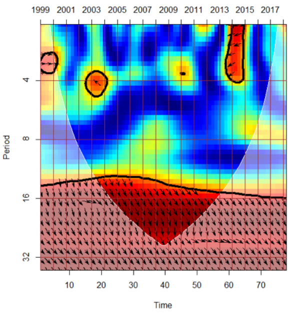
(a) Austria



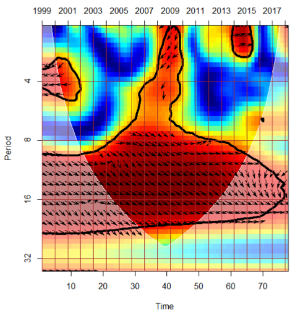
(b) Finland



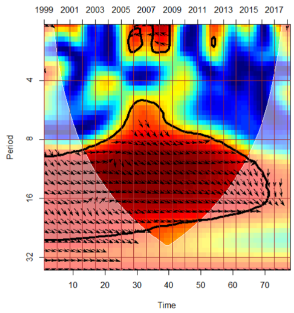
(c) France



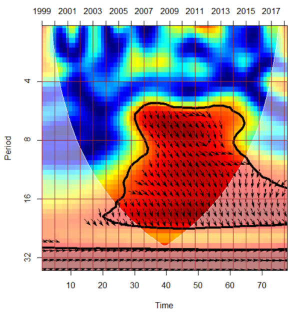
(d) Ireland



(e) Italy



(f) Netherlands



(g) Portugal

Note: Morlet mother wavelets, 1/12 frequency step, phase difference plotted with arrows, significance of R^2 at 5% by Monte-Carlo method (300 simulations). If the arrows are pointing right then X (here, Spain) and Y (here, countries mentioned below the graph) are in phase (positive correlation). If the arrows are pointing left then X and Y are in anti-phase (negative correlation). The phase difference, θ, is useful to analyze "lead-Lag" indicating if X (or Y) leads Y (or X):

- If $\theta \in [\frac{\pi}{2}, \pi]$,then Y lead X in anti-phase: arrow pointing **up-left**.
- If $\theta \in [\frac{-\pi}{2}, 0]$, then Y lead X in phase: arrow pointing **down-right**.
- If $\theta \in [0, \frac{\pi}{2}]$, then X lead Y in phase: arrow pointing **up-right**.
- If $\theta \in [-\pi, \frac{-\pi}{2}]$, then X lead Y in anti-phase: arrow pointing **down-left**.

through trade. However, significant flows and trade specialization make countries more vulnerable to fluctuation of their partners' demands, and in consequence, can lead to business cycle divergences. The difference in labor costs plays a positive role on BCS. Put differently, an increase in the labor cost difference, proxying the wage difference, increases the synchronization of the business cycles. In that sense, our results are in conflict with the findings of Gächter et al. (2017). The saving rate difference also plays a positive role with a coefficient that equals to 0.287. The BCS is sensible to the difference in consumption and saving structure between economies. Surprisingly, the divergence in implemented fiscal policies has a negative impact on BCS (-0.031). This result reflects different reactions to country-specific economic stimuli, since the timeframe of our sample contains important crisis periods. Finally, the coefficient associated to our variable of interest SSR_t is significant: -0.276. Thus, at a very short-term, a decrease of the shadow rate and/or the implementation of unconventional monetary policy helps the synchronization of the European business cycles.

Models at a 1-year and 2-years frequency point approximately in the same direction: the labor difference, here as a negative impact (-0.0178 and -0.0172), which is more coherent with what we find in the literature. The fiscal policy divergence also has a reverse impact: 0.027 and 0.0200. With a "one-size-fits-all" monetary approach, fiscal policy is the main tool to balance the specificity of countries . It is then not a surprise to see a positive impact of divergent fiscal policies adopted, supporting growth of countries with country-adequate policies. The Shadow Short Rate impacts also positively the BSC, indicating that a tighter monetary policy improves the BSC in Europe at a short-medium term. Eventually, we notice that trade impacts positively the BCS, contrary to its effect at the short frequency.

Finally, the model at a 4-years frequency brings us more information on the determinants of long-term synchronization. The SSR has a negative impact: a reduction of SSR leads, at long-term, to an increase in BCS between European countries (-0.0772). Numerous explanations can be given to explain the results, such as the positive impact that low interest rates can have on investment, which in turn, affects the economy. The reduction of labor cost differences decreases the BCS (0.0097), which coincides with the effect this variable has at the very short-term (6 months). The difference in fiscal policies reappears as a negative determinant of the BCS with a positive coefficient at -0.00843. In this way, the effect of un-synchronized fiscal policies on BCS is twofold: they are useful to correct country-specific features at short-medium term, but they worsen the BSC at long-term. The labor cost difference plays an unexpected positive role (0.00976), as at short-term frame, which worth an analysis on its own. It reveals the role played by conventional and unconventional monetary policies led since 2009. Indeed, with the 2007-2008 financial crisis and the sovereign debt crisis in 2010, the ECB has implemented a set of unconventional monetary policy which are not transcripted in the MRO rates. To incorporate them in a unique indicator like the SSR, the latter must be able to be negative. In our case, it seems that a negative SSR, proxying UMP, has a positive impact on BCS on the long-run.

It is important to check for any level effect since a positive or a negative SSR embodies different monetary policy, using different channels and, consequently, having different magnitudes and amplitudes. This implies adopting a non-linear approach with interaction variables, as presented in equation (22). Table 3 displays the estimation results of this model where SSR interacts with two variables, depending on its value: $I_t^{\mathrm{SSR}^+}$ and $I_t^{\mathrm{SSR}^-}$.[17]

Broadly speaking, our previous results are not affected by our new specification. Trade has still a significant and negative effect on the BCS (except at a 2-year frequency), supporting the idea of *de*-synchronizing trade specialization. Labor cost difference fosters the BCS at almost every frequency, while the effect of the saving rate difference is ambiguous: it has a strong negative effect at a 2-year frequency (-0.118) but a positive one at a 4-year frequency (0.0165). The effects of fiscal policy differences seem to diverge following the frequency adopted: at very short- and long-terms, divergence in the adopted fiscal policy reduces the BCS, while it amplifies it at medium-term (1 and 2 year frequencies). As it can be seen, a positive SSR, mainly corresponding to the period of conventional monetary policy (2000-2011), negatively impacts the BCS of European countries (-0.242 for 6-months frequency, -0.119 for 4-years frequency), except at a 1-year and 2-year time-frame. The monetary policy also has an appreciable effect when it is composed of unconventional policy, i.e., mostly when the SSR is negative (2012-2018). A negative SSR has a positive impact in the 6-months and 4-years time-frames (resp. -0.0593 and -0.0126). At short- and at long-term, the adoption of unconventional monetary policy seems to improve the synchronization of business cycles.

4. Conclusion and policy implications

This paper contributes to the literature on business cycle factors by looking at the link between monetary policy and synchronization of business cycles in Europe. So far, the literature has investigated the role of monetary policy by reducing it to the adoption of the euro or the interest rate

[17]In Table 3, $\mathrm{SSR}_t * I_t^{SSR^+}$ is named $\mathrm{SSR}_t(+)$ and $\mathrm{SSR}_t * I_t^{\mathrm{SSR}^-}$ is named $\mathrm{SSR}_t(-)$.

Table 2: Impact of Monetary and Fiscal Policies on business cycle Correlations (unique SSR)

	(1)	(2)	(3)	(4)
Variables	$Corr.\,6m_t$	$Corr.\,1y_t$	$Corr.\,2y_t$	$Corr.\,4y_t$
Sum of Exports	-4.86e-10**	1.73e-10	1.12e-10**	-2.39e-10**
	(2.37e-10)	(1.18e-10)	(4.80e-11)	(1.03e-10)
Labor difference	0.0987****	-0.0178***	-0.0172***	0.00976**
	(0.0257)	(0.00600)	(0.00643)	(0.00410)
Saving difference	0.287**	0.0116	-0.0298	0.00453**
	(0.114)	(0.00743)	(0.0299)	(0.00227)
CALB difference	-0.0319***	0.0274****	0.0200**	-0.00843**
	(0.0103)	(0.00760)	(0.00782)	(0.00359)
SSR	-0.276***	0.0676**	0.0694****	-0.0772**
	(0.0978)	(0.0283)	(0.0170)	(0.0307)
$Corr.\,6m_{t-1}$	0.832****			
	(0.0189)			
$Corr.\,1y_{t-1}$		0.766****		
		(0.0502)		
$Corr.\,2y_{t-1}$			0.773****	
			(0.0696)	
$Corr.\,4y_{t-1}$				0.974****
				(0.0305)
Country fixed effects	yes	yes	yes	yes
Time fixed effects	yes	yes	yes	yes
N	3330	3330	3330	3330
Sargan-Hansen test	0.2705	0.9976	0.9777	0.2705
Arellano-Bond test (AR(1))	0.0000	0.0027	0.0000	0.0001
Arellano-Bond test (AR(2))	0.8911	0.1169	0.1875	0.1586

Note: the dependent variables are the correlations at a 6 months ($Corr.\,6m_t$), 1 year ($Corr.\,1y_t$), 2 years ($Corr.\,2y_t$) and 4 years ($Corr.\,4y_t$) frequency. Standard errors are corrected with the Windmeijer (2005) finite-sample correction. To estimate our model, we used a two-step system GMM estimator. All the variables are endogenous. Robust standard errors in parentheses, $*: p < 0.1, **: p < 0.05, ***: p < 0.01, ****: p < 0.001$. The values for the tests are the *p-values*.

Table 3: Impact of Monetary and Fiscal Policies on business cycle Correlations (dual SSR)

	(1)	(2)	(3)	(4)
Variables	$Corr.\,6m_t$	$Corr.\,1y_t$	$Corr.\,2y_t$	$Corr.\,4y_t$
Sum of Exports	-3.17e-10**	-1.25e-10**	2.02e-10**	-1.41e-10*
	(1.35e-10)	(4.95e-11)	(9.80e-11)	(7.90e-11)
Labor difference	0.0300****	0.00349	-0.0109***	0.00370**
	(0.00901)	(0.00422)	(0.00353)	(0.00189)
Saving difference	0.0153	-0.00724	-0.118**	0.0165**
	(0.0117)	(0.0249)	(0.0469)	(0.00779)
CALB difference	-0.0193***	0.0134***	0.0194**	-0.00689**
	(0.00737)	(0.00456)	(0.00869)	(0.00325)
SSR (-)	-0.0593**	-0.0640*	0.0111	-0.0126**
	(0.0247)	(0.0336)	(0.0374)	(0.00630)
SSR (+)	-0.242***	0.0326	0.0637	-0.119***
	(0.0861)	(0.0322)	(0.0431)	(0.0451)
$Corr.\,6m_{t-1}$	0.795****			
	(0.0191)			
$Corr.\,1y_{t-1}$		0.903****		
		(0.0317)		
$Corr.\,2y_{t-1}$			0.841****	
			(0.0343)	
$Corr.\,4y_{t-1}$				0.858****
				(0.0267)
Country fixed effects	yes	yes	yes	yes
Time fixed effects	yes	yes	yes	yes
N	3330	3330	3330	3330
Sargan-Hansen test	0.3081	0.9859	0.7747	0.3081
Arellano-Bond test (AR(1))	0.0000	0.0000	0.0044	0.0057
Arellano-Bond test (AR(2))	0.4035	0.1052	0.1910	0.2000

Note: the dependent variables are the correlations at a 6 months ($Corr.\,6m_t$), 1 year ($Corr.\,1y_t$), 2 years ($Corr.\,2y_t$) and 4 years ($Corr.\,4y_t$) frequency. Standard errors are corrected with the Windmeijer (2005) finite-sample correction. To estimate our model, we used a two-step system GMM estimator. All the variables are endogenous. Robust standard errors in parentheses, $* : p < 0.1, ** : p < 0.05, *** : p < 0.01, **** : p < 0.001$. The values for the tests are the *p-values*.

spread evolution, excluding the variety of monetary policies implemented and their time-varying aspect. While previous works have treated business cycles with a unique frequency dimension, we adopt a more detailed approach involving a frequency-dependent analysis. From a macroeconomic point of view, our paper investigates a well-known issue with a new approach, the wavelet method, allowing us to study the monetary policy-BCS relationship at different terms. To our knowledge, this method has never been used to study the relationship between monetary policy and business cycle synchronization.

In a second step, we use a system GMM dynamic panel to study the relationship between the shadow short rate and time-varying pairwise synchronizations at different frequencies. It helps us distinguish the short-, medium- and long-term effect of monetary policy on synchronization. We took into account the potential level effect by dividing the SSR between its positive and its negatives values. As regards the control variables, our model included the differences in labor cost, the saving rates and the cyclically adjusted net lending and net borrowing, as well as the sum of exports divided by the sum of GDP.

Relying on a sample of European countries over the period 2000Q1-2018Q4, we find evidence of a connection between business cycle synchronization and monetary policy. At a short-term level, monetary policy has a noticeable relationship with the European BCS, along with other factors such as labor costs, saving rates and CALB differences. The CALB difference, proxying fiscal policy divergence (or convergence), interestingly has "switching" effects: it positively impacts the BCS at short- to medium-term period, indicating that the country-adapted fiscal policy might be better for business cycle synchronization in regular time, but reduce the latter at very-short- and long-term, highlighting the importance of sound and sustainable public finances.

Finally, our findings offer an empirical contribution to the literature on the endogeneity of optimal currency areas. Synchronization of business cycles is a key aspect for the optimal efficiency of monetary policy and, in this work, we show the strong relationship between the two. Focusing on the difference between the positive and negative SSR, we may think of an optimal interest rate, i.e. a value of the interest rate that achieve the greatest business cycle synchronization. In regard to the value of the coefficient, this hypothetical optimal interest rate may be very close to zero. On the long-run, policy makers may consider unconventional monetary policy as a relevant tool to result in greater BSC in Europe.

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