Measuring Financial Cycle Length using Wavelets

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Abstract

Identifying financial cycle dynamics is an important endeavour 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 probability 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 behaviour. 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. The main conclusion is that policymakers from emerging economies should closely monitor 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.

Keywords: wavelets, financial cycle, filtering, countercyclical capital buffer, macroprudential policy
JEL classification: C49, E32, E44

1 Introduction

Over time, deregulated financial markets were oftentimes subjected to volatile and manic behavior from the part of investors, leading to heightened prices and quantities of assets being traded. These 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, more often than not, encourage these overly optimistic expectations by increasing the issuance of credit. This type of behavior has 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 upon the world the Great Depression, made its appearance again in the last 20 years, changing the structure of the financial system and contributing significantly to 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 regulation were to deal with shadow banking appropriately today, this type of financial intermediation will most likely re-emerge under a different form, because as Lorenzi and Berrebi (2016) put it, the increasing demand for equity and liquidity will produce workaround movements to bypass regulation.

By the end of the most recent global financial crisis, the Bank of England concluded that events have "highlighted the need for a fundamental rethink of internationally appropriate safeguards against systemic risk, including through the development of macroprudential polices to dampen the financial cycle". The interest of 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, 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 monetary authorities in their quest to smoothen the volatility of such a cycle. To do so, we employ the algorithm proposed by ... The paper is structured as follows:

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 little importance given to the correlations across borrowers and institutions. They believe that these practices may fail to increase bank provisions and capital ratios in economic booms, 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 amplifies 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 good accuracy. More specifically, measures of global liquidity seem to be the the best performing indicators, as well as having a good amount of predictive power as early warning indicators of an 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 due not mainly 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 through which 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 part of monetary authorities, the output cost of crises has remained relatively large.

Adrian and Shin (2010) explore the hypothesis according to which 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 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 ratio of credit-to-GDP and its long-term trend best represents 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 with 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 banking crises, and recommend that macro-prudential policies be more oriented towards diminishing these cycles, by increasing costs of managing risky portfolios and through an expectations channel that operates via banks' perceptions of other banks' actions.

3 Data and estimation

4 Wavelet Theory

In order to uncover cyclical and structural dynamics, on a relatively wide scale of frequencies, we have chosen to implement a wavelet analysis approach, which is a relatively recent development in applied mathematics. We will argue this 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 an amplitude that begins at zero, and then decreases back to the origin. As such they must have a defined number of oscillations and last a certain period of time or space, irrespective of their shape. It is obvious that these functions are ideally suited to locally approximating 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, and some which are not. The main advantages that wavelet analysis has to offer refers to its abilities to deal with both stationary and non-stationary data, its localization in time and its capacity to decompose and analyze fluctuations in a variable.

To formally define this mathematical instrument, consider the set of square integrable functions, noted $L^2(\mathbb{R})$, defined on the real axis such that $\int\limits_{-\infty}^{\infty} |x(t)|^2 dt < \infty$ i.e. the function has finite energy, since the squared norm of $x(t)$, $||x(t)||^2 = \int\limits_{-\infty}^{\infty} |x(t)|^2 dt$, is usually referred to as the energy of x. The inner product is defined as usually by $\langle x, y\rangle = \int\limits_{-\infty}^{\infty} x(t)\, y^*(t)\, dt$ 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):

$$C_\psi = \int\limits_{-\infty}^{\infty} \frac{|\Psi(\omega)|}{\omega} d\omega < \infty \tag{1}$$

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:

$$\int\limits_{-\infty}^{\infty} \Psi(t)\, dt = 0 \quad \text{and} \quad \int\limits_{-\infty}^{\infty} \phi(t)\, dt = 1 \tag{2}$$

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 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:

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

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 $\psi(\cdot)$ 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 $|s| > 1$.

4.1 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:

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

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:

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

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 formula[1]:

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

Daubechies shows that no information is lost when we restrict our computation of the CWT only on 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 can be also represented in the frequency domain, which turns out to be very useful in elaborating an efficient computational methodology:

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

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

$$\mathrm{WPS}_x(u,s) = |W_x(u,s)|^2 \tag{8}$$

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

[1] Proof of this statement is given in Daubechies (1993) Ten Lectures on Wavelets, p23.

5 Results

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 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).

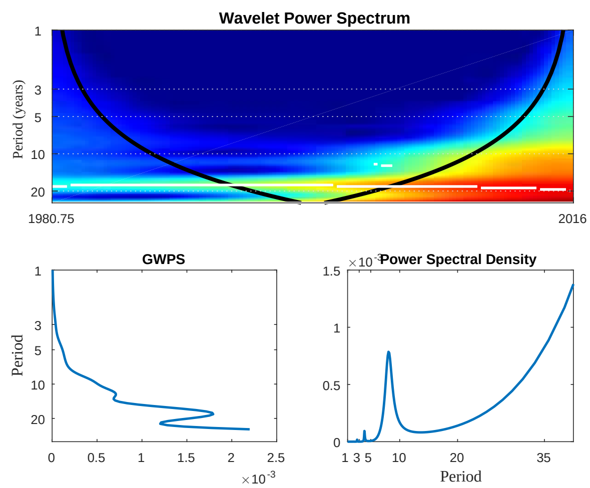

Figure 1: WPS and GWPS results for Belgium

In some cases, the data reveals 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, in which available data sets are shorter, we only uncover cycles with higher frequencies, the lack of data rendering these results inconclusive. This can bee seen in the cases of Poland and Romania with financial cycles no longer 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.

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 1600, similar to business cycle analysis, and 400,000, recommended by the BIS methodology framework). Figure 5 displays the results obtained for 2 CEE economies, namely Hungary and Poland. We

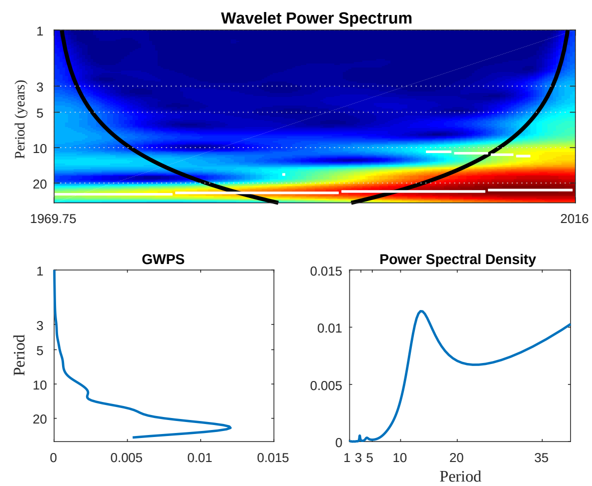

Figure 2: WPS and GWPS results for France

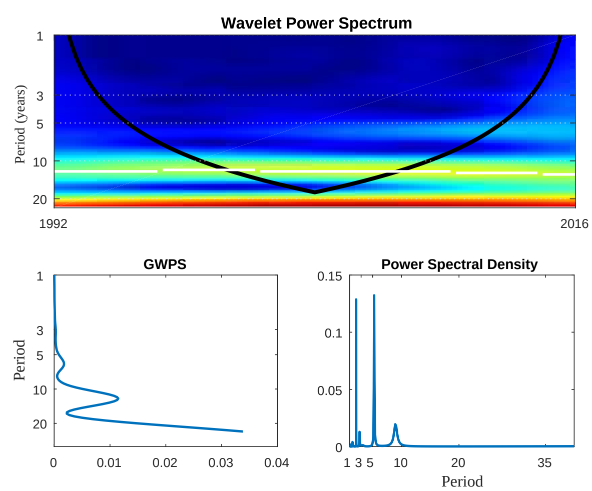

Figure 3: WPS and GWPS results for Poland

can 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 dynamic over recent years, while lower values of λ, i.e. short financial cycle, identify an upwards tendency in the cyclical dynamics of the credit-to-GDP gap, potentially signalling the start of a new expansionary phase. From a macroprudential perspective, early warning signalling power of this indicator is crucial in mitigating excessive growth and the build-up of sys-

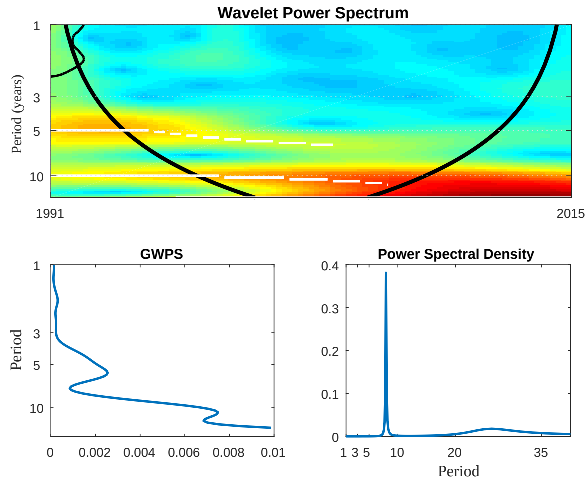

Figure 4: WPS and GWPS results for Romania

temic risk. The main conclusion is that relying solely on an approach based on long financial cycle assumptions can potentially fail to identify entering into a new expansionary phase of the financial cycle, especially in the case of emerging market economies, where macro-financial variables tend to exhibit a higher degree of volatility.

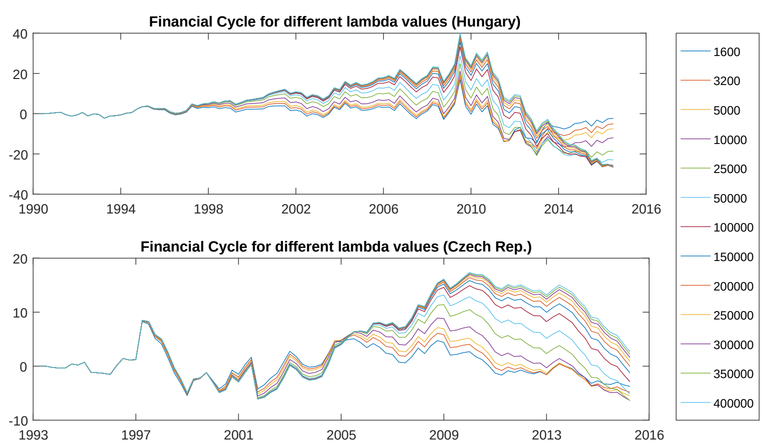

Figure 5: Estimated financial cycle for CEE economies using different λ values

This should be taken into account by policy makers as it can prove useful when calibrating the rates of the Countercyclical Capital Buffer (CCB), following the

Recommendation[2] of the European Systemic Risk Board (ESRB). This research can be extended by applying the same algorithm to measure the business cycle and doing a comparison between the two.

6 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 business cycles, in the case of developed economies, underpinning the European framework for setting the countercyclical buffer rates. Although some differences can be found, the average financial cycle length is around 23 years for developed countries with a longer historical dataset. In the case of emerging market economies, we find statistically significant cyclical behaviour on much shorter periods, on average around 10 years, as well as some evidence of longer cycles, which can not be statistically validated due to limited data availability. The main conclusion is that policymakers from emerging economies should closely monitor 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.

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Annex

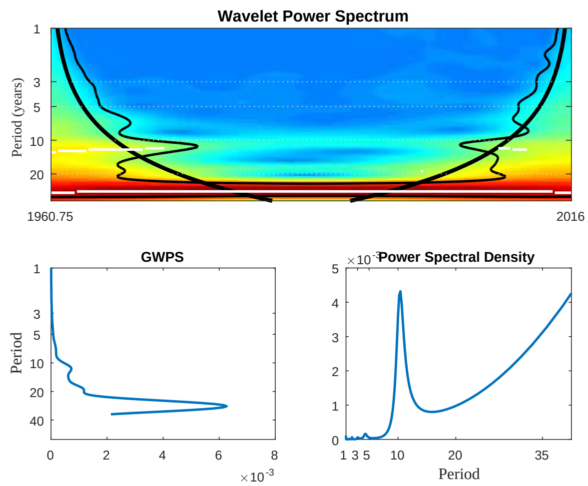

Figure 6: WPS and GWPS results for Austria

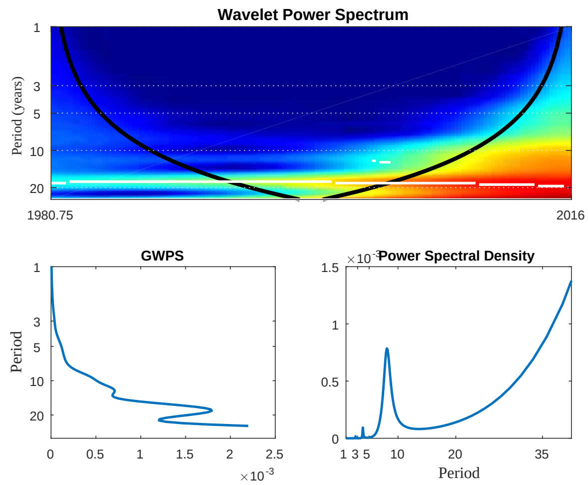

Figure 7: WPS and GWPS results for Belgium

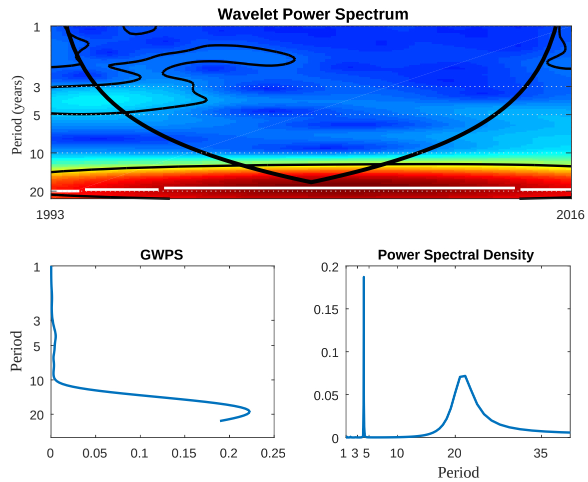

Figure 8: WPS and GWPS results for Czech Republic

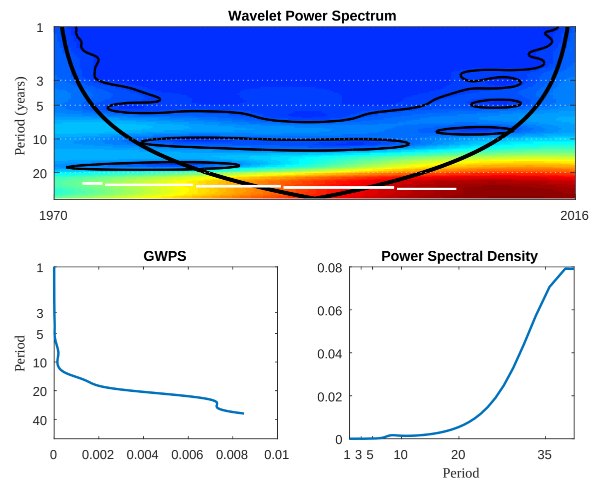

Figure 9: WPS and GWPS results for Spain

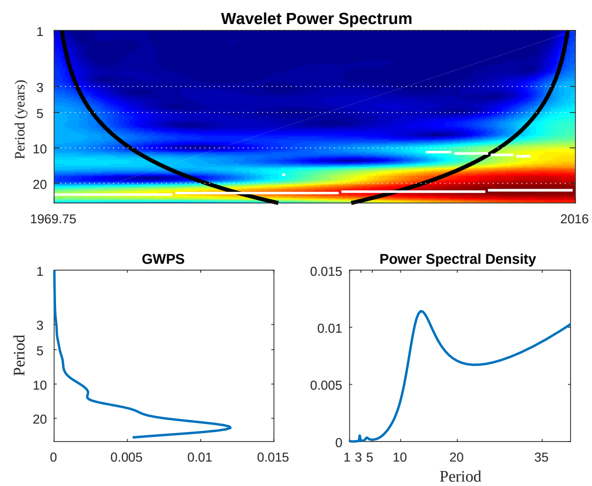

Figure 10: WPS and GWPS results for France

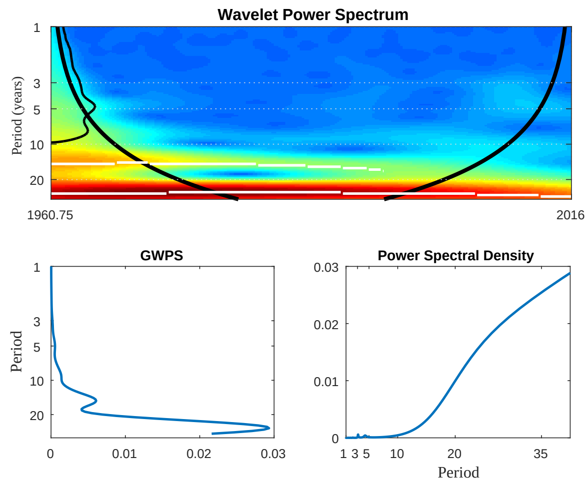

Figure 11: WPS and GWPS results for Germany

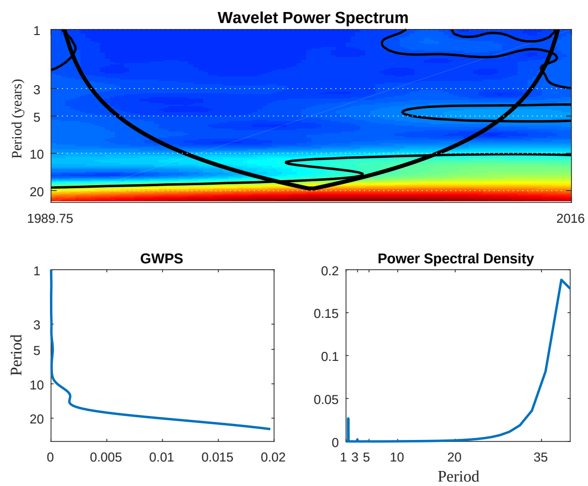

Figure 12: WPS and GWPS results for HUN

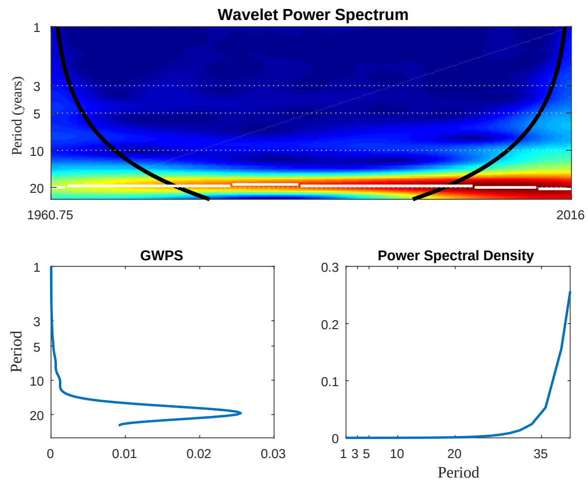

Figure 13: WPS and GWPS results for Italy

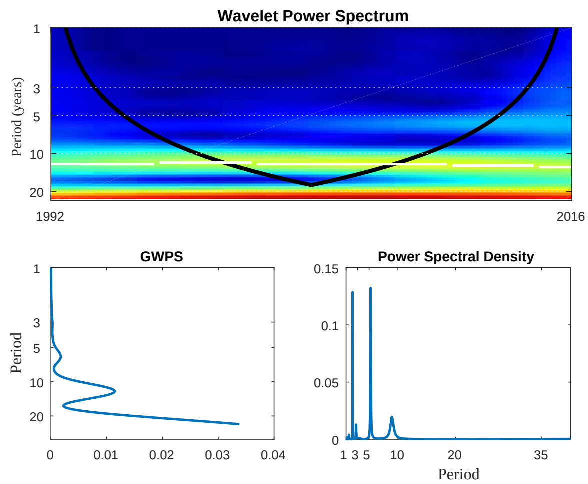

Figure 14: WPS and GWPS results for Poland

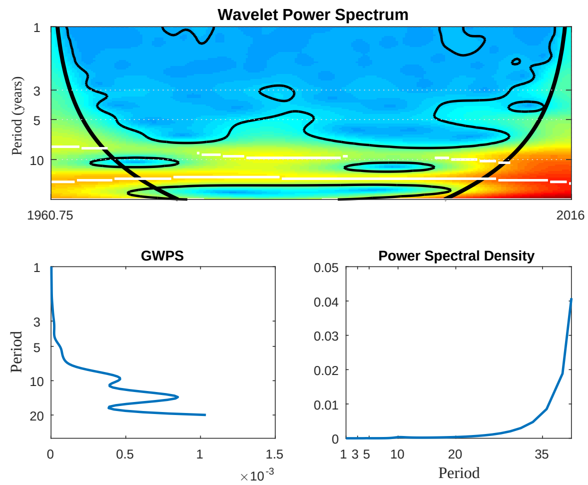

Figure 15: WPS and GWPS results for Portugal

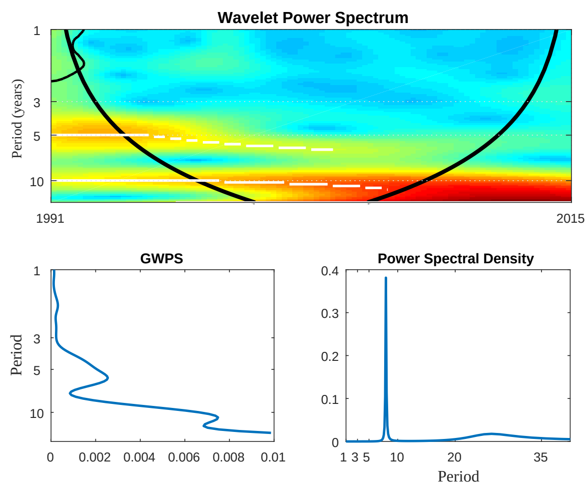

Figure 16: WPS and GWPS results for Romania

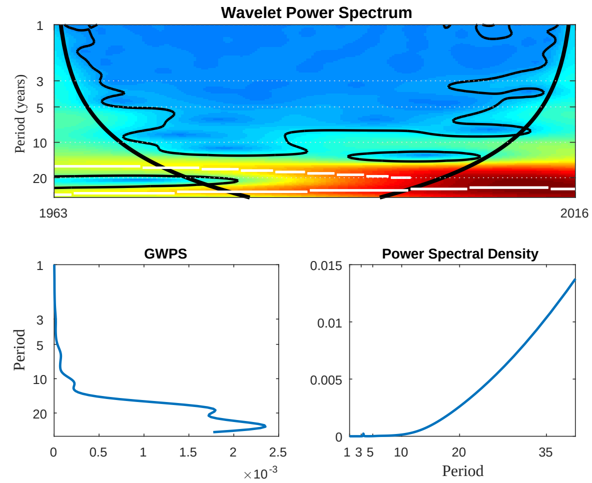

Figure 17: WPS and GWPS results for United Kingdom

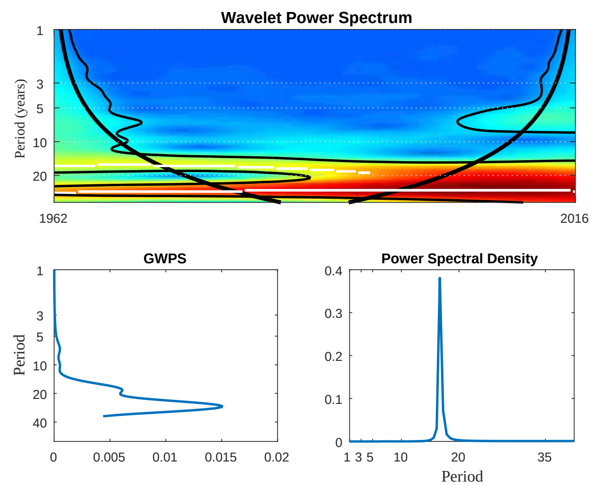

Figure 18: WPS and GWPS results for USA