



MEASURING FINANCIAL CYCLE LENGTH AND ASSESSING SYNCHRONIZATION USING WAVELETS

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Abstract

Identifying financial cycle dynamics is an important endeavor for researchers and policymakers alike, due to the new architecture of the macroprudential framework in which mitigating excessive credit growth, through countercyclical capital buffers, plays a central role in limiting the likelihood of future crises. The present paper focuses on measuring financial cycle length for a series of developed as well as emerging economies by applying Continuous Wavelet Transform (CWT) techniques, which have the ability to decompose time series on a wide range of frequencies and identify statistically significant cyclical behavior. Using credit-to-GDP data collected by the Bank for International Settlements (BIS) for 13 countries, our results confirm the established hypothesis that financial cycles are significantly longer than business cycles, in the case of developed economies, underpinning the European framework for setting the countercyclical buffer rates. Using Wavelet Coherence measures, we find statistically significant co-movement in time-frequency between several EU members, as well as tighter relationships between euro area members. The main conclusion is that policymakers from emerging economies should monitor financial cycle dynamics more closely, using the additional assumption of shorter cycles, in order to identify the build-up of systemic risk through excessive credit growth in a timely manner.

Keywords: wavelets, financial cycle, filtering, countercyclical capital buffer, macroprudential policy

JEL Classification: C49, E32, E44

1. Introduction

Over time, deregulated financial markets were often subjected to volatile and hectic behavior from the part of investors, leading to higher prices and quantities of assets. These

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unsustainable levels would then produce misaligned signals regarding the underlying fundamentals of assets, initiating a cycle of unrealistic expectations for future performance. Furthermore, despite burdened balance sheets, the banking system would, rather often, encourage these overly optimistic expectations by increasing the issuance of credit. This type of behavior led each time, almost inevitably, to a financial crisis, when a combination of sufficient push and pull factors were present in the market.

Ironically, the system of "shadow" or "parallel" banking, working without precise regulation, which, almost one hundred years ago, brought the Great Depression, emerged again in the last 20 years, changing the structure of the financial system and contributing significantly to the systemic risk. Intrinsically, the unstable and risky nature of this type of banking activity increases both the expansion as well as the contraction phases of financial cycles. Even if public regulations were to deal with shadow banking appropriately today, this type of financial intermediation would most likely re-emerge under a different form, because, as Lorenzi and Berrebi (2016) considered, the increasing demand for equity and liquidity will produce workaround movements to bypass regulation.

At the end of the most recent global financial crisis, the Bank of England concluded that events have "highlighted the need for a fundamental rethinking of internationally appropriate safeguards against systemic risk, including the development of macroprudential policies to dampen the financial cycle". Literature has since shifted its focus accordingly, from using mostly interest rates to capture financial-real sector interactions, to incorporating complex financial systems and taking a wide range of financial variables into consideration, in order to determine the position of an economy within the financial cycle.

In this paper we explore and measure the financial cycle and its synchronization across several EU members, find out how its properties differ from those of the business cycle and how they have changed over time, and conclude with some general guidelines that may prove useful for the monetary authorities in their quest to smoothen the volatility of these cycles.

2. Literature Review

The literature on financial cycles and the role played by regulation in their development is a vast one. Borio, Furfine and Lowe (2001) argue that financial regulation at the time was procyclical, with short horizons underlining most risk measurements, along with the small importance given to correlations across borrowers and institutions. They believe that these practices may fail to increase bank provisions and capital ratios during economic boom, increasing the amplitude of the financial cycle. Recommendations made by the authors include creating additional "cushions" during good times (higher capital requirements) and a more vigorous response of public policy to the cycles in financial system risk which amplify the business cycle.

Danielsson, Shin and Zigeand (2002) show that regulations using asset returns as an exogenous variable determined through historical data exacerbate financial instability and cycles by failing to take into account the feedback effect of trading decisions on prices, therefore lowering prices and liquidity, but increasing volatility.

Kashyap and Stein (2004) analyze the implications of the Basel II regulations with regard to business and financial cycles. They find that the Basel III approach of having a single time-invariant risk curve that links risk measures to capital requirements is suboptimal and may exacerbate cyclical fluctuations, as opposed to using a "family of risk curves" with reduced requirements at times when bank capital is scarce economy-wide.

Alessi and Detken (2009) link the financial cycle with financial crises by measuring the accumulation of stress in real time with high accuracy. More specifically, measures of global liquidity seem to be the best performing indicators, as well as having a good amount of predictive power as early warning indicators of a bust in the financial cycle with "relatively serious real economy consequences".

Brunnermeier *et al.* (2009) note that the bust of the latest financial cycle has been mainly due not to the lack of regulation, but to its quality. They argue that, instead of an over-reaction to the particular characteristics of this crisis, future crises could be averted by better and different regulation able to remedy fundamental market failures, like countering the natural proclivities of managers (by adjusting incentives, sanctions and trade-offs).

Schularick and Taylor (2009) study extremely long time series spanning from 1870 to 2008 in order to find events most often associated with financial crises. They find credit growth rate to be a good predictor for crises, enforcing the hypothesis of a "credit boom gone wrong". Moreover, their findings indicate that money and credit supply have decoupled in the second half of the twentieth century and that, in spite of more aggressive responses from the monetary authorities, the output cost of crises has remained relatively large.

Adrian and Shin (2010) explore the hypothesis that financial intermediaries drive the business cycle through the role they play in setting the price of risk and reach the conclusion that, indeed, the monetary policy should pay attention to the balance sheet quantities, as opposed to the traditional focus on money stock.

Drehman, Borio and Tsatsaronis (2011) look for ways to set the countercyclical regulations regarding capital buffer requirements for banks and deduce that the gap between the credit-to-GDP ratio and its long-term trend is the best indicator for the build-up of system vulnerabilities that usually lead to financial crises.

Ng (2011) defines the financial cycle as "fluctuations in perceptions and attitudes about financial risk over time, often marked by swings in credit growth, asset prices, terms of access to external funding, and other financial developments" and attempts to develop a composed measure of the financial cycle with predictive power for the short- and medium-term output growth.

Recent studies, like Drehmann *et al.* (2012) or Strohsal *et al.* (2015) measure the length of financial cycles and find that it has increased significantly beginning in the mid '80s, having a much lower frequency than the business cycle. While the latter involves frequencies anywhere from 1 to 8 years, the financial cycle is historically repeated approximately every 16 years.

Aikman, Haldane and Nelson (2015) focus on credit cycles, correlating the pick-up in the credit-to-GDP ratio with the banking crises, and recommend the macro-prudential policies to be more oriented towards diminishing these cycles, by increasing the cost of managing risky portfolios and through an expectation channel that operates via banks' perceptions of other banks' actions.

3. Methodology

3.1 Wavelet Theory

In order to reveal cyclical and structural dynamics, on a relatively wide scale of frequencies, we have chosen a wavelet analysis approach, which is a relatively recent development in applied mathematics. We justify our choice by presenting the main characteristics and advantages that

this approach provides, in the context of measuring and identifying significant financial cycles.

Extending the definition, a wavelet is a wave-like oscillation with amplitude that begins at zero, and then decreases back to the origin. Therefore, they must have a defined number of oscillations and last a certain period of time, irrespective of their shape. It is obvious that these functions are ideally suited to locally approximate variables, as they have the capacity to be manipulated by being either "stretched" or "squeezed" in order to simulate the series under observation. As a mathematical tool, wavelets can be used to extract information from many different types of data.

Due to its interdisciplinary origins, *i.e.* engineering, physics and pure mathematics, they appeal to scientists from many different backgrounds. On the other hand, wavelets are a fairly simple mathematical instrument with a great diversity of potential applications, in fields such as acoustics, astronomy, engineering, medicine, physics and many others. Although some research has been done in the field of economics, the true potential of wavelet analysis remains untapped. This is curious, because wavelets possess many desirable properties, some of which are suitable for economics and finance. The main advantages of the wavelet analysis refer to its ability to deal with both stationary and non-stationary data, localization in time and capacity to decompose and analyze fluctuations in a variable.

To formally define this mathematical instrument, consider the set of square integrable functions, denoted by $L^2(\mathbb{R})$, defined on the real axis such that $\int_{-\infty}^{\infty} |x(t)|^2 dt < \infty$ *i.e.* the function has finite energy, since the squared norm of $x(t)$, $\|x(t)\|^2 = \int_{-\infty}^{\infty} |x(t)|^2 dt$ is usually referred to as the energy of x . The inner product is defined as usual by $\langle x, y \rangle = \int_{-\infty}^{\infty} x(t)y^*(t)dt$ and associated norm $\|x\| = \langle x, x \rangle^{1/2}$. The prerequisite imposed on a function $\psi(t) \in L^2(\mathbb{R})$, to qualify for being a *mother* (admissible or analyzing) wavelet is to satisfy the admissibility condition (Daubechies, 1992):

$$C_{\psi} = \int_{-\infty}^{\infty} \frac{|\psi(\omega)|}{\omega} d\omega < \infty \quad (1)$$

It has been shown that square integrability of $\psi(t)$ is a very mild decay condition; consequently, more rigorous conditions need to be imposed. Daubechies (1992) demonstrates that, for functions with sufficient decay, the admissibility condition reduces to:

$$\int_{-\infty}^{\infty} \psi(t)dt = 0 \quad \int_{-\infty}^{\infty} \phi(t)dt = 1 \quad (2)$$

In plain terms, the mother wavelets represent the high frequency or detailed parts on each scale, by noting the amount of stretching of the wavelet (dilatation). The father wavelet or scaling function essentially represents the smooth trend or low-frequency part of the time series, and it is required to meet the condition above. Starting with a mother wavelet, we can construct a family of "daughter wavelets" by a simple process of scaling and translating:

$$\psi_{s,u}(t) = \frac{1}{\sqrt{|s|}} \psi\left(\frac{t-u}{s}\right) \quad (3)$$

Here, the parameter s is a scaling or dilation factor, controlling the length of the wavelet, and, similarly, u is a location parameter that indicates where the wavelet is centered. We say that the function $\psi(t)$ is "concentrated" around u , with size proportional to s . It is easy

to see that scaling a wavelet simply means stretching it, *i.e.* $|s| < 1$ or compressing it, by choosing $|s| > 1$.

3.2 The Continuous Wavelet Transform (CWT)

Conducting a wavelet analysis in discrete terms implies choosing an orthogonal basis and convolving the data with a wavelet filter in order to produce a set of coefficients or crystals from which we can reconstruct the original series. In contrast to the Discrete Wavelet Transform (DWT), its continuous counterpart operates on a continuous set of scales, thus selecting a non-orthogonal basis that accepts highly redundant results. Given a time series $x(t) \in L^2(\mathbb{R})$ we can define its continuous wavelet transform or CWT, as follows:

$$W_x(s, u) = \langle x(t), \psi_{s,u}(t) \rangle = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{|s|}} \psi\left(\frac{t-u}{s}\right) dt \quad (4)$$

The position of the wavelet in the time domain is given by u and its position in the frequency plane by s . This is the reason why, by mapping the original time series into a function of u and s , we obtain information simultaneously in time and frequency. If the admissibility condition, defined in the introductory chapter about wavelets, is fulfilled, this guarantees that the energy of the original function $x(t)$ is fully preserved by the wavelet transform

$$\int |x(t)|^2 dt = \int \int |W_x(s, u)|^2 \frac{duds}{s^2} \quad (5)$$

In other words, this ensures that it is possible to recover the original function or signal from its associated wavelet transform. In the case of a real-valued wavelet function, we can reconstruct the time series using the formula⁴:

$$x(t) = \frac{2}{C_\psi} \int_0^\infty \left[\int_{-\infty}^\infty W_x(s, u) \psi_{s,u}(t) du \right] \frac{ds}{s^2} \quad (6)$$

Daubechies shows that no information is lost when we restrict our computation of the CWT only to a positive interval of the scaling parameter, which is a common prerequisite in practice. Furthermore, Aguiar-Conraria and Soares (2011) propose limiting the integration over a specific range of scales, practically performing a band-pass filtering of the series. They argue that not much insight is gained when comparing this type of filtering to the classical formulations, given by Baxter and King (1999) and Christiano and Fitzgerald (2003). Using the properties of the Fourier Transform, the CWT may be also represented in the frequency domain, which turns out to be very useful in elaborating an efficient computational methodology:

$$W_x(s, u) = \frac{\sqrt{|s|}}{2\pi} \int_{-\infty}^{\infty} \Psi^*(s\omega) X(\omega) e^{i\omega u} d\omega \quad (7)$$

The wavelet power spectrum or scalogram is defined, in analogy with the Fourier Theory, as:

$$WPS_x(u, s) = |W_x(u, s)|^2 \quad (8)$$

This indicator provides a measure of the variance distribution found in the time series, over the time-scale plane and is useful for business cycle analysis, because of its ability to detect the cyclical behavior in a time series.

⁴ Proof of this statement can be found in Daubechies (1993), *Ten Lectures on Wavelets*, pp. 23.

3.3 Wavelet Coherency and Phase Difference

The concept of complex wavelet coherency, borrowed from the Fourier analysis, is defined as⁵:

$$\rho_{xy} = \frac{S(W_{xy})}{[S(|W_x|^2)S(|W_y|^2)]^{1/2}} \quad (9)$$

As with any complex representation, the complex wavelet coherency can be written in polar form, as $\rho_{xy} = |\rho_{xy}|e^{i\phi_{xy}}$. Consequently, two new measures arise, namely the wavelet coherency and the phase-difference:

$$R_{xy} = \frac{|S(W_{xy})|}{[S(|W_x|^2)S(|W_y|^2)]^{1/2}} \quad (10)$$

$$\phi_{xy} = \text{Arctan} \left(\frac{\Im(S(w_{xy}))}{\Re(S(w_{xy}))} \right) \quad (11)$$

The interpretation of the phase-difference is crucial, in the context of business cycle synchronization, as a value of zero indicates that the series move together, at a specific time-frequency; if $\phi_{xy} \in (0, \frac{\pi}{2})$ we can conclude that the series are in the same phase, but the first one leads the second one, and conversely, if $\phi_{xy} \in (-\frac{\pi}{2}, 0)$ then the second series is leading. An anti-phase relationship is indicated by a value for the phase difference of π .

4. Dataset and Results

We use a dataset of quarterly credit-to-GDP ratios compiled by BIS for a number of countries from the EU, Asia or America, publicly available on their website. One of the main challenges in measuring financial cycle length resides in data availability, especially considering that most research points toward the fact that financial cycles are generally longer (20-30 years) than the business cycles.

Our results are in line with Drehmann, Borio and Tsatsaronis (2012) showing the clear difference between the widely discussed business cycle and the financial cycle. We find that, for most of the Western economies, with longer data sets available, there is a statistically significant financial cycle with a length of approximately 23 years. This is the case for Belgium (19 years), Spain (24 years), France (23 years), Germany (23 years), Italy (20 years), the United Kingdom (25 years), and the United States (24 years).

⁵ *S* denotes a smoothing operator, necessary because, otherwise, the indicator would be 1, at all scales and times.

Figure 1

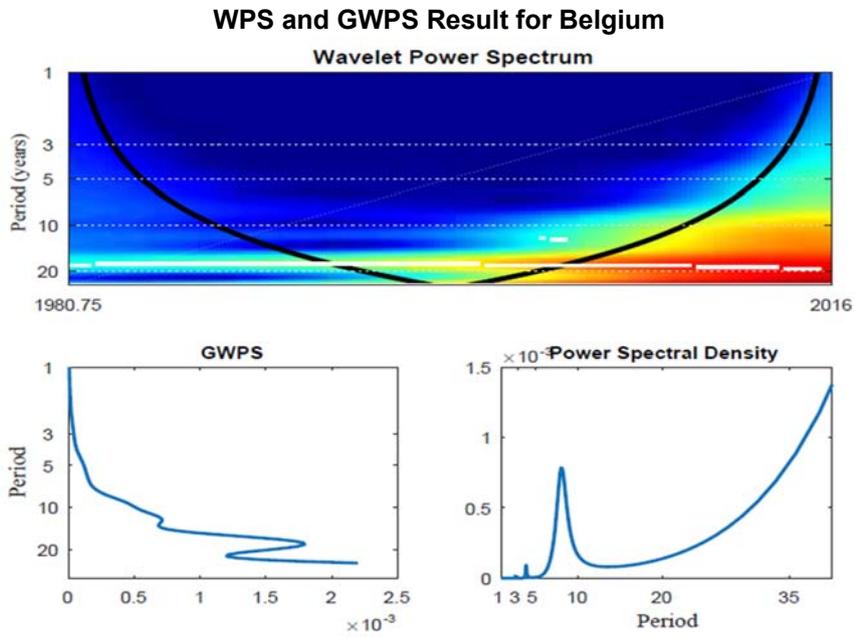
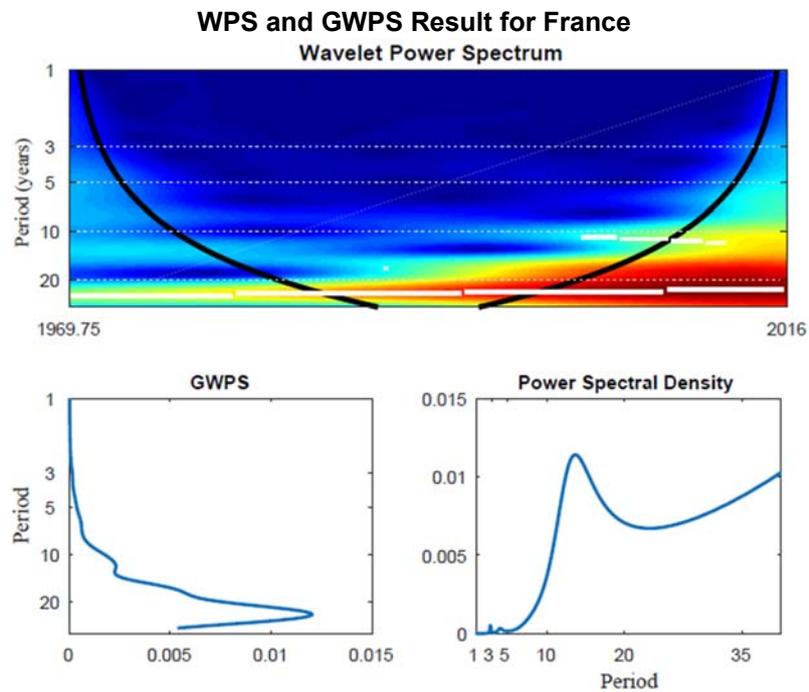
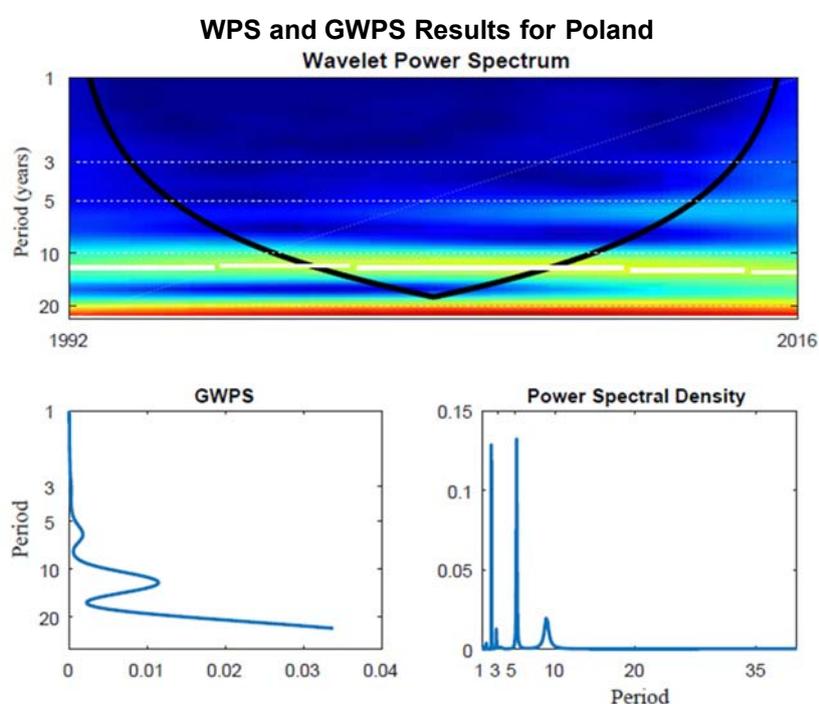


Figure 2



In some cases, the data reveal another cycle, with a higher frequency and a lower duration of a little over 10 years, but not as statistically significant. This is apparent for Austria, with a smaller cycle of around 12 years, Germany with a cycle of 17 years, Poland, the UK, as well as the U.S. For some countries, for which available data sets are shorter, we only reveal cycles with higher frequencies, the lack of data rendering these results inconclusive. This may be noticed in the cases of Poland and Romania, with financial cycles shorter than 12 years, as well as in Portugal, for which data is available and results are convincing. However, we find significant cyclicity in the Czech Republic, at a 20 year interval, despite short spanned data sets. Finally, Hungary's economy is the only one to exhibit no signs of having a financial cycle in the 25 years of available data.

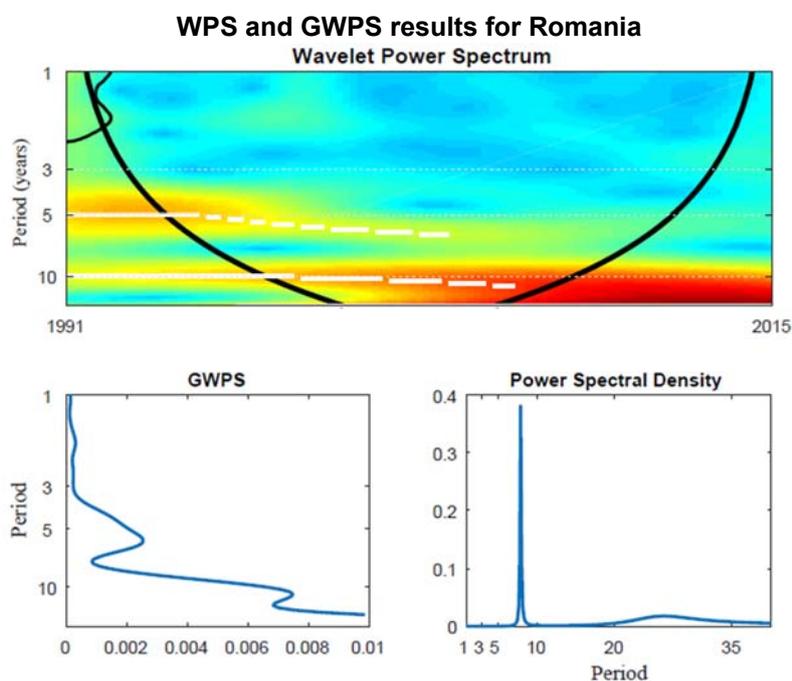
Figure 3



In order to highlight the importance of the financial cycle length hypothesis, we employ a one-sided recursive Hodrick-Prescott filter using different smoothing parameter choices (between 1,600, similar to business cycle analysis, and 400,000, recommended by the BIS methodology framework).

Figure 5 displays the results obtained for two CEE economies, namely Hungary and Poland. We may clearly see that the results are significantly influenced by the choice of the smoothing parameter: higher values for λ , which imply a long financial cycle, have a pronounced negative dynamics over recent years, while lower values of λ , *i.e.* short financial cycle, identify an upward tendency in the cyclical dynamics of the credit-to-GDP gap, potentially signaling the start of a new expansionary phase.

Figure 4



From a macroprudential perspective, the early warning signaling power of this indicator is crucial in mitigating excessive growth and the build-up of systemic risk. The main conclusion is that relying solely on an approach based on long financial cycle assumptions can potentially fail to identify the beginning of a new expansionary phase of the financial cycle, especially in the case of the emerging market economies, where macro-financial variables tend to exhibit a higher degree of volatility. This should be taken into account by policymakers as it may prove useful when calibrating the rates of the Countercyclical Capital Buffer (CCB), following the Recommendation⁶ of the European Systemic Risk Board (ESRB). This research can be extended by applying the same algorithm in order to measure the business cycle and by doing a comparison between the two.

Examining the results obtained for wavelet coherency, we arrive at several interesting conclusions. Firstly, in the case of Germany, we find statistically significant evidence of synchronization with several Euro Zone members, as well as with the USA on short (8-10 years), and high periodicity time frame (around 20 years). Secondly, we observe that synchronization on a longer cycle period is more evident in the case of the Euro Zone members, with stronger economic and financial relationships (*i.e.* the "strong" core). Thirdly, in most cases, by analyzing phase differences, the results show that the German financial cycle is in phase with the rest of the analyzed countries and is generally leading them. Additionally, phase difference indicators show that the time-varying relationships among the financial cycles tend to be smoother on the larger scales (12-25 years), while exhibiting a volatile behavior for the 1-12 years frequency bands.

⁶ Recommendation of the European Systemic Risk Board of 18 June 2014 on guidance for setting countercyclical buffer rates (ESRB/2014/1).

Figure 5

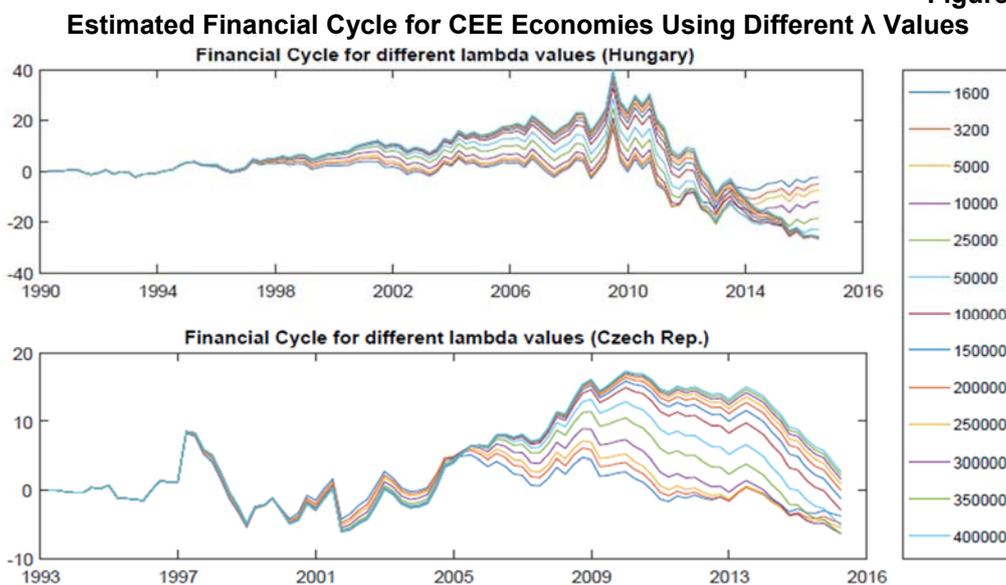
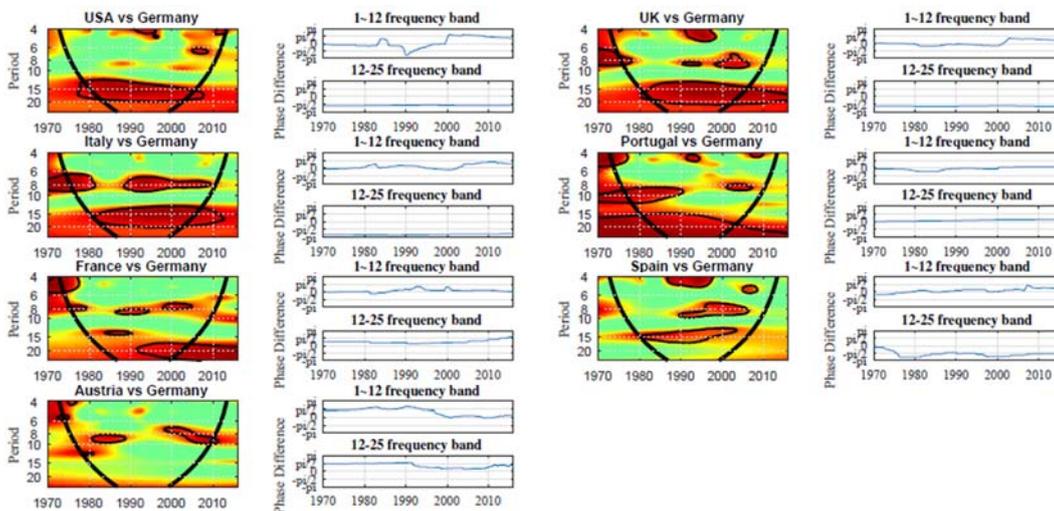


Figure 6.

Wavelet Coherence Plots for the Financial Cycles of Selected EU Members and Germany



Looking at France and Italy (figures found in the Appendix), some similar results may be found. Italy's financial cycle is more synchronized with Spain, as opposed to Germany and France, while France displays a stronger co-movement with Austria. In an analogous manner, results show that throughout the analyzed period all the countries are in the same phase of

the financial cycle, although for France and Italy we observe a number of cases where lagging relationships are found. Another interesting observation can be made regarding the significant coherence between the UK, on one side, and France and Italy, on the other side. Further analysis on cross-border financial exposures and banking sector interconnectedness could reveal some of the underlying factors which may contribute to the empirically observed relationships. It is, of course, difficult to assess this matter thoroughly due to dataset limitations for some countries and, therefore, these conclusions should be interpreted with caution.

Conclusions

Recently, the financial cycle has become a key indicator of the Macroprudential Policy framework, with significant policy implications in the process of setting countercyclical capital buffer rates.

Using credit-to-GDP data collected by the Bank for International Settlements (BIS) for 13 countries, our results confirm the established hypothesis that financial cycles are significantly longer than the business cycles in the case of the developed economies, underpinning the European framework for setting the countercyclical buffer rates. Although some differences may be found, the average financial cycle length is around 23 years for the developed countries with a longer historical dataset. In the case of the emerging market economies, we find statistically significant cyclical behavior on much shorter periods; on average, around 10 years, as well as some evidence of longer cycles, which cannot be statistically validated due to limited data availability.

Using the Wavelet Coherence measures, we find statistically significant evidence of synchronization within several Euro Zone members as well as with the USA on short (8-10 years), and high periodicity (around 20 years). Secondly, we observe that synchronization on a longer cycle period is more evident in the case of the Euro Zone members, with stronger economic and financial relationships (*i.e.* the "strong" core).

The main conclusion is that policymakers (mainly from, but not limited to, the emerging economies) should closely monitor the financial cycle dynamics using the additional assumption of shorter cycles, in order to timely identify the build-up of systemic risk through excessive credit growth.

Acknowledgements

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Appendix

Figure 7

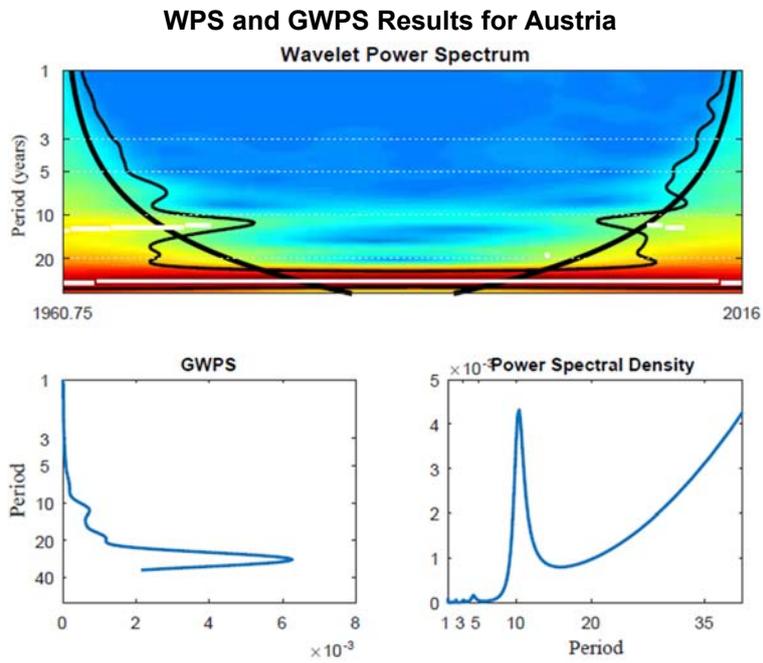


Figure 8

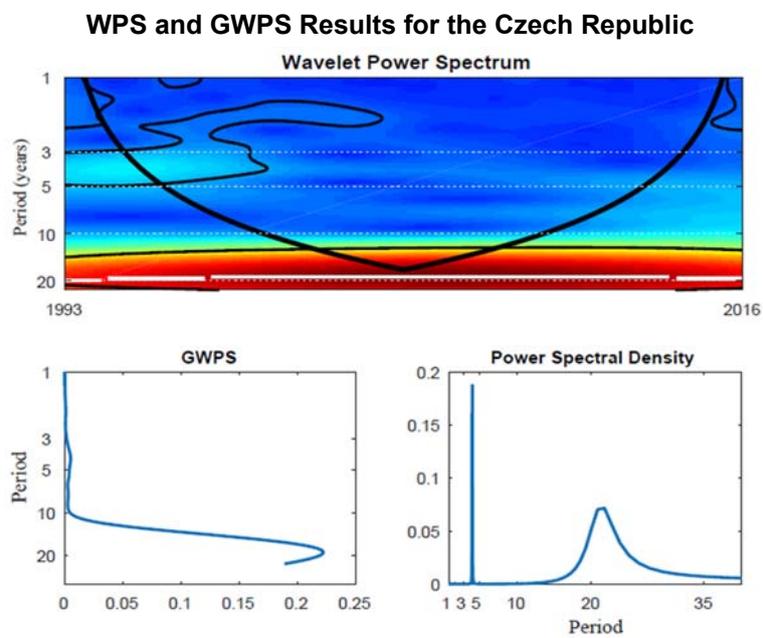


Figure 9

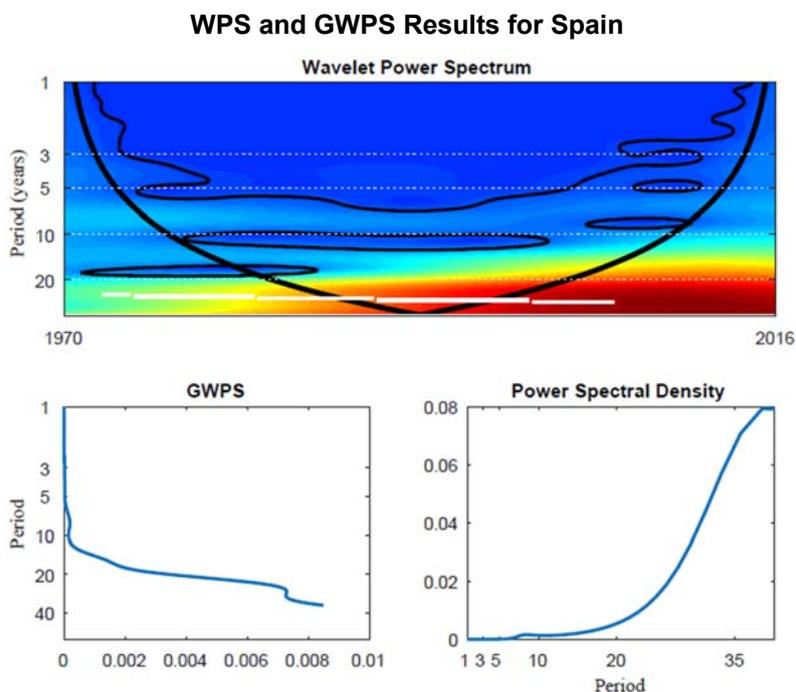


Figure 10

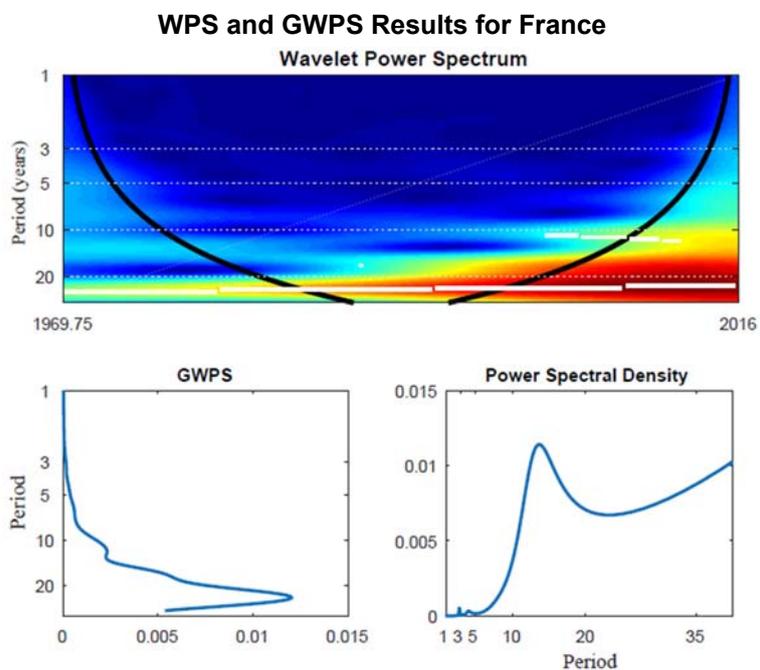


Figure 11

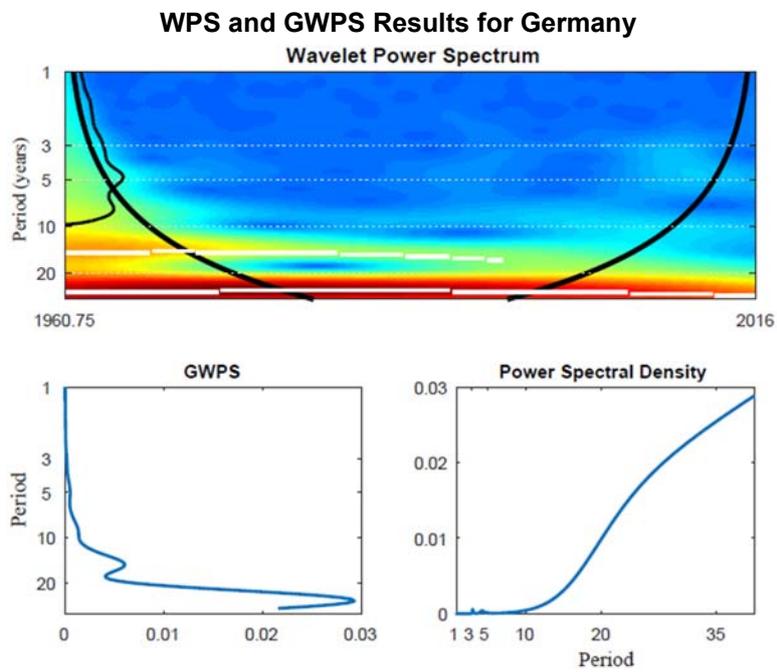


Figure 12

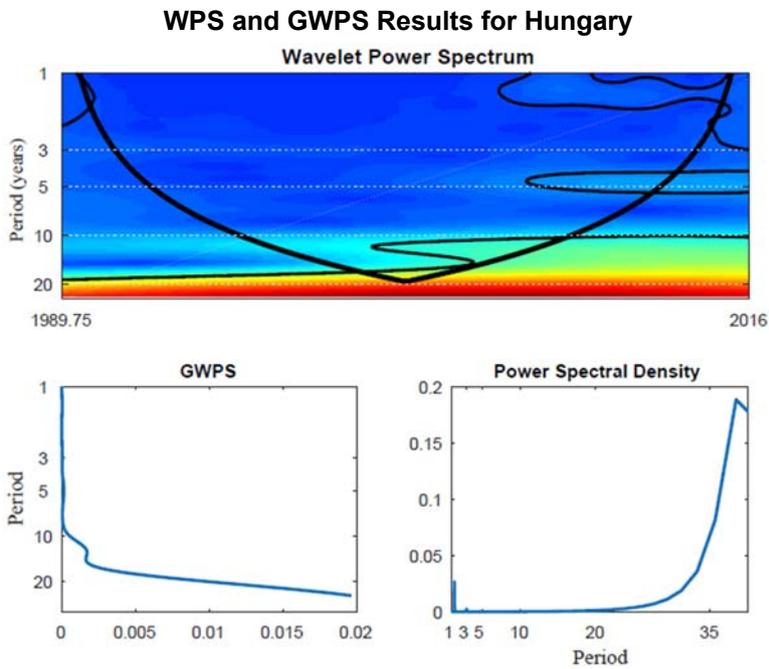


Figure 13

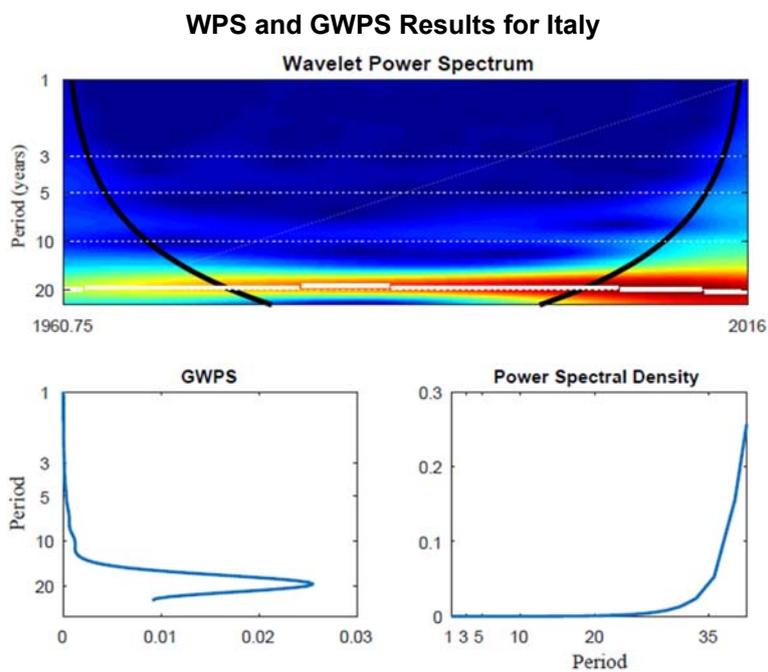


Figure 14

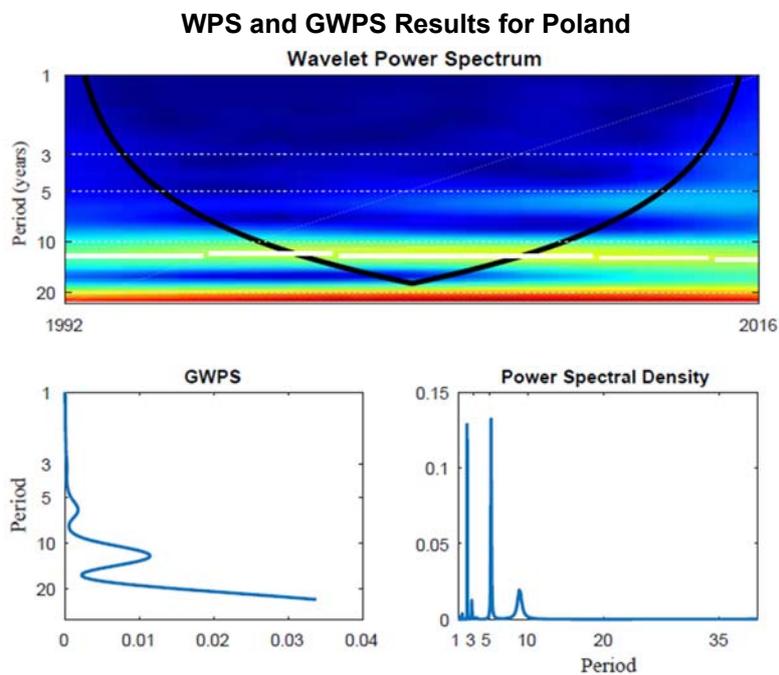


Figure 15

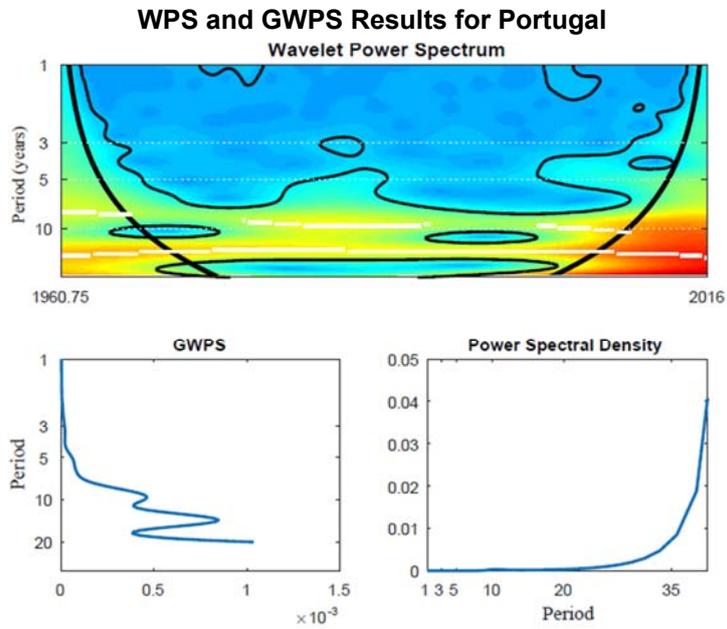


Figure 16

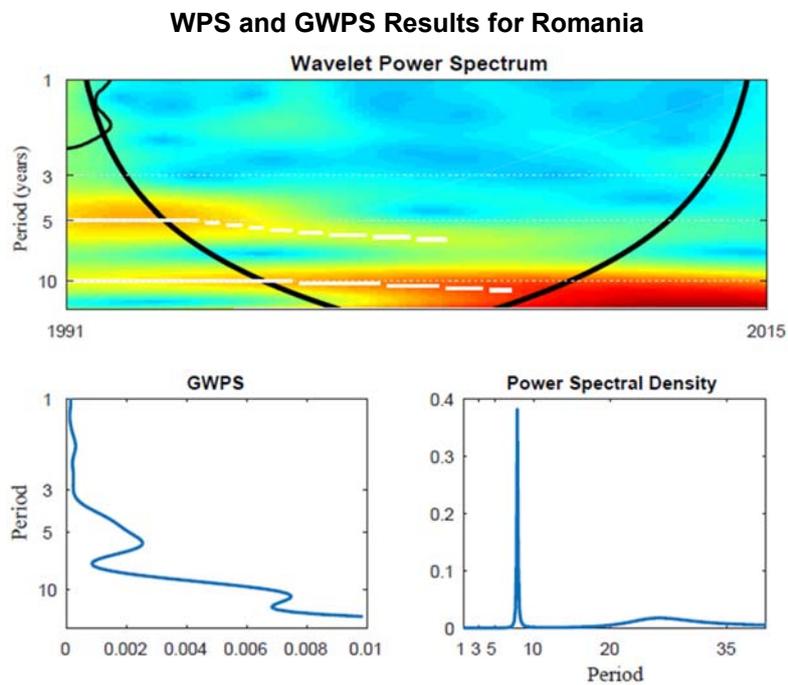


Figure 17

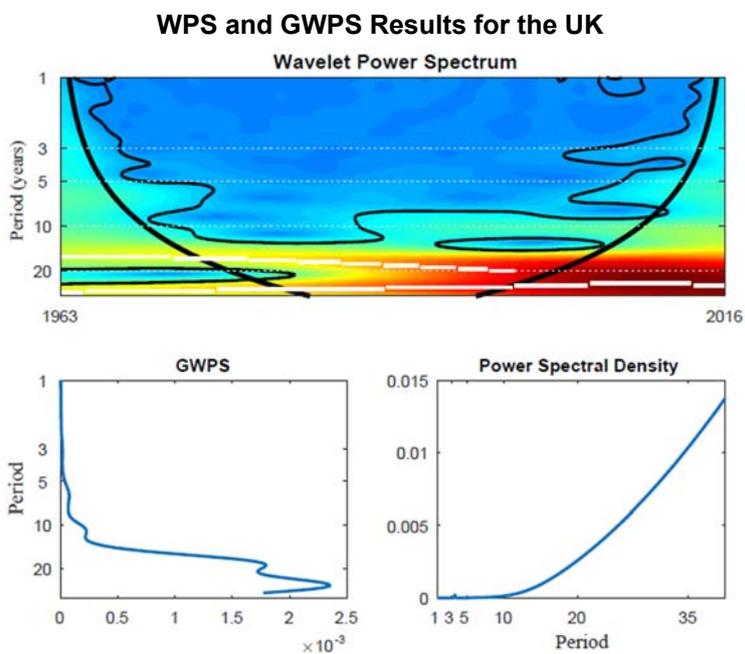


Figure 18

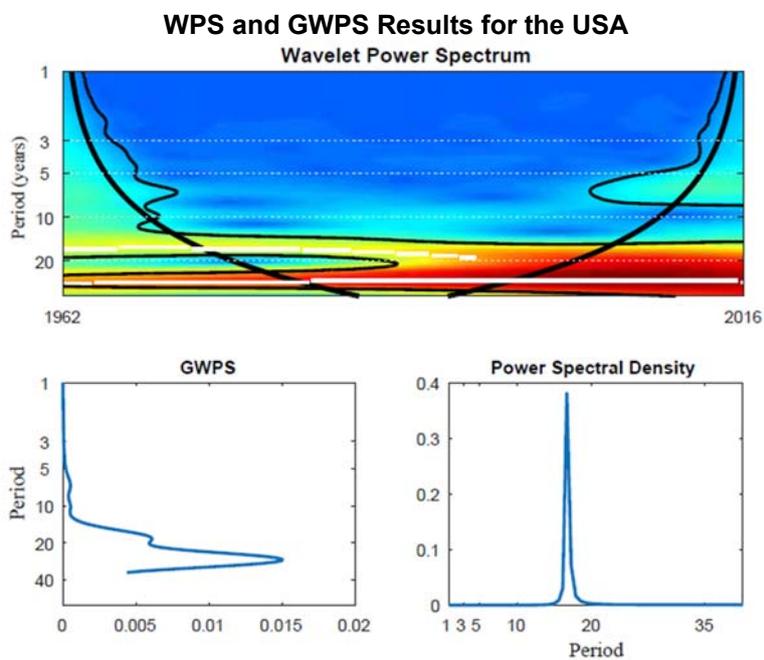


Figure 19
Wavelet Coherence Plots for the Financial Cycles of Selected EU Members and France

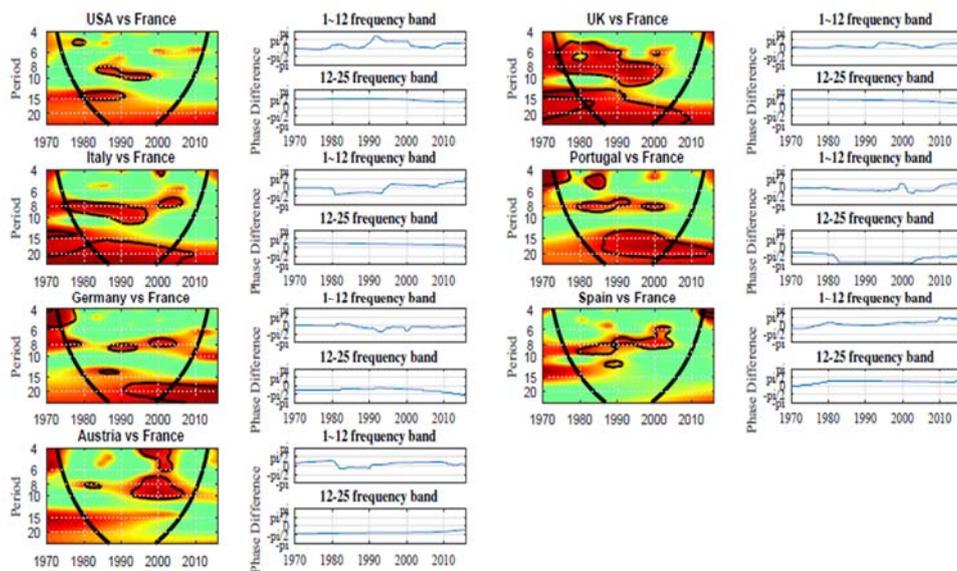


Figure 20
Wavelet Coherence Plots for the Financial Cycles of Selected EU Members and Italy

