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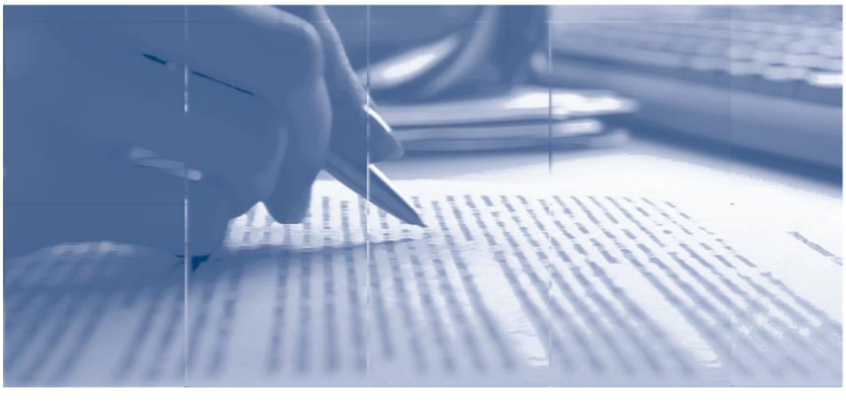

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Business and Financial Cycles: an estimation of cycles' length focusing on Macroprudential Policy*

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Abstract

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Business and financial cycles' interactions are important to Monetary and Macroprudential Policies. The Countercyclical Capital Buffer (CCB) proposed by the Basel Committee on Banking Supervision (BCBS) assumes that the financial cycle is four times longer than the business one with direct impacts over its main indicator, the credit-to-GDP gap. This paper addresses the issue of estimating credit and business cycles' length using Bayesian Structural Time Series Models of unobserved components (STM) and Singular Spectrum Analysis (SSA) followed by Fourier-based Spectral Analysis. The results, considering 28 countries, suggest that financial cycles, measured by the credit-to-GDP gap, could indeed be longer than the business one, but definitely shorter than the one implied in the cut-off frequency used by the BCBS. We find that most countries in the sample have financial cycles between 13 and 20 years, but there is a smaller group of countries whose estimates are close to those of the business cycle, i.e., 3 to 7 years. Finally, we estimate q-ratios objectively using STM and find that a HP smoothing factor that closely relates to the gain functions of our estimated state space form is HP(150).

Keywords: business cycle, financial cycle, singular spectrum analysis (SSA), bayesian, structural time series methods (STM), spectral analysis

JEL Classification: E44, E51, E32, C11, C22

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1. Introduction

There is an extensive literature covering several aspects of business cycles including its duration through a wide range of alternative estimation procedures. The OECD estimates that the business cycle duration ranges between 5 to 8 years. Regarding the financial cycle, Drehmann et al. (2010) propose the distance between financial crises as a definition. To the authors, these figures range from 5 to 20 years with a cross-country median around 15 years. However, Drehmann et al. (2011) suggest that the financial cycle should be considered four times longer than the business cycle when it comes to anticipating credit crises. As a consequence, they put forward a possible credit cycle metric consisting of a one-sided Hodrick-Prescott (HP) filter credit-to-GDP gap estimated using a lambda factor of 400k for quarterly data. We will denote this filter HP(400k). Such metric is suggested to be a leading indicator to Macroprudential Policy decisions concerning the Countercyclical Capital Buffer (CCB) (BSBC, 2010).

Because the HP is a high-pass filter, such calibration implies that periods longer than roughly 39.5 years are considered trend components, while all other higher frequency components are considered cyclical components (Iacobucci and Noullez, 2004, Ravn and Uhlig, 2002). One should notice that very long periodic (low frequency) components are being regarded as cycle movements. In most countries, the available quarterly credit series is shorter than the implicit "cut period", making the gap estimates possibly biased. Also, because a one-sided filter is being put forward by the Committee, all *gap* estimates are subject to end-point bias (Mise et al., 2005).

To overcome these issues, we fit trend and cycles using Singular Spectrum Analysis (SSA) and Structural Time Series Models (STM). We also adopt Fourier-based spectral analysis and parametric techniques (ESPRIT) to estimate cycles' length. In both SSA and STM, the estimates are not (or at least are less) biased when the series are short or at the end-points. More importantly, the more representative spectral component, cycle frequency, is being estimated objectively. Another benefit of using Bayesian STM is exploring the information contained in its posterior joint distribution, which pinpoints the degree of uncertainty around the parameters and the state of the cycle in any given point in time.

To the best of our knowledge, this is the first paper to use these techniques to estimate objectively financial cycles' length and access possible limitations of HP(400k) as a financial cycle metric. Based on our results, we suggest HP(150) as another alternative to more accurately describe financial trends and cycles.

2. Literature Review

The literature on financial cycles' length is relatively scarce. Drehmann et al. (2010) propose the distance between financial crises as a definition and use the credit-to-GDP gap as a leading indicator to anticipate these events.

Drehmann et al. (2012) use analysis of turning points and the Christiano-Fitzgerald filter (Christiano and Fitzgerald, 2003) to analyze the financial cycle and its relation with business cycle in 7 countries. They find financial cycles averaging 16 years and considered such duration after and before 1998, finding 20 years for the former and 11 years for the latter.

Claessens et al. (2009 and 2011) and Mendoza and Terrones (2008) also evaluate interactions between credit and business cycles, as well as the length and severity of financial cycles and their synchronization among countries. Bordo and Haubrich (2009), Laeven and Valencia (2008, 2010), Reinhart and Rogoff (2009) and Drehmman et al. (2011) contribute identifying major periods of credit distress that can be related to busts. Dell'Ariccia et al. (2012) is more concerned with policy responses to credit booms and Che and Shinagawa (2014) with financial stability across different stages of the financial cycle.

Financial cycles have also been proxied by equity indexes, credit spreads (Claessens et al., 2009 and 2011), credit growth (Che and Shinagawa, 2014) and several other macroeconomic and financial variables (Drehmman et al., 2011). Lown and Morgan (2006) take an alternative approach looking at opinion surveys from loan officers. In this paper, we take credit-to-GDP as a proxy just as in BCBS (2010) and take the expressions credit and financial cycles as perfect substitutes.

Trend-cycle decomposition is fundamental in macroeconomics. Nonetheless, de-trending methods may lead to spurious cycles and misleading results (e.g. Nelson and Kang, 1981, Harvey and Jaeger, 1993 and Cogley and Nason, 1995). In other words, it is important to evaluate if the leading gap estimate put forward by the Basel Committee, i.e., HP(400k), is not resulting in spurious financial cycles as illustrated in Harvey and Jaeger (1993) and Harvey and Trimbur (2003) in the classic investment cycle example. There are also other structured alternatives to more robustly estimate cycles (see Areosa, 2008).

Drehmann et al. (2011) suggest credit-to-GDP gap, estimated with HP(400k), as a financial cycle metric. Their conclusion is based on better tracking crisis performance as compared to other variables and alternative HP smoothing parameters.

They also support setting the smoothing parameter λ_s^{HP} to 400k following Ravn and Uhlig (2002) conversion formula (1):

$$\lambda_s^{HP} = s^4 \cdot \lambda_q^{HP} \tag{1}$$

where $\lambda_q^{HP} = 1600$ is the value for quarterly sampled series (this value was suggested by Hodrick and Prescott, 1997 for the US GDP) and *s* is the new sampling frequency relative to one quarter (1/4 for annual and 3 for monthly, for example). That is to say, *s* is no longer 1 but 4 leading to $\lambda_s^{HP} = 4^4 \cdot 1600 = 400k$. Using s=4 implies that the credit cycle could be four times longer than the business one (see Drehmann et al., 2010 and 2011).

Setting the λ_s^{HP} to 400k has other implications though. An *ad hoc* cut-off period (T_c) of 39.5 years is implied. Thus, only extremely low frequency components are indeed cut-off by the filter (see Iacobucci and Noullez, 2004 and formula 2[1,2]).

$$T_c = \frac{\left(\frac{\pi}{4}\right)}{\arcsin\left(\frac{\lambda^{-1/4}}{2}\right)} \tag{2}$$

In this paper, we adopt a different strategy than Drehmann et al. (2010) and Drehmann et al. (2011) and look into a more refined country-by-country assessment of credit cycles' length. Moreover, we estimate objectively the signal-to-noise (q) ratio that feeds the Hodrick and Prescott (1997) filter looking into an alternative specification of

[1] This formula may be obtained as the point where the frequency response of HP filter reaches 0.5
[2] The frequency response of HP filter is not a step function, but it is clearly a high-pass filter (supposing the output of the filter is the cycle, not the trend).

the HP filter that more closely relates to the gain functions of our state space models (Harvey, Jaeger, 1993; Harvey, Trimbur, 2008).

3. Data and Methodology

The data we use for credit aggregates is the same provided by and publicly available from the BIS website (see Dembiermont et al., 2013 for more details on this database). The quarterly GDP is extracted from the OCDE database[3]. Following BCBS (2010) and Dembiermont et al. (2013), we use a broader definition of credit to account for risks that may be originated outside the banking system.

We use two alternative methods to evaluate length and amplitude of financial cycles. We adopt a model-free technique called Singular Spectral Analysis (SSA) for trend extraction and, as a parametric alternative, we calibrate Bayesian Structural Time Series Models (STM). In the first case, spectral analysis is carried out on the residuals to identify significant periodic components and, in the latter, cyclical components are directly estimated in the state equations.

3.1 Non-parametric approach to estimate financial cycle´s length

The main tool used in this paper for non-parametric estimation of the credit cycle’s length is spectral analysis. However, economic series frequently have trends, causing difficulties to estimate periodic components and leading to the need of de-trending tools.

We use Singular Spectrum Analysis (SSA) also known as “Caterpillar” SSA or simply SSA to de-trend series. This model-free procedure is very well suited for short and noisy time series (Golyandina et al., 2001, Golyandina and Zhigljavsky, 2013). After de-trending the series, we estimate the main periodicities using four alternative techniques: raw and smoothed periodograms (Bloomfield, 2000), multitapering spectral estimation (Thomson, 1982), and SSA combined with the estimation of signal parameters via rotational invariance techniques (ESPRIT) algorithms (Roy and Kailath, 1989; Golyandina and Zhigljavsky, 2013).

[3] For Brazil, we use quarterly GDP available at Central Bank of Brazil website. We also construct the broad credit to non-financial private sector series using data available at the same source.

Singular Spectrum Analysis

SSA decomposes the time series in additive components that can be interpreted as trend, periodicities and noise (Golyandina and Zhigljavsky, 2013). We choose this de-trending method to go around more subjective issues usually embedded in band-pass (e.g. Christiano-Fitzgerald) or high-pass filters (e.g. Hodrick-Prescott) such as defining an *ad hoc* cut-off frequency or smoothing parameter. The procedure is less dependent on calibration issues, but sufficiently sensitive for complex trend extraction[4] (Golyandina et al., 2001).

The Basic SSA is comprised of two stages, namely, decomposition and reconstruction. The former uses singular value decomposition (SVD) of a trajectory matrix constructed from the time series, and the latter groups the elements of this SVD to reconstruct the components of the time series (see Appendix A and Golyandina et al. (2001) for more details).

In general, the concept of trend is not closely defined in the literature and there is some degree of subjectivity in its definition. Chatfield (1996) defines trend as "a long-term change in the mean", considering it as an additive component of the time series which describes its global changes. For our purposes, trend is some rough movement of the series, *without periodic components*, which is smooth and accounts for most of the variance of the original times series.

Figure 1 presents, as an example, the logarithm of an annual real GDP series from Brazil between 1996 Q4 and 2013 Q2. The SSA trend was estimated aggregating the two main eigentriples on window length L = 20. In other words, the trend (T) = $F_{I_1} + F_{I_2}$ and cycle (C) = $F_{I_3} + \ldots + F_{I_m}$ (see appendix A for notation and details). We follow Golyandina et al. (2001) on grouping strategy.

[4] There is a certain degree of subjectivity in selecting the L windows and the number of eigentriples in the reconstruction step. However, there are objective ways to minimize this ad hoc nature (see more on Appendix A).

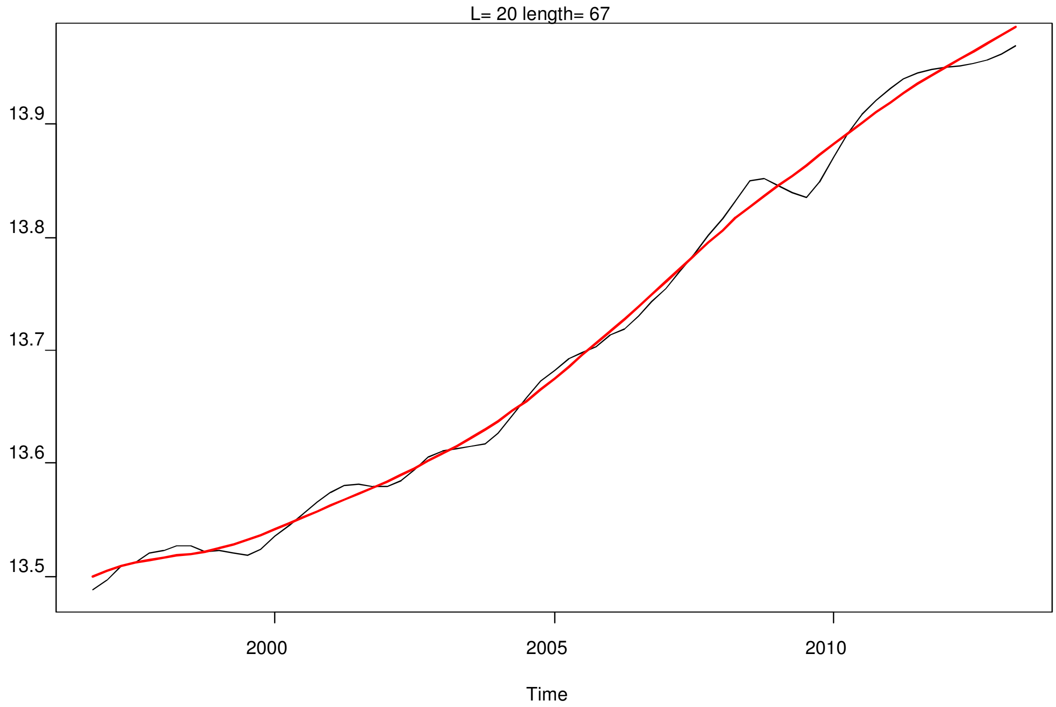

Figure 1: Log of real GDP from Brazil (black) and trend extracted with SSA (red).

In Figure 2, the residual of this extraction is plotted together with the cycles extracted using STM and the HP filter ($\lambda = 1600$). In this case, the three methods present relatively similar results and show a clear cyclical behavior.

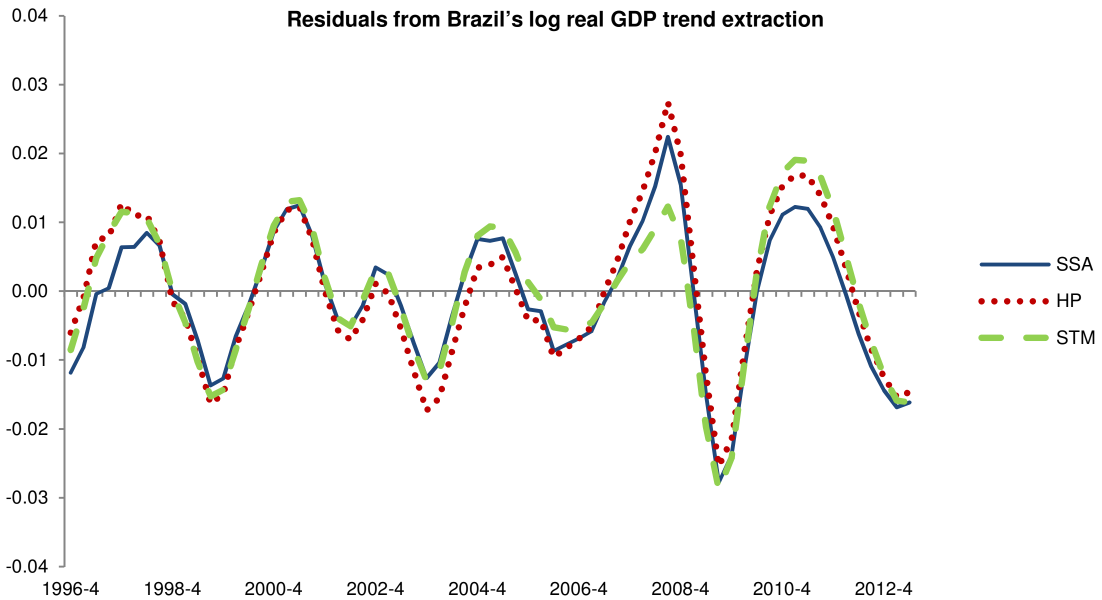

Figure 2: Brazil's business cycle extracted through singular spectrum analysis (SSA), Hodrick-Prescott filter (HP) and structural time series model (STM).

After de-trending, a more straightforward parametric alternative related to SSA called ESPRIT is used to estimate cycles' length as well as three other Fourier-based spectral estimation alternatives such as raw and smoothed periodograms, and multitapering.

3.1.1 ESPRIT

ESPRIT is an algorithm for high resolution spectral estimation which exploits the subspace properties of the signal. This characteristic connects ESPRIT with SSA, because the latter includes the construction of a subspace which approximates the subspace generated by the signal (Roy and Kailath, 1989; Golyandina and Zhigljavsky, 2013). Following our previous example, we use the total least squares ESPRIT (TLS-ESPRIT) algorithm for period length estimation (Figure 3). The results point to a 3.2 years period for our example.

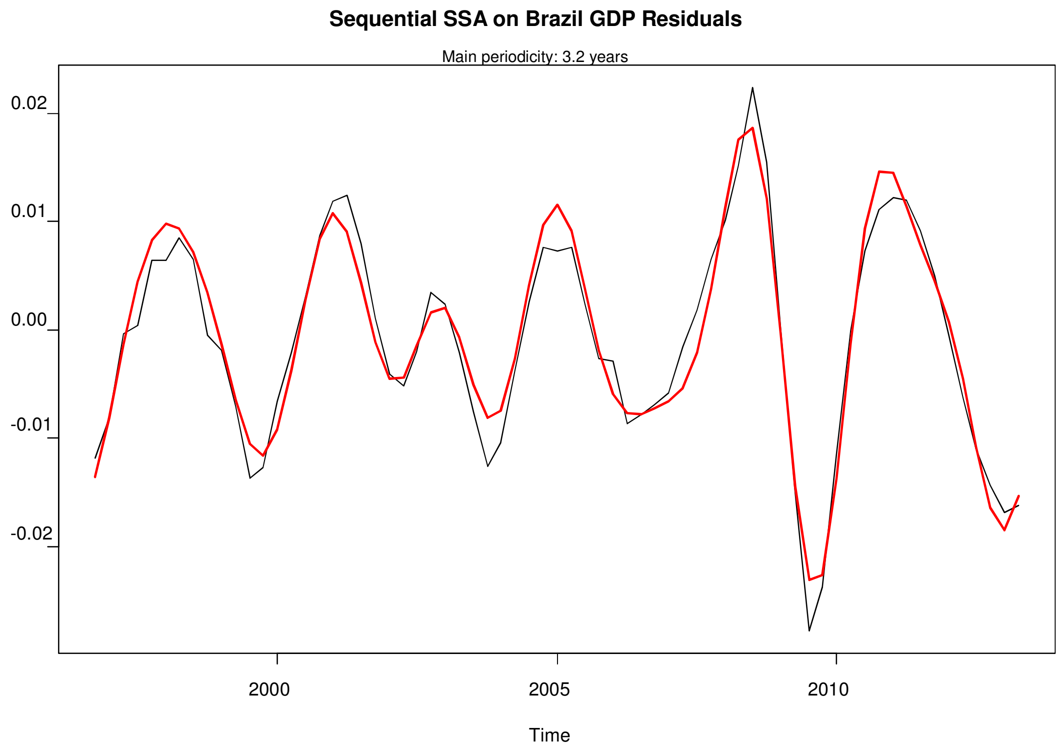

Figure 3: Signal extraction from Brazil's business cycle. TLS-ESPRIT shows a component of the signal with a 3.2 years period. The signal extracted from residuals is the red curve.

3.1.2. Spectral estimation: raw and smoothed periodograms, and multitapering

Spectral analysis to estimate main periodicities (frequencies) in numerical sequences is commonly used in Engineering, Physics and Geosciences by means of raw and smoothed periodograms, as well as multitapering techniques. There is vast literature covering the use of these techniques and related references in Economics, e.g. Granger (1964) and Hamilton (1994) among others.

However, the use of raw periodograms creates some problems such as the high variance of spectral estimates (Priestley, 1981; Bloomfield, 2000). In this paper, we use it as benchmark altogether with the suggested corrections, namely: smoothing and tapering (windowing). The smoothing is carried out with a modified Daniell window of length 3.

Additionally, it is possible to have confidence bands on smoothed spectral estimation, raising the possibility of a hypothesis test (Bloomfield, 2000). The null hypothesis may be the spectrum of some process, and we refer to it as “null continuum”. For most applications, the null continuum is simply a white noise process, which has a constant spectrum (Priestley, 1981). But, for our purposes, a “red noise” null continuum is more suitable, because economic time series are often characterized by strong positive autocorrelations and have a typical spectral shape (Granger, 1966, Levy and Dezhbakhsh, 2003). As AR(2) processes may show pseudo-periodic behavior (Anderson, 1976), we fit an AR(2) model to each series and use its theoretical spectrum as our null continuum. More details on Appendix B.

Thomson (1982) criticizes the use of smoothed periodograms. He argues that, as the raw periodogram is an inconsistent estimate of spectrum in the sense that its variance does not decrease with the sample size, the procedures of tapering (for bias control) and smoothing (for variance control) are necessary, but pose some problems for the estimates. To the author, tapering reduces bias, but also reduces variance efficiency, while smoothing is unsatisfactory, unless there is reason to believe that the underlying spectrum is smooth. Additionally, as smoothing operates on raw spectrum estimates, phase information present in the original data is not used, making line detection less efficient.

As an alternative, Thomson (1982) proposes a Multitaper Method (MTM) that we also implement here. This procedure uses multiple pairwise orthogonal tapers to obtain statistically independent spectral estimates of the underlying spectrum from the same sample. The final spectrum estimate is obtained through a weighted average of the independent estimates.

He also proposes a statistical test for spectral line significance, called Harmonic F-test, which is a test for line component significance against a smooth “locally white” spectral background. We use it as our test for periodicities on MTM estimates[5].

3.2 Bayesian Structural Time Series Model (STM)

Structural time series models could be formulated directly in terms of its unobserved components (Koopman et al., 2009). Harvey and Jagger (1993) strongly suggest the use of these models to both represent stylized facts about macroeconomic series and assess limitations of alternative *ad hoc* methods. The authors also demonstrate that the HP filter can easily create spurious cycles and illustrate how structural time series analysis can be used to detect cyclical, trend, and seasonal components (Harvey and Trimbur, 2003; Harvey and Trimbur, 2008). We use a similar approach to estimate trend and cycle components.

Harvey (1989) describes our full model in terms of a measurement equation (3) and state equations (4 to 7), where μ_t represents a local level, ψ_t the cyclical state vector, and ε_t a white noise:

$$y_t = \mu_t + \psi_t + \varepsilon_{t,} \ \varepsilon_t \sim NID(0, \sigma_\varepsilon^2) \tag{3}$$

The state vector (4) represents the trend component and (5) the slope component that feeds into the trend component, where β_t represents the slope, η_t a white noise for local level and ζ_t the slope vector residual. Observe that σ_η^2 is set to zero, because we specify a smooth trend (Koopman et al., 2009a).

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_{t,} \ \eta_t \sim NID\left(0, \sigma_\eta^2 = 0\right) \tag{4}$$

$$\beta_t = \beta_{t-1} + \zeta_{t,} \ \zeta_t \sim NID\left(0, \sigma_\zeta^2\right) \tag{5}$$

In our model, the typical cyclical state component (6) proposed by Harvey (1989) is actually replaced by the (7) from Harvey and Trimbur (2003):

5 The test assumes a highly concentrated spectral line against a smooth spectrum, but it is not well suited for time series with “red noise” background and quasi-periodic components (See Mann and Lees, 1996).

$$\begin{bmatrix} \psi_t \\ \psi_t^{\ *} \end{bmatrix} = \rho \begin{bmatrix} cos\lambda_c & sin\lambda_c \\ -sin\lambda_c & cos\lambda_c \end{bmatrix} \begin{bmatrix} \psi_{t-1} \\ \psi_{t-1}^{\ *} \end{bmatrix} + \begin{bmatrix} \kappa_t \\ \kappa_t^{\ *} \end{bmatrix}, \ t = 1, \dots T \tag{6}$$

where λ_c is the frequency in radians, in the range [0, π], κ_t and $\kappa_t^{\ *}$ are two mutually uncorrelated white noise disturbances with zero means and common variance σ_κ^2. The cycle period is $2\pi/\lambda_c$ and this stochastic cycle becomes an AR(1) if λ_c is 0 or π (Koopman et al., 2009b). It is important to highlight that the cycle is stochastic only in terms of amplitude.

Harvey and Trimbur (2003) extend this framework to cyclical (smoother) processes of order k, specified as $\psi_t = \psi_t^{(k)}$. In that case, for j = 1,…, k:

$$\begin{bmatrix} \psi_t^{(j)} \\ \psi_t^{\ *(j)} \end{bmatrix} = \rho \begin{bmatrix} cos\lambda_c & sin\lambda_c \\ -sin\lambda_c & cos\lambda_c \end{bmatrix} \begin{bmatrix} \psi_{t-1}^{(j)} \\ \psi_{t-1}^{\ *(j)} \end{bmatrix} + \begin{bmatrix} \psi_t^{(j-1)} \\ \psi_t^{\ *(j-1)} \end{bmatrix}, \text{ where} \tag{7}$$

$\begin{bmatrix} \psi_t^{(0)} \\ \psi_t^{\ *(0)} \end{bmatrix} = \begin{bmatrix} \kappa_t \\ \kappa_t^{\ *} \end{bmatrix}$ are two mutually uncorrelated white noise disturbances with zero means and common variance σ_κ^2.

A higher k leads to more pronounced cut-offs of the band-pass gain function at both ends of the range of cycle frequencies centered at λ_c, rendering smoother cycles. We follow Harvey and Trimbur (2003) and Harvey et al. (2007) and test several k orders of the cycle for robustness.

The signal-to-noise (q-ratio) in this model can be expressed in (8),

$$q = \frac{\sigma_\zeta^2}{\sigma_\varepsilon^2 + \sigma_\psi^2} \tag{8}$$

where σ_ψ^2 is the variance of the state component ψ, closely related to σ_κ^2 and ρ .

Harvey et al. (2007) extend this framework for Bayesian estimation of five of these parameters, $\theta = \{\sigma_{\zeta}^2, \sigma_{\kappa}^2, \sigma_{\varepsilon}^2, \rho, \lambda_c,\}$.The posterior distribution can be accessed using (9):

$$p(\theta|y) = L(\theta; y)p(\theta), \tag{9}$$

where the likelihood function $L(\theta; y)$ is evaluated using the Kalman Filter.

Similarly, the marginal likelihood $M(y)$ is described in (10) and Bayes factors are computed as the ratio of marginal likelihoods for different model specifications $\{L(\theta; y)p(\theta)\}$, a convenient way to choose between them.

$$M(y) = \int L(\theta; y)p(\theta)d\theta \tag{10}$$

The constant of proportionality is naturally not available analytically; as a consequence Markov Chain Monte Carlo (MCMC) methods are a suitable way to sample parameter drawings from the posterior.

To Harvey et al. (2007), there are two great advantages in adopting the MCMC algorithm to STM: 1) avoid fitting implausible models and 2) investigate parameter uncertainty in the posterior distribution of the components. Moreover, the MCMC produces draws from the joint posterior both of the trend and cyclical components that we are interested in investigating. We follow the same computational procedure in this work (see also Koop and Van Dijk, 2000 and Durbin and Koopman, 2002 for details on the simulation smoother).

As in Harvey et al. (2007), we are interested in the λ_c parameter and we set a beta prior distribution for the quarterly frequency parameter λ_c with mode on $2\pi/20$ for the business cycle (5 years) and three sets of “spreads” to account for different levels of informativeness about the shape of the distribution. For the widest prior (σ_y/μ_y) = 40%, for the intermediate (σ_y/μ_y) =13% and for the sharp (σ_y/μ_y) = 4% (see Figure 4). We set non-informative flat distributions to all other four parameters. The parameter ρ is also truncated to lay in the interval [0,1] as expected in the model. These are the same priors used by Harvey et al. (2007).

For the financial cycle, we rely on Drehmann et al. (2010) and set the prior mode of λ_c to meet the median distance between crisis, 15 years, i.e., $2\pi/60$. However, as the degree of uncertainty is higher in the financial cycle than in the business one, we choose even wider priors than the original ones proposed by Harvey et al. (2007). We set our wider priors in a way that could (if necessary) encompass the business cycle. These priors are (σ_y/μ_y) =100%, (σ_y/μ_y) =70% and (σ_y/μ_y) =40% (see Figure 4).

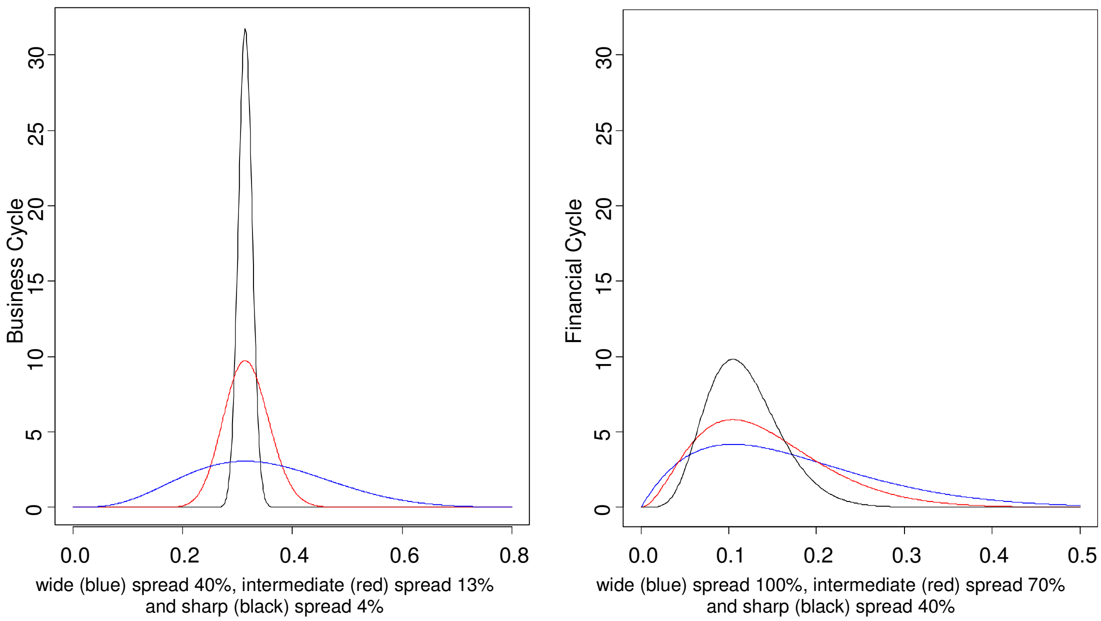

Figure 4: Beta priors for business and financial cycles

4. Results

In this section, we present several financial cycles' length estimates using univariate structural time series models (STM) and spectral analysis for 28 countries. The credit-GDP gap is the adopted financial cycle proxy. We also use STM to evaluate the business cycles' of these countries replicating Harvey et al. (2007) and taking logarithm of GDP as proxy.

Regarding SSA (session 4.1), we use the procedure detailed in Appendix A to decompose and reconstruct all series in the sample and run spectral analysis in their residuals (Appendices B and C).

Regarding STM (session 4.2), we first analyze the sensitivity of the parameters with respect to the choice of the frequency priors. Second, we evaluate model fit looking at marginal likelihoods and finally we focus on posterior means and overall distribution of the parameters and state estimates to draw conclusions about main cycles' length, amplitude, and variances. Most of our analysis focuses on the financial cycle. However, we rely on cross-country median estimates to better explore some differences between the business and financial cycle. Naturally, this kind of parameter comparison cannot be carried out objectively in the non-parametric techniques.

4.1 SSA and Spectral Analysis

In this session, we use "Caterpillar" SSA as a de-trending method and estimate main periodicities in the residuals using spectral decomposition over raw and smoothed periodograms, and MTM. We evaluate 28 countries credit-to-GDP series in this exercise.

Table 1 shows the main periodicities detected with all methods. We show only significant results at 5% (against a "red noise") for the Smoothed Periodogram and significant results at 5% (against a local white noise) for the Multitaper F-test (see Appendices B and C, and Thomson, 1982 for more details). In all these methods, we present the main significant periodicities on a spectral neighborhood, i.e., the highest significant peak on a Smoothed Periodogram, the highest peak on a Raw Periodogram and the highest F-statistic on MTM. The ESPRIT results represent those close to the neighborhood of the other estimations[6]. We present detailed results concerning these estimates in Appendix D.

[6] As the ESPRIT results do not have a statistical significance test, we use the proximity to spectral estimates to choose the results of interest. Note that, in some cases, there is just one estimate.

Country	*Raw Periodogram*	*Smoothed Periodogram*	*MTM F-test*	*ESPRIT*	*Mean*
Australia	18	18	21.3	19	19.1
Austria	10	10	9.8	10.3	10.0
Belgium	8.4	8.4	9.1	9.5	8.9
Brazil	6	6	7.1	9.4	7.1
Canada	15	10	16	15.4	14.1
Czech_Republic	4	NA	3.8	3.9	3.9
Denmark	18	18	18.3	26.4	20.2
France	15	15	16	17.1	15.8
Finland	11.2	11.2	11.6	8.4	10.6
Germany	18	18	16	17.5	17.4
Hungary	2.9	1.4	2.9	3.3	2.6
Korea	15	11.2	14.2	13.5	13.5
Indonesia	3.4	3.4	4	4	3.7
Ireland	9	NA	9.1	13.5	10.5
Italy	16.9	8.4	14.2	15.8	13.8
Japan	16.7	NA	21.3	19	19.0
Mexico	8.4	8.4	9.1	10	9.0
Netherlands	12	NA	18.3	18.7	16.3
Norway	24	NA	21.3	18.4	21.2
Poland	6.7	NA	9.1	8	7.9
Portugal	13.5	13.5	14.2	16.7	14.5
South_Africa	16.7	NA	18.3	9.4	14.8
Spain	9	7.5	8	8.8	8.3
Sweden	16.9	11.2	18.3	19.1	16.4
Switzerland	10.8	10.8	11.6	11.3	11.1
Turkey	13.5	NA	10	17.6	13.7
United_Kingdom	22.5	15	16	18.2	17.9
United_States	20.8	20.8	21.3	17.9	20.2
Median	13.5	11.0	14.2	14.5	13.8

Table 1: Main periodicities (years) for each method over 28 countries sample. NA means that the highest peak was not significant

Notice on Table 1 that results are approximately similar for different approaches. Some countries showed more ambiguous results, e.g., Denmark, Sweden, Norway, Japan, South Africa, Italy, and Turkey. But, for all countries, at least three different estimates show relatively close results. One should bear in mind mentioned limitations such as spectral resolution and leakage effects (see also Appendices A to C).

Observe on Figure 5 the concentration of periodicities of over 15 years. Nonetheless, it is also possible to identify a smaller group (around 9 countries) with mean periodicities below 10 years. Significant periodicities close to the business cycle range can also be found for most of these countries in the Periodograms (see more on Appendix D). We focus our analysis in longer periodic components though.

In some countries we failed to estimate significant lower frequency components. For instance, Brazil, Indonesia, Czech Republic, and Hungary have mean frequency domains close to those expected in a business cycle. These are also countries with short series. Naturally, the availability of only short series compromise the estimation of low frequency domains and this is an issue impossible to go around. However, series' length is not the main factor driving our estimates. Hungary, for instance, has series just as long as Poland, but a cycle two times larger. Poland slightly exceeds the 7.5 years boundary that we consider for the business cycle range. On the opposite side, Spain has a mean frequency pointing to 8.3 years, while countries with series just as long, such as France, Ireland, and Finland are over 10 years figures. Turkey, with smaller series, is also above the 13 years figures (Appendix E2 has information on the credit series length as well as STM estimates).

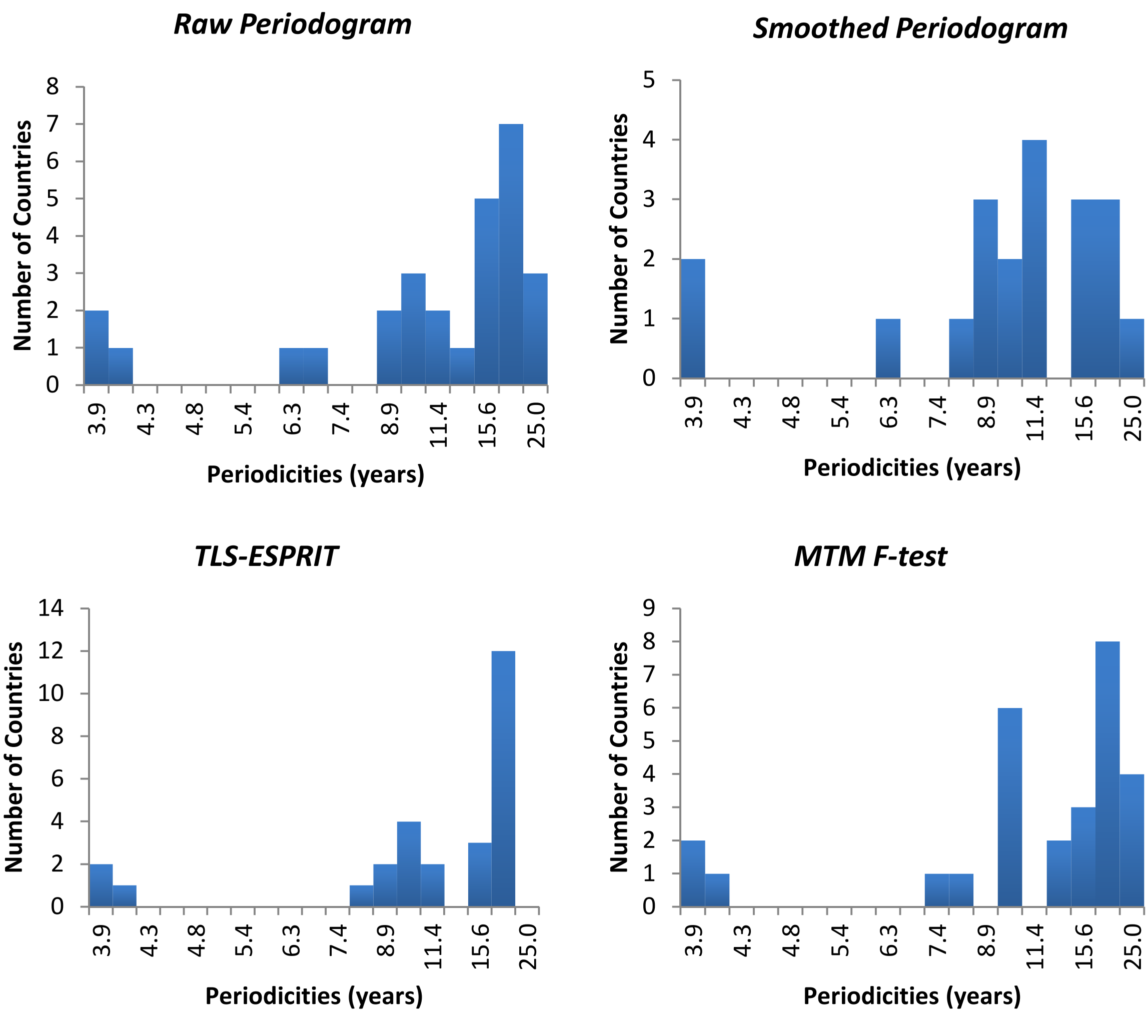

Figure 5. Histogram of estimated periodicities

4.2.1 STM for Business Cycle

We estimated posterior means of the five aforementioned parameters $= \{\sigma_\zeta^2, \sigma_\kappa^2, \sigma_\varepsilon^2, \rho, \lambda_c\}$, σ_ψ^2 (variance of amplitude), q-ratio, and the marginal likelihood, M(y), for the 28 countries. The period is simply $2\pi/\lambda_c$ (in quarters). We present it altogether with Highest Posterior Densities (HPD) for $2\pi/\lambda_c$ in years for simplicity. We estimate the model for every country using four orders of cycles, k ={1,..,4}, and the three sets of priors detailed before. Individual results are available upon request. Variance terms are multiplied by 10^7.

Table 2 presents the cross-country median estimates. Note that λ_c mean and, as consequence, period mean estimates do not seen to be influenced by our set of priors. In line with literature, ρ and σ_κ^2 diminish as cycle order (k) increases, but also have no effects on the period density (Harvey and Trimbur, 2003).

k	*Prior Type*	σ_ζ^2	σ_κ^2	σ_ε^2	ρ	λ_c	*M(y)*	σ_ψ^2	*Q ratio*	*HPD (10%)*	*Period (years)*	*HPD (90%)*
1	Intermediate	73	379	86	0.77	0.32	251.0	1896	0.14	4.2	4.9	5.8
1	Sharp	74	388	83	0.77	0.32	251.0	1673	0.13	4.7	5.0	5.3
1	Wide	78	365	94	0.78	0.36	250.7	1719	0.15	3.0	4.8	6.9
2	Intermediate	64	214	158	0.57	0.32	254.1	2179	0.15	4.2	5.0	5.9
2	Sharp	63	215	160	0.58	0.32	254.1	2252	0.14	4.7	5.0	5.3
2	**Wide**	**71**	**213**	**154**	**0.56**	**0.35**	**253.8**	**2519**	**0.17**	**3.1**	**5.0**	**7.5**
3	Intermediate	90	154	185	0.43	0.32	254.3	2293	0.17	4.2	5.0	5.9
3	Sharp	88	157	188	0.43	0.32	254.4	2853	0.19	4.7	5.0	5.3
3	Wide	99	153	182	0.42	0.36	253.9	2265	0.21	3.0	4.9	7.4
4	Intermediate	103	114	199	0.35	0.32	253.9	3081	0.22	4.2	5.0	5.9
4	Sharp	103	115	199	0.35	0.32	253.9	2760	0.22	4.7	5.0	5.3
4	Wide	110	111	196	0.34	0.36	253.4	2825	0.27	2.9	4.9	7.3

Table 2. Cross-country median estimates across priors and business cycle orders[7]

The marginal likelihood M(y) across model specifications was found maximum in 13 of the 28 countries in cycles of order k=2. In other words, this specification usually renders the preferred model (Kass and Raftery, 1995). Results are in consonance with Harvey et al. (2007). We present individual and more detailed results only for wide priors and cycles of order k=2 in Appendix E1. All others are available upon request.

Figure 6 illustrates, using the UK Output, the posterior densities of all four parameters for which flat priors are used. The red curve is a Kernel density estimate. Figure 7 illustrates λ_c and $2\pi/\lambda_c$ (in quarters) as well as marginal posterior densities of the slope and cyclical components, $\beta_{t,T}$ and $\psi_{t,T}$, of the UK Output in 2013Q4. Note that High Posterior Densities (HPD) for λ_c are directly obtained from our data. We present these same results in period densities for simplicity. In the case of the UK, mean estimates for Period point to a 6.11 years business cycle, with HPD bands stemming

[7] We use the OX language described by Doornik (1999) and SSFpack 3.0 from Timberlake Consultants to estimate all these figures. The original codes of Harvey et al.(2007) were kindly made available to us by the authors. Graphs and local Gaussian kernels were generated using STAMP and OxMetrics 6.01 (see more on Koopman et al., 2000).

from 3.99 to 8.32 years. This mean estimate points to a one year larger than average cycle as compared to other countries in the sample (Appendix E1). The UK Output gap mean is still at the negative side in 2013Q4, but very close to zero. It is straightforward to calculate the probability that this figure is effectively below the trend, 78.8%, as opposed to 25.8% on 2006, before the crisis effects hit the real economy. The UK Output gap mean has been mostly on the negative side since 2010.

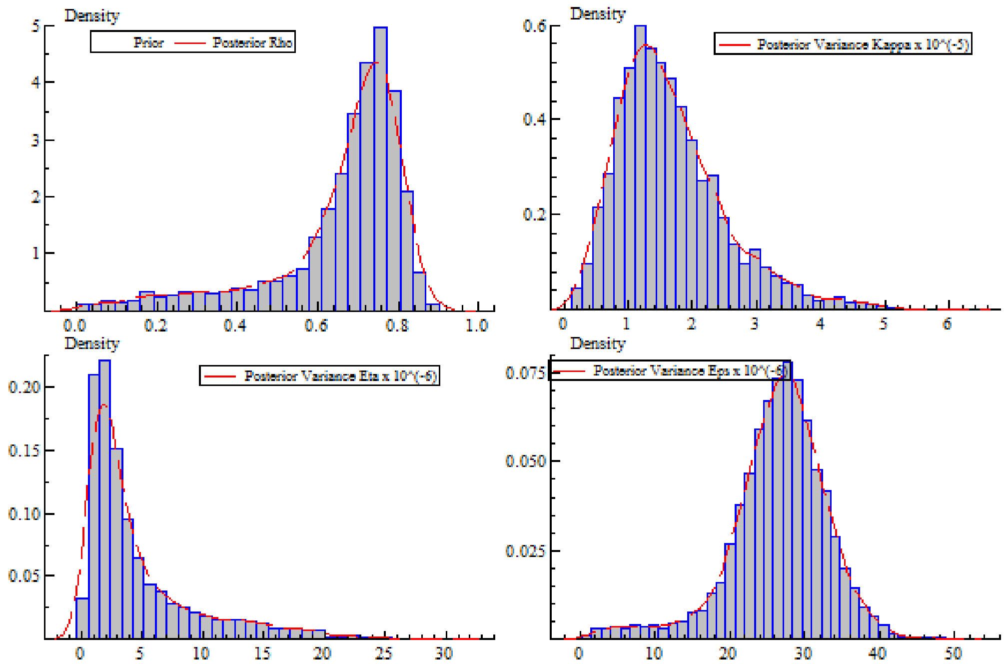

Figure 6. Marginal posterior densities of $\boldsymbol{\rho}, \boldsymbol{\sigma_\kappa^2}, \boldsymbol{\sigma_\zeta^2}$ **and** $\boldsymbol{\sigma_\varepsilon^2}$ for n=2, with wide prior for UK GDP.

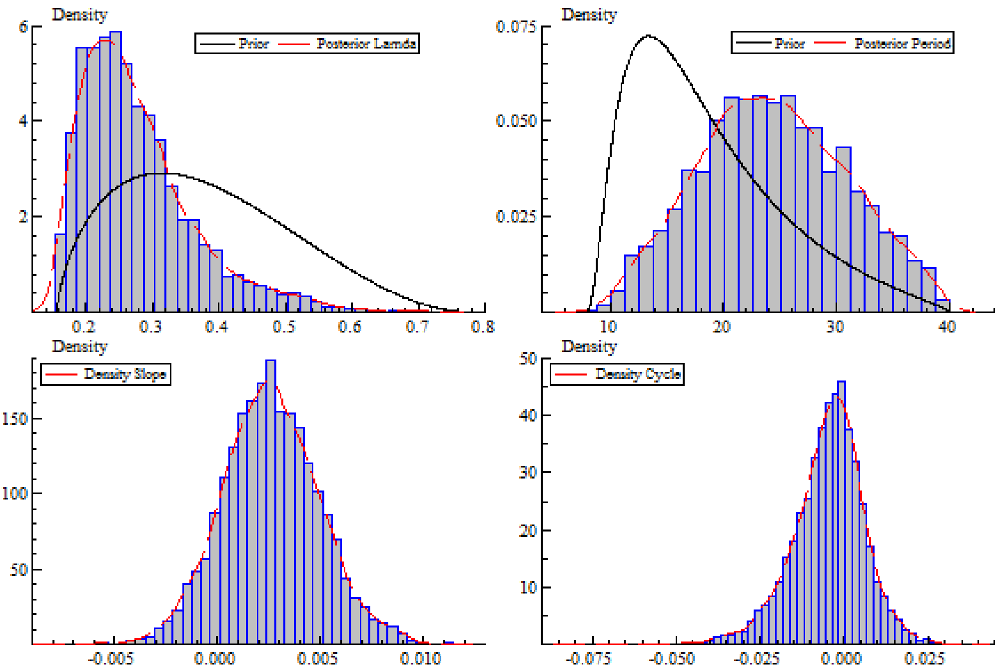

Figure 7. UK Marginal posterior densities of $\boldsymbol{\lambda_c}$ (Top left) and $\boldsymbol{2\pi/\lambda_c}$ (in quarters – Top right) for n=2 with wide informative prior on $\boldsymbol{\lambda_c}$. (Bottom) Marginal posterior densities of the slope and cyclical components, $\boldsymbol{\beta_{t,T}}$ and $\boldsymbol{\psi_{t,T}}$, for 2013Q4.

4.2.2 STM Financial Cycle

Following the same dynamics, Table 3 presents cross-country median results for our four alternative specifications of the model and the three prior sets that we elaborate for the financial cycle. We also present results when a flat prior is used for λ_c.

n	*Prior Type*	σ^2_ζ	σ^2_κ	σ^2_ε	ρ	λ_c	*M(y)*	σ^2_ψ	*Q_c ratio*	*HPD (10%)*	*Period*	*HPD (90%)*
1	Intermediate	168	1986	286	0.83	0.16	421.5	30395	0.04	5.3	13.0	24.1
1	Sharp	159	2017	279	0.83	0.14	421.6	27114	0.04	6.9	13.9	23.5
1	Wide	175	1942	291	0.81	0.20	421.4	21798	0.05	3.9	11.6	24.3
2	Intermediate	187	1346	532	0.54	0.15	421.6	17580	0.06	5.5	14.6	27.9
2	Sharp	183	1398	533	0.55	0.13	421.7	14911	0.05	6.9	15.1	26.1
2	**Wide**	**193**	**1262**	**533**	**0.53**	**0.19**	**421.4**	**14385**	**0.07**	**4.1**	**13.5**	**29.5**
3	Intermediate	205	1000	646	0.38	0.16	421.5	8978	0.13	5.3	14.1	27.2
3	Sharp	198	1019	651	0.38	0.14	421.5	9551	0.12	6.9	14.8	25.6
3	Wide	215	964	639	0.37	0.20	421.3	7388	0.14	3.8	12.7	28.1
4	Intermediate	230	741	770	0.32	0.16	421.3	8537	0.15	5.2	13.8	26.8
4	Sharp	222	751	740	0.32	0.14	421.4	8366	0.14	6.8	14.6	25.3
4	Wide	246	736	728	0.30	0.21	421.2	6792	0.16	3.7	12.4	27.5
1	Flat	235	1503	350	0.78	0.37	422.1	10642	0.09	2.4	7.1	13.7
2	Flat	251	987	548	0.47	0.65	418.6	6032	0.22	1.3	7.5	18.4
3	Flat	330	633	623	0.31	0.84	420.0	4208	0.30	0.9	5.5	13.5
4	Flat	372	432	683	0.26	1.05	424.5	3168	0.34	0.7	4.3	10.5

Table 3. Cross-country median estimates across priors and financial cycle orders

It is important to highlight some aspects of Tables 2 and 3. First, (σ_{ψ}^{2}) is on average six times lower in the business cycle than in the financial one, reflecting the higher amplitude of the latter. Moreover, the variance of the state equation residuals is also higher for the slope, (σ_{ζ}^{2}), and the cycle, (σ_{κ}^{2}), reflecting the greater uncertainty on the state estimates. Figures 8 and 9 illustrate these aspects for the UK. Notice the slope and cycle densities of credit-to-GDP on 2013Q4 as compared to those of the business cycle (Figure 6 and Figure 7)

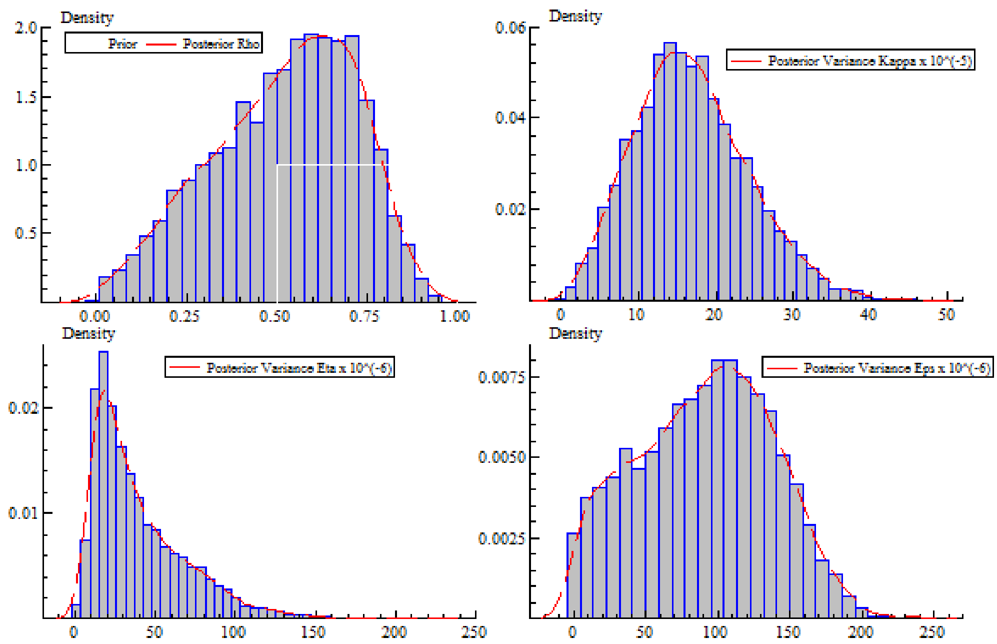

Figure 8. Marginal posterior densities of $\boldsymbol{\rho}, \boldsymbol{\sigma_{\kappa}^{2}}, \boldsymbol{\sigma_{\zeta}^{2}}$ **and** $\boldsymbol{\sigma_{\varepsilon}^{2}}$ for n=2, with wide prior for UK credit/GDP.

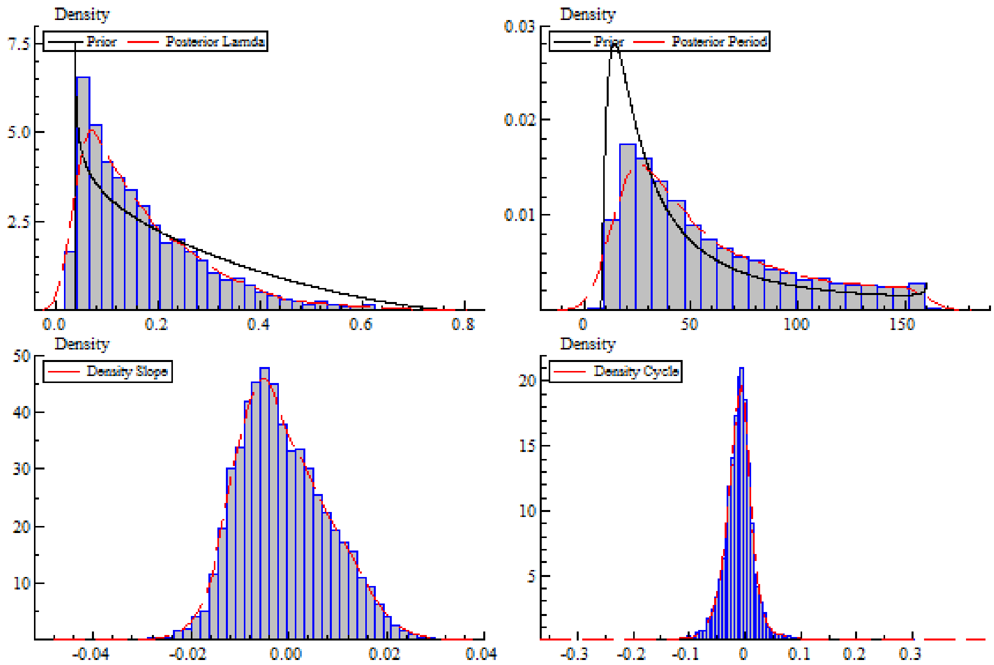

Figure 9. UK Marginal posterior densities of $\boldsymbol{\lambda_c}$ (Top left) and $\boldsymbol{2\pi/\lambda_c}$ (in quarters – Top right) for n=2 with wide informative prior on $\boldsymbol{\lambda_c}$. (Bottom) Marginal posterior densities of the slope and cyclical components, $\boldsymbol{\beta_{t,T}}$ and $\boldsymbol{\psi_{t,T}}$, for 2013Q4.

Once again, the marginal likelihood M(y) across model specifications is maximized in cycles of order k=2. This smoothed cycle was the preferred specification in 12 out of 28 countries. As a consequence, we choose the wide prior with cycle of order k=2 as our favorite model specification. The last rows of Table 3 pretty much illustrate the rationale to be using priors on λ_c. Observe that our mean period estimates collapse to the business cycle. Moreover, we find cyclical components that should be treated as seasonal or irregular in the lower bound HPDs. These are good examples of implausible models that Harvey et al. (2007) and ourselves are trying to avoid with Bayesian estimates.

To our understanding, the business cycle is the "strongest" cyclical component in the series and we need some (prior) knowledge about these longer cycles to help us estimate the lower frequencies we are interested in. Observe that the variance we set in our wide prior is large enough to accommodate the business cycle in case any single of the 28 countries' data in our sample cannot fit a financial cycle. We report individual data on Table 4 and more detailed information on Appendix E2.

Our cross-country mean period estimate is 13 years with a minimum of 7 years and a maximum of 17. However, HPD bands would stem in a 4 to 27 years range to fully account for parameter uncertainty on density estimates in 10% to 90% quantiles (Table 4). Our sharper prior would produce a tighter range, 7 to 26 years (Table 3).

Country	*HPD (10%)*	*Period*	*HPD (90%)*	*Country*	*HPD (10%)*	*Period*	*HPD (90%)*
Australia	3.96	13.00	28.42	Korea	5.41	16.32	32.34
Austria	4.36	14.88	30.92	Mexico	3.70	11.56	23.94
Belgium	4.15	13.83	30.20	Netherlands	3.94	12.90	27.91
Brazil	3.37	8.08	14.67	Norway	4.62	14.43	29.92
Canada	5.84	16.73	32.14	Poland	3.57	8.65	15.52
Czech_Republic	3.67	8.53	15.37	Portugal	3.82	13.28	29.09
Denmark	4.41	14.08	30.17	South_Africa	5.60	17.12	32.58
Finland	3.82	13.66	29.43	Spain	3.56	12.58	27.85
France	4.47	14.77	30.52	Sweden	5.18	15.89	31.62
Germany	5.34	15.17	30.50	Switzerland	4.11	13.52	29.60
Hungary	3.45	8.20	14.91	Turkey	3.65	10.15	20.05
Indonesia	3.34	7.07	11.80	United_Kingdom	4.60	14.54	30.44
Ireland	3.86	13.43	29.77	United_States	4.83	15.85	31.92
Italy	4.10	13.11	28.13	**Min/Max Period**		**7.07 / 17.12**	
Japan	4.11	13.34	28.16	**Mean**	**4.24**	**13.02**	**26.71**

Table 4. Period density estimates (in years)

In Table 4 and Figure 10, we can clearly notice some countries where mean period density estimates lay closer to the figures of the business cycle than the average estimates for the financial one. In particular, Brazil, Czech Republic, Hungary, Indonesia, and Poland stand out with mode estimates for Period significantly below 15 years. These are also countries with shorter credit-to-GDP series (see Appendix E2 for more information).

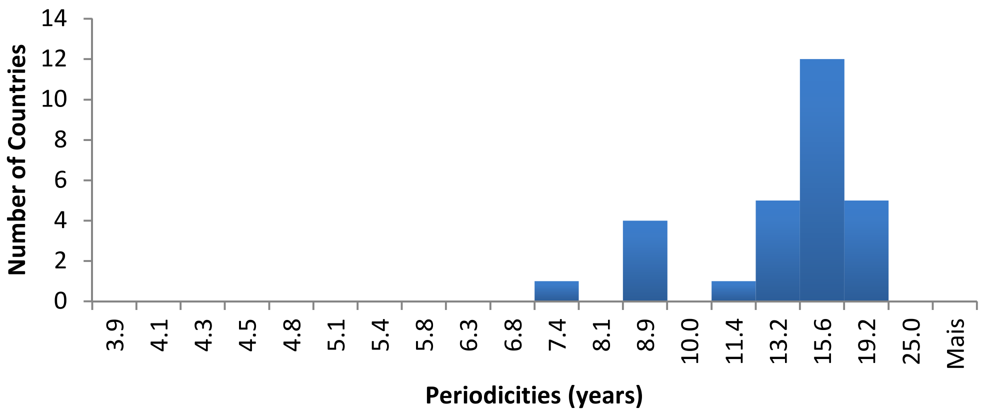

Figure 10. STM mean period estimate

Figures 11 and 12 illustrate the cyclical and slope state equations for the UK respectively; the confidence intervals are quantiles extracted from the posterior joint distributions. As in Figure 9, it is possible to observe that both the slope and cycle's mode are on the negative side in 2013Q4. Cycle density is actually very much concentrated on the zero bound (Figure 9), as opposed to mean cycle amplitudes close to 8.5% in 2009Q1 (Figure 11).

Naturally, our cycle density estimates are not comparable to those of the HP(400k), because our stochastic slope component is very different from the almost linear one embedded in HP(400k). Observe in Figure 11 that HP(400k) cycle has higher amplitudes than the estimated one.

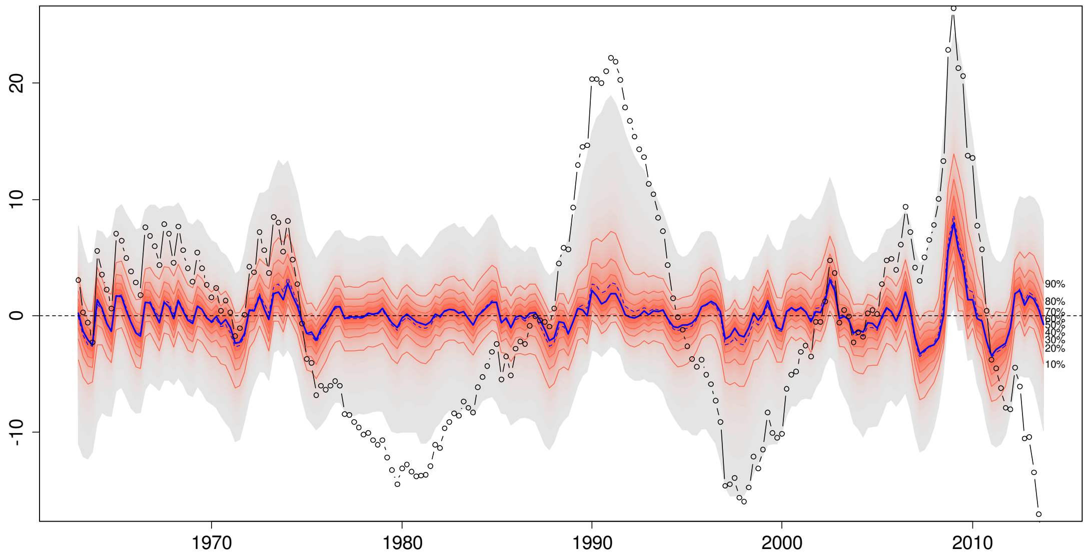

Figure 11. UK financial gap with cycle order (k=2) and wide priors and HP(400k) gap in points-lines black curve

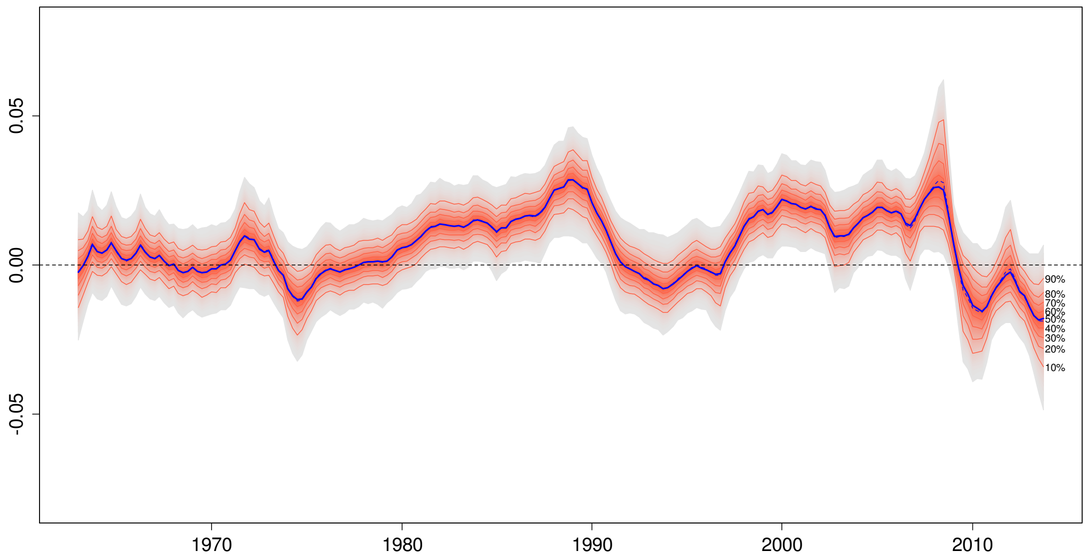

Figure 12. UK credit/GDP quarterly growth

The q-ratio we are estimating with STM, q_c, can relate directly to the gain function of the Hodrick-Prescott filter (Hodrick and Prescott, 1997; Harvey and Trimbur, 2008). However, the minimum figure we could observe for q_c on Appendix E2 is 0.02. If we match the gain function of HP filter and our estimated STM (that rendered q_c= 0.02) at the point where gain equals 0.5, we arrive at q=0.006567 or HP(152.27). For simplicity, HP(150). If we match all countries parameters individually, results would lay bellow this figure, but differences are negligible (Figure 13). See Appendix E2.

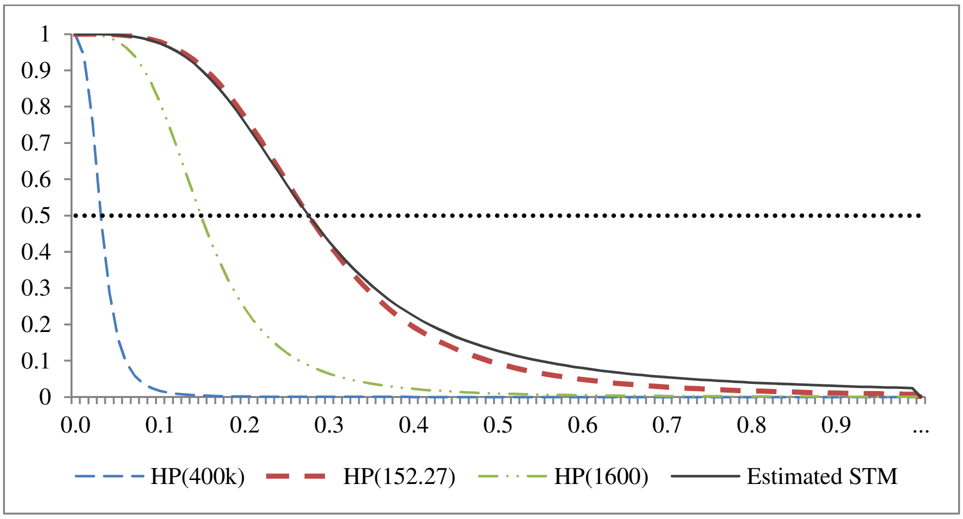

Figure 13. Gains for an estimated STM with q_c=0.02,ρ=0.6 and λ_c=0.154; HP(400k); HP(1600) and our “matched” HP(150)

Notice that our estimates point in the opposite direction of Drehmann et al. (2011). The rationale to increase lambda factors (or decrease q) is illustrated in Harvey and Jaeger (1993) and Harvey and Trimbur (2003) with the Investment function. “Investment and GDP are assumed to have a common trend, but it is an established stylized fact that the variance of the cycle in investment is greater than that of GDP. Thus the signal-noise ratios in the individual series must be different. “A factor of around 20 to 30 for the ratio of the investment to the GDP cycle emerges”. As a consequence, HP(32k) is suggested to better proxy the Investment gap (Harvey and Trimbur, 2008).

Nonetheless, our results suggest that the innovations of the slope component capture too much variance from the data to consider a common slope with GDP and such a responsive high amplitude cycle.[8]

In other words, a model that best fit these series should more quickly adjust to innovations of the slope component as the one implied in HP(400k). Moreover, the filtered embedded in our STM has higher cut-off frequencies. Even higher than the typical business cycle (Figure 13).

Drehmann et al. (2011) heavily support HP(400k) gap in its anticipating power of banking crisis, an argument hard to beat when financial stability is the ultimate goal of Macroprudential Policy. We note though that the slope component can possibly be more appealing to anticipate these events. From Figure 12, it is possible to observe that nominal credit is outpacing nominal GDP growth substantially since 1998 in the UK. Another aspect worth noting is the degree of uncertainty around the state of the cycle in Figure 11. From a probabilistic standpoint, Figure 12 more clearly points that nominal credit has outpaced GDP growth significantly since 2002.

STM provides a convenient framework to investigate early warnings as filtered estimates of the states can easily be accessed to represent one-sided estimates (see more on Harvey, 1989, Harvey and Trimbur, 2003). However, examining these aspects, as in Drehmann et al. (2011), is left for further studies.

[8] From equation (8), it is straightforward to observe that, everything else constant, the higher is σ_{ψ}^{2}, the smaller is q. However, the increase in σ_{ζ}^{2} is non-negligible when one observes the business cycle as opposed to the financial one.

4.3 All-in-all cycles' length

Figure 14 summarizes our results in terms of financial cycles' length. We consider five techniques, i.e., all four alternative spectral estimates as well as mean of the results of STM.

Observe that most countries in our sample have cycles in the range of 13 to 20 years. A second smaller group of countries with cycles shorter than 10 years can also be identified. Periodicities very close to those of the business cycle can be found in Brazil, Indonesia, Czech Republic, and Hungary. However, we note that the business cycle is indeed present in all our results either in STM with flat estimates or SSA (see Appendix D for more details).

The business cycle, estimated for the same group of countries using STM, lay in the 3 to 7.5 years range (Appendix E1) with a mean on 5 years. The financial cycle in STM would lay in 4 to 30 years with a mean on 13 years (Table 3) and cross-country median on 13.5 years (Table 2). Cross-country minimum and maximum mean estimates lay in the 7 to 17 years interval. Using Spectral Analysis, median cross-country estimates across the four techniques we use lay in the 11 to 14.5 years, with a mean on 13.8 years.

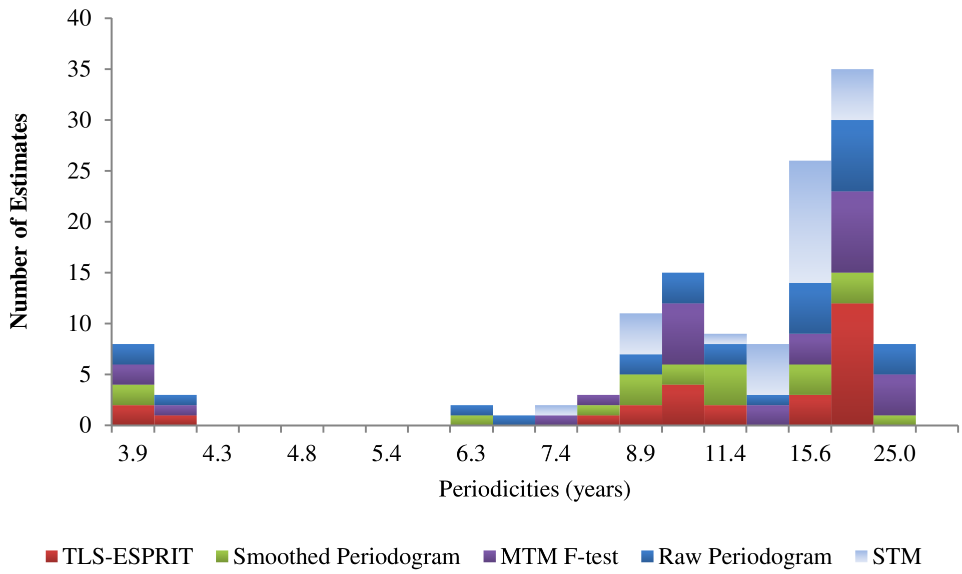

Figure 14: Histogram summarizing all results, highlighting each technique.

5. Final Remarks

We evaluate credit cycles and business cycles' length over several countries using non-parametric de-trending techniques known as SSA followed by spectral analysis and Bayesian STM. To the best of our knowledge, this is the first paper looking into cross-country financial cycle length estimates using these techniques.

We focus on objectively estimate periodic components and q-ratios that could help Policy Makers and researchers to better understand the duration of these cycles and more consistently and coherently fit financial cycles.

We could find financial cycles averaging 13.8 years using Spectral Analysis and 13 years investigating the posterior estimates of the period parameter $2\pi/\lambda_c$ in Structural Time Series Models. In the last case, we use wide priors on λ_c to estimate these longer periodic components.

Most countries in our sample present significant periodic components in the range of 13 to 20 years, but a group with shorter than 10 years cycles could be clearly detected. Moreover, both spectral analysis and STM (with flat priors) point to shorter periodic components even when longer ones are also detected, suggesting that the business cycle (3 to 7.5 years) is an important driver of the credit one. In some countries, it is the most significant one.

Finally, our results suggest that the credit-to-GDP gap estimated using HP(400k) as proposed by Drehmann et al. (2011) to be a leading Macroprudential Policy indicator may be mispecified as a throughout representation of the credit cycle. The gain function of our STM relates more closely to the one of HP(150), where the slope component captures more variance from the original series. The use of this class of model or HP(150) to anticipate crisis is left for further studies.

6. References

ANDERSON, O.D. (1976): “Time series analysis and forecasting: the Box-Jenkins approach”, Butterworths, London, 182 p.

AREOSA, M. (2008): “Combining Hodrick-Prescott Filtering with a Production Function Approach to Estimate Output Gap”, Working Paper No. 172, Central Bank of Brazil (August 2008).

BARAJAS, A., DELL’ARICCIA, G. and LEVCHENKO, A. (2008): “Credit Booms: The Good, the Bad, and the Ugly”, Unpublished manuscript, International Monetary Fund (Washington, DC).

BASEL COMMITTEE ON BANKING SUPERVISION (BCBS) (2010a): “Guidance for national authorities operating the countercyclical capital buffer”. December.

BASEL COMMITTEE ON BANKING SUPERVISION (BCBS) (2010b): “Countercyclical capital buffer proposal”. July.

BLOOMFIELD, P. (2000): “Fourier analysis of time series: an introduction”, second edition: New York, John Wiley & Sons, Inc., 261 p.

BORDO, M. D. and HAUBRICH, J. G. (2009): “Credit crises, money, and contractions: A historical view”, Working Paper 0908, Federal Reserve Bank of Cleveland.

CANOVA, F. (1998): “Detrending and Business Cycles Facts”, Journal of Monetary Economics, 41: 475-512.

CHATFIELD, C. (1996). “The analysis of time series: An introduction”. Chapman & Hall/CRC.

CHE, N. X. and SHINAGAWA, Y (2014): “Financial Soundness Indicators and the Characteristics of Financial Cycles”, IMF Working Paper WP/14/14.

CHRISTIANO, L.J. and FITZGERALD, T.J. (2003): “The Bandpass filter”, International Economic Review 44(2), 435-465.

CLAESSENS, S, KOSE, M A and TERRONES, M E (2009): "Financial cycles: What? How? When?", IMF Working Paper WP/11/76.

CLAESSENS, S, KOSE, M A and TERRONES, M E (2011): "How do business and financial cycles interact?", IMF Working Paper WP/11/88.

COGLEY, T., and NASON, J. M. (1995): “Effects of the Hodrick-Prescott filter on trend and difference stationary time series: implications for business cycle research”, Journal of Economic Dynamics and Control 19, 253-78.

Committee on Global Financial Stability (CGFS) (2012): “Operationalizing the selection and application of macroprudential instruments”, Report (restricted), October.

DELL'ARICCIA, G, IGAN, D., LAEVEN, L, TONG, H., BAKKER, B. and VANDENBUSSCHE, J. (2012): “Policies for Macrofinancial Stability: How to Deal with Credit Booms”, IMF Staff Notes, June.

DEMBIERMONT, C, DREHMANN, M. and MUKSAKUNRATANA, S. (2013): “How much does private sector really borrow – a new database for total credit to the private non-financial sector” BIS Quarterly Review, March.

DOORNIK, J.A (1999): “Ox: An Object-Oriented Matrix Programming Language”. Timberlake Consultants Press, London.

DREHMANN, M., BORIO, C., GAMBACORTA, L., JIMÉNEZ, TRUCHARTE, C. (2010): “Countercyclical capital buffers: exploring options”, *BIS Working Papers*, no 317.

DREHMANN, M., BORIO, C., and TSATSARONIS, K. (2011): “Anchoring countercyclical capital buffers: the role of credit aggregates”, *BIS Working Papers*, no 355.

DREHMANN, M., BORIO, C., and TSATSARONIS (2012), K: “Characterizing the financial cycle: don’t lose sight of the medium term!”, *BIS Working Papers*, no 380.

DURBIN, J. and KOOPMAN, S.J. (2002): “A simple and efficient simulation smoother”. Biometrika 89, 603-16.

GOLYANDINA, N., NEKRUTKIN, V. and ZHIGLJAVSKY, A. (2001): “Analysis of Time Series Structure: SSA and related techniques”, Chapman and Hall/CRC. ISBN 1584881941.

GOLYANDINA, N. and ZHIGLJAVSKY, A. (2013): “Singular Spectrum Analysis for time series”, Springer Briefs in Statistics. Springer.

GRANGER, C. W. J. and HATANAKA, M. (1964): “Spectral Analysis of Economic Time Series”, Princeton University Press, Princeton, New Jersey.

GRANGER, C. W. J. (1966): “The typical spectral shape of an economic variable”, Econometrica 34 (1), 150-161.

HAMILTON, J. D. (1994): “Time series analysis”, Princeton University Press, Princeton, New Jersey.

HARVEY, A. C. (1989): “Forecasting, Structural Time Series Models and the Kalman Filter”, Cambridge University Press, Cambridge.

HARVEY, A. C. and JAEGER, A. (1993): “Detrending, stylized facts and the business cycle”, Journal of Applied Econometrics 8, 231-247.

HARVEY, A. C. and TRIMBUR, T. (2003): “General model-based filters for extracting cycles and trends in economic time series”, Review of Economics and Statistics, 85, 244–255.

HARVEY, A. C., TRIMBUR, T. and VAN DIJK, H. (2007): “Trends and cycles in economic time series: A Bayesian approach”, Journal of Econometrics 140, 618-649.

HARVEY, A. C. and TRIMBUR, T. (2008): “Trend estimation and the Hodrick-Prescott filter”, J. Japan Statist. Soc., Vol. 38, No. 1, pp. 41-49.

HODRICK, R.J. and PRESCOTT, E.C. (1997): “Postwar US business cycles: an empirical investigation”, Journal of Money, Credit, and Banking, 29(1):1-16, 1997.

IACOBUCCI, A and NOULLEZ, A. (2004): “A Frequency selective filter for short-length time series”. In: Spectral Analysis for Economic Time Series. OFCE Special Edition.

KASS, R.E., RAFTERY, A. E. (1995): “Bayes Factors”. Journal of American Statistical Association, 90, 773-795.

KOOP, G., and VAN DIJK, H. (2000) "Testing for integration using evolving trend and seasonals models: A Bayesian approach." Journal of Econometrics, 97,Is,2,261-291.

KOOPMAN, S.J., SHEPARD, N. and DOORNIK, J. (2008): “Ssfpack 3.0: Statistical Algorithms for Models in State Space Form”. Timberlake Consultants Press.

KOOPMAN, S.J., HARVEY, A. C., DOORNIK, J. and SHEPARD, N. (2009a): “STAMP 8.2: Structural Time Series Analyser, Modeller and Predictor”, Timberlake Consultants Press..

KOOPMAN, S.J., OOMS, M. and HINDRAYANTO, I. (2009b): “Periodic Unobserved Cycles in Seasonal Time Series with an Application to U.S. Unemployment”, Oxford Bulletin of Economics and Statistics 2009, Volume 71, Pages 683-713.

LAEVEN, L. and VALENCIA, F (2008): “Systemic Banking Crisis: a New Database”. IMF Working Paper WP/08/224.

LEVY, D. and DEZHBAKHSH, H. (2003): “On the Typical Spectral Shape of an Economic Variable”, Applied Economics Letters, Vol. 10, No. 7, pp. 417-423.

LOWN, C. and MORGAN, D. (2006): “The credit cycle and the business cycle: new findings using loan officer opinion survey”, Journal of Money, Credit and Banking, 38(6), 1575-97.

MANN, M. E. and LEES, J. M. (1996): “Robust Estimation of Background Noise and Signal Detection in Climatic Time Series”, Climate Change, 33, 409-445.

MENDOZA, E. G. and TERRONES, M E (2008): “An anatomy of credit booms: evidence from macro aggregates and micro data”, IMF Working Paper WP/08/226.

MISE, E., KIM, TH. and NEWBOLD, P. (2005): “On sub optimality of the Hodrick-Prescott filter at time series endpoints”, Journal of Macroeconomics 27, pp.53-67.

NELSON, C. R. and KANG, H. (1981): "Spurious Periodicity in Inappropriately Detrended Time Series", Econometrica, Econometric Society, vol. 49(3), pages 741-51, May.

PERCIVAL, D.B. and WALDEN, A.T. (1993): “Spectral Analysis for Physical Applications: Multitaper and Conventional Univariate Techniques”. Cambridge University Press, Cambridge, UK.

PEREIRA DA SILVA, L.A. and HARRIS, R.E. (2012): “Sailing through the Global Financial Storm: Brazil's recent experience with monetary and macroprudential policies to lean against the financial cycle and deal with systemic risks”. Working Paper No. 290, Central Bank of Brazil (August 2012).

PRIESTLEY, M. B. (1981): “Spectral Analysis and Time Series”, Academic Press, London.

RAVN, M., and UHLIG, H. (2002): “On adjusting the HP-filter for the frequency of observations”. Review of Economics and Statistics, vol. 84 (2), pp 371–376.

REINHART, C. and ROGOFF, K. (2009): “This time is different: Eight centuries of financial folly, Princeton and Oxford. Princeton University Press.

ROY, R., and KAILATH, T. (1989): “ESPRIT: estimation of signal parameters via rotational invariance techniques”. IEEE Transactions on Acoustics, Speech, and Signal Processing, 37(7), 984–995. July.

SLEPIAN, D. (1978): “Prolate spheroidal wavefunctions, Fourier analysis, and uncertainty: the discrete case”. Bell System Tech. J., 57, 1371–1429.

THOMSON, D. J (1982): “Spectrum estimation and harmonic analysis”. Proceedings of the IEEE Volume 70, Number 9, pp. 1055–1096.

THOMSON, D.J. (1990): “Quadratic-inverse spectrum estimates: applications to Paleoclimatology”, Phys. Trans. R. Soc. London. 332, 539–597.

TRIMBUR, T. M. (2006): “Properties of higher order stochastic cycles”. Journal of Times Series Analysis 27(1), 1-17.

Appendix A – Singular Spectral Analysis (SSA)

Decomposition

Consider a real valued time series $F = (f_0, f_1, \ldots, f_{N-1})$ of length *N*. The first step on decomposition stage is the *embedding* procedure. It maps the original time series to a sequence of multidimensional lagged vectors in the following way: let *L* (*window length*) be an integer between 0 and *N*. The *embedding* procedure creates $K = N - L + 1$ *lagged vectors* $X_i = (f_{i-1}, f_i, \ldots, f_{i+L-2})^T, 1 \leq i \leq K$, and defines them as columns of the *L-trajectory matrix:*

$$\boldsymbol{X} = (x_{ij}) = \begin{pmatrix} f_0 & \cdots & f_{K-1} \\ \vdots & \ddots & \vdots \\ f_{L-1} & \cdots & f_{N-1} \end{pmatrix} \tag{A1}$$

Note that $x_{ij} = f_{i+j-2}$ so that the elements of each anti-diagonal are the same, that is to say that $\boldsymbol{X}$ is a *Hankel* matrix.

The next step on the decomposition stage is the singular value decomposition of the trajectory matrix $\boldsymbol{X}$. Let $\boldsymbol{S} = \boldsymbol{X}\boldsymbol{X}^{\boldsymbol{T}}$ and denote by $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_L \geq 0$ the eigenvalues of $\boldsymbol{S}$ taken in decreasing order and denote by $U_1, U_2, \ldots, U_L$ the corresponding system of orthonormal eigenvectors. Let $d = \max\{i; \lambda_i > 0\}$. Then, defining $V_i = \boldsymbol{X}^{\boldsymbol{T}} U_i / \sqrt{\boldsymbol{\lambda_i}}, 1 \leq i \leq d$, the singular value decomposition of $\boldsymbol{X}$ may be written as

$$\boldsymbol{X} = \boldsymbol{X_1} + \boldsymbol{X_2} + \cdots + \boldsymbol{X_d} \tag{A2}$$

where $\boldsymbol{X_i} = \sqrt{\lambda_i} U_i V_i^T$ and the collection $\left(\sqrt{\lambda_i}, U_i, V_i^T\right)$ is called the *i*th eigentriple of the decomposition.

Reconstruction

After the decomposition stage, we proceed to reconstruct the components of the time series. First, we group the components of the sum (A2) through a partition of the set of indices $\{1, \ldots, d\}$, composed by m disjoint subsets $I_1, \ldots, I_m$. Letting $I = \{i_1, \ldots, i_p\}$, the resultant matrix $\boldsymbol{X}_I = \boldsymbol{X}_{i_1} + \cdots + \boldsymbol{X}_{i_p}$ is the matrix corresponding to the grouping *I*. Computing this for each grouping $I_1, \ldots, I_m$ leads to the following decomposition of $\boldsymbol{X}$:

$$\boldsymbol{X} = \boldsymbol{X}_{I_1} + \boldsymbol{X}_{I_2} + \cdots + \boldsymbol{X}_{I_m} \tag{A3}$$

Finally, we transform this matrix decomposition into time series decomposition through the process of diagonal averaging. In other words, taking the averages of the anti-diagonals elements of each matrix to find the decomposition of the time series *F*. Doing this for each matrix in (A3) leads to the decomposition of the time series:

$$F = F_{I_1} + F_{I_2} + \cdots + F_{I_m} \tag{A4}$$

where $F_{I_k}$is the *k*-th component of (A3) diagonal averaged.

The process depends on the choice of two parameters: the window length *L* and the grouping $I_1, \ldots, I_m$. There are some principles for those choices, but there is not yet a fully satisfactory automated way to do it. Such principles lay over the concept of separability (see Golyandina et al. 2001 for details).

Appendix B – Raw and smoothed periodograms

The raw periodogram is defined as:

$$I_j = \frac{1}{4N}\left|\sum_{t=1}^{N} x_t e^{-i\lambda_j t}\right|^2 \tag{B1}$$

where x_t is the time series, N is the series length, $-\left\lfloor\frac{N-1}{2}\right\rfloor \leq j \leq \left\lfloor\frac{N}{2}\right\rfloor$, and $\lambda_j = \frac{4j}{N}$. We use a scale suitable for a quarterly sampled series, such that the period in years may be easily calculated as $T_j = \frac{1}{\lambda_j}$.

Tapering the series with a split cosine bell in 10% of the data at the beginning and the end is found to reduce *leakage*. Moreover, we pad the series with zeroes so that the length becomes the next integer number which can be obtained as a product of powers of 2, 3 and 5. Padding allows Fast Fourier transform to be computed quickly and it also improves the resolution of the spectrum, at the expense of lower stability of the spectral estimate. Finally, smoothing is done with a modified Daniell window of length 3. According to Bloomfield (2000), this suggested smoothing should be done because the raw periodogram is quite unstable (see Bloomfield (2000) for further information on these issues).

Periodicities extracted from smoothed periodograms may not be significant (at least for practical standards). To overcome this issue, we need a null hypothesis for spectral peaks. A common approach is the null continuum, e.g., the theoretical spectrum of an AR(2) – red noise – becomes the null. This null is well suited for our problem because economic series have strong autocorrelation and it is necessary to distinguish between peaks caused by real periodicities and those caused by the natural autocorrelation structure of the time series (Granger, 1966; Levy and Dezhbakhsh, 2003).

The confidence bands are computed considering that the periodogram estimates are independent and exponentially distributed. So, the spectral estimate using the Daniell window is approximately χ^2 distributed. The degrees of freedom are dependent of the *span* of the Daniell filter, as well as the process of padding and tapering (see Bloomfield (2000) for further details).

In Figures B1 and B2, we examine the residuals from trend extraction of UK broad credit series with the smoothed periodogram.

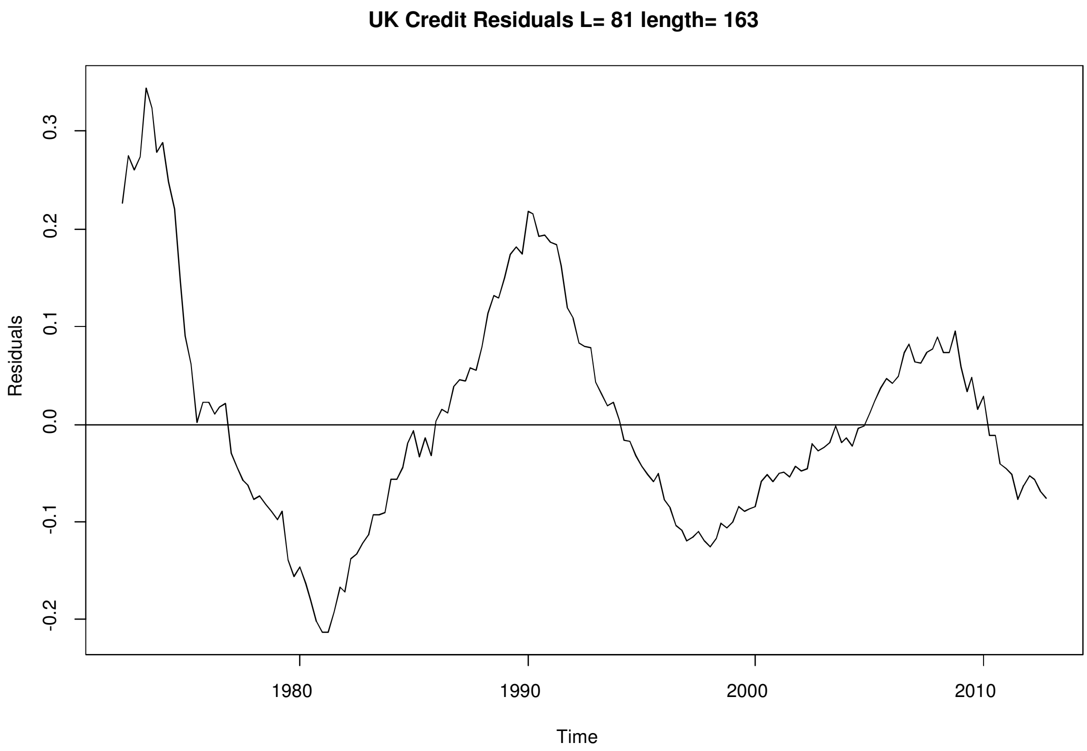

Figure B1: Residuals of trend extraction using SSA on UK broad credit series. The parameters are L=81 and grouping 1st and 4th eigentriples.

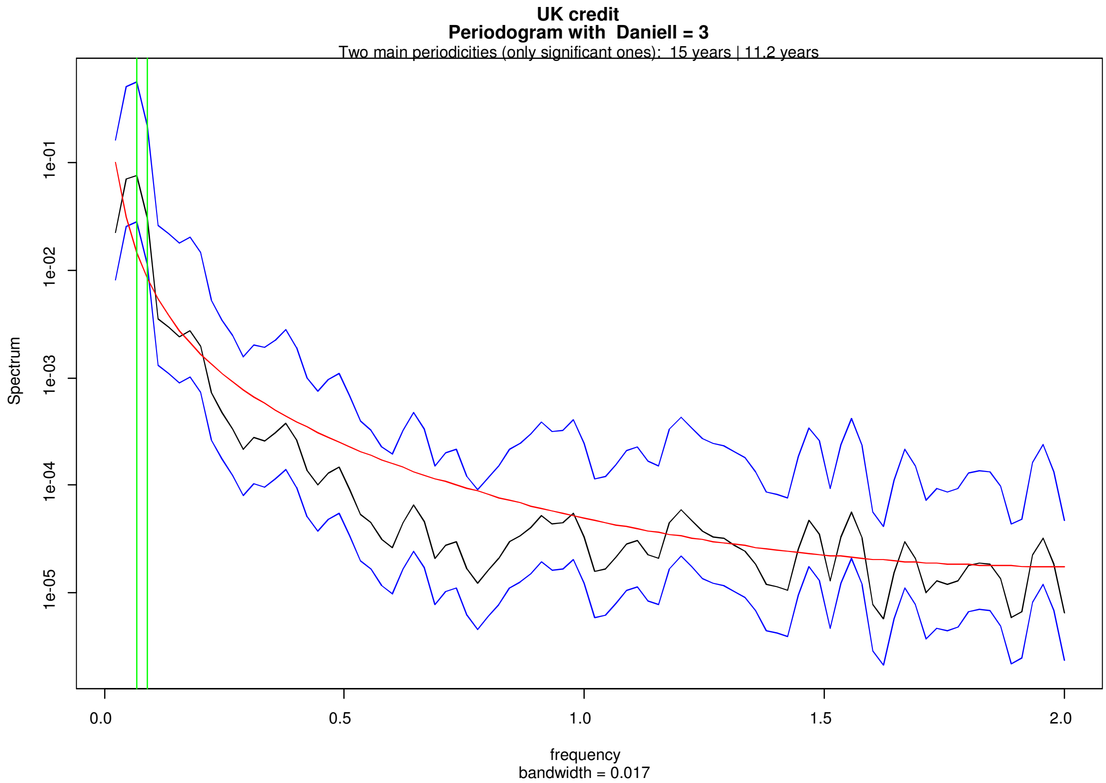

Figure B2: Smoothed periodogram of UK broad credit residuals. The red line is the AR(2) null continuum, the blue lines are 95% confidence bands and the green lines highlights the significant frequencies. The correspondent periods are 15 and 11.2 years. Note that those relatively different periods are neighbors, a consequence of the bad spectral resolution at low frequencies.

Observe that the lower (blue) band is exceeded by the null continuum, red curve, in the peaks corresponding to periodic components of 15 and 11.2 years for this series. Note that these are neighbor frequencies of the frequency domain. Therefore, probably there is a *leakage* effect affecting our results and the true periodicity lies somewhere between these figures. Leakage is a problem difficult to overcome in relatively short series, because the spectral resolution at low frequencies strongly depends on the series length. As a consequence, we present several results and point out a conservative domain for our estimates.

Appendix C – Multitapering Method (MTM)

The spectrum estimate based on a smoothed periodogram is criticized by Thomson (1982). He argues that, as (B1) is an inconsistent estimate of the spectrum, in the sense that its variance does not decrease with the sample size, the procedures of tapering, for bias control, and smoothing, for variance control, are necessary, but pose some problems for the estimates.

Tapering reduces bias, but reduces variance efficiency, while smoothing is unsatisfactory, unless there is reason to believe that the underlying spectrum is smooth. Further, as smoothing operates on raw spectrum estimates, phase information present in the original data is not used, which makes line detection less efficient.

We follow Thomson (1982) in an alternative multitapering method (MTM) with slightly different conventions. The time series is assumed to have length N and is represented by $\{x_t\}, t = 0, \dots, N-1$. The method is based on Cramér spectral theorem:

Theorem (Cramér): Let x_t be a second order stationary process with zero mean and spectral distribution function $F(f)$. Then,

$$x_t = \int_{-1/2}^{1/2} e^{2\pi i \nu t} dZ(\nu) \tag{C1}$$

for all t, where $dZ(f)$ is an orthogonal incremental process. Also, the random orthogonal measure has the following properties:

$$E[dZ(f)] = 0 \tag{C2}$$

$$dF(f) = S(f)df = E[|dZ(f)|^2] \tag{C3}$$

where $S(f)$ is defined as the spectral density function of the process.

In the theorem above, it is assumed a unity sampling rate for the process. Define the Fourier transform of the observations $\{x_t\}, t = 0, \dots, N-1$:

$$I(f) = \sum_{t=0}^{N-1} x_t e^{-2\pi i f t}, \quad -\frac{1}{2} \le f \le \frac{1}{2} \tag{C4}$$

Note that, since (C4) may be inverted to recover the data, no information is lost in the process and we may use interchangeably $\{x_t\}$ and $I(f)$ as data. Plugging (C1) into (C4) gives the basic integral equation (Thomson 1982, 1990):

$$I(f) = \int_{-1/2}^{1/2} \left\{ \frac{\sin[N\pi(f-\nu)]}{sin[\pi(f-\nu)]} e^{\pi i(f-\nu)(N-1)} \right\} dZ(\nu) \qquad \text{(C5)}$$

The figures in brackets are a modified Dirichlet kernel (see Thomson 1990; Percival and Walden 1993) and (C5) can be interpreted as a convolution describing the "smearing" or "frequency mixing" of the true $dZ(f)$ projected onto $I(f)$ due to the finite length of $\{x_t\}$. The main idea is view (C5) as an integral equation for $dZ(\nu)$ with the goal of obtaining approximate solutions whose statistical properties are close to those of $dZ(f)$.

As (C5) represents a projection of an infinite stationary process onto a finite sample, it does not have an inverse. The multitaper spectrum estimate is an approximate least-squares solution to (C5) that uses an eigenfunction expansion.

The approximate solution is achieved by eigenfunction expansion of $dZ(f)$ over a limited bandwidth. The expansion uses basis functions known as discrete prolate spheroidal wave functions, also known as Slepian functions. The Fourier Transform of these Slepian functions are known as discrete prolate spheroidal sequences (DPSS) or Slepian sequences (Thomson 1982 and Slepian 1978). Those sequences maximize spectral concentration over a given bandwidth *W*. Also, the DPSS are orthonormal in time domain and frequency domain, and in frequency domain the orthogonality holds in the whole and inner intervals (Slepian 1978). The estimation uses *K* Slepian sequences as tapers to obtain *k* components:

$$Y_k(f) = \sum_{t=0}^{N-1} x_t v_k(t) e^{-2\pi i f t} \qquad \text{(C6)}$$

So we obtain *K* spectral estimates:

$$\hat{S}_k(f) = |Y_k(f)|^2 \tag{C7}$$

Finally, calculate a weighted average spectrum to obtain the multitaper spectrum estimate:

$$\hat{S}(f) = \frac{\sum_{t=0}^{K} d_k^2 \hat{S}_k(f)}{\sum_{t=0}^{K} d_k^2} \tag{C8}$$

The weighting process is known as adaptive weighting and further details are available in Thomson (1982) and Percival and Walden (1993).

For calculation of the spectral estimate, it is necessary to determine the parameters W and K. We have chosen NW=4 (N is the length of the series) and K=8 for our estimations, which is a common practice in the literature.

There is also a test for line significance in this approach. It assumes a local continuous spectrum in each point and it estimates its variance. Comparing this estimation of background spectra with the power in the line component leads to an F variance-ratio test with 2 and 2K-2 degrees of freedom, known as harmonic F-test (Thomson 1982). We assume a confidence of 95% for line detection within this approach. As an example, see the graph below showing the F-test for United States credit-to-GDP gap spectrum.

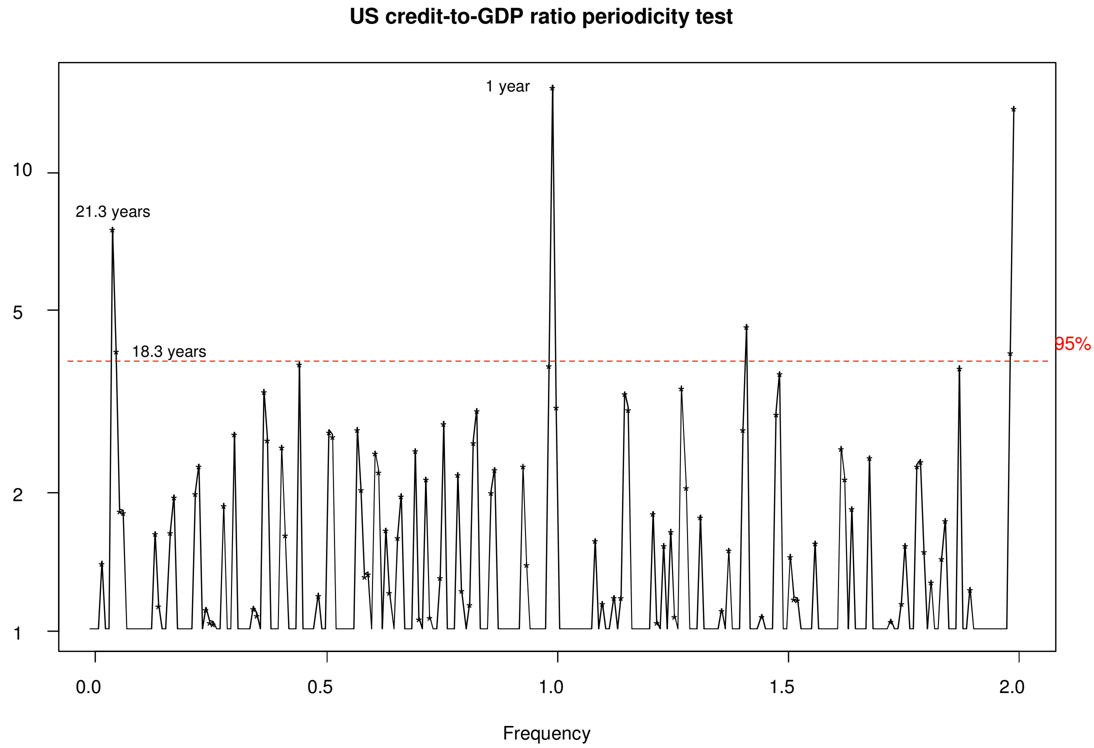

Figure C1: Harmonic F-test statistic for US credit-to-GDP ratio spectrum. Note the 21.3-18.3 years cycle, lying above the 95% confidence. This is a possible credit cycle. Also note the large peak at 1 year line. This is an obvious seasonal component.

The results for credit-to-GDP gap in the United States show significant periodicities at some points. We highlight 21.3 and 18.3 years lines as a possible credit cycles. Note that this kind of cycle is not exactly periodic and there are also leakage effects, so the resolution of the peak will not be perfect. Some remarks are also necessary: these peaks represent the *F* statistic value, so its height means statistical significance, not practical significance. For example, the 21.3 years peak has a spectral value much larger than the 1 year peak, meaning that its contribution for the variance of the series is more significant economically, despite its lower *F* value.

Appendix D – Tables SSA

Below we present the full results for financial cycle's length estimation. Tables D1 to D4 are organized as follows: above the thick black line are the parameters of SSA trend extraction (*L* and grouping) and the cycle's length estimated for each country using the smoothed periodogram and the MTM F-test for periodicities. We highlight with (*) the results for smoothed periodogram significant at 5% level against an AR(2) null continuum. All MTM F-test results showed are significant at 5% level against a local white noise (see Appendix C and Thomson (1982) for more details).

Below the thick black line are the sequential SSA parameters and ESPRIT results. If the sequential *L* is the same as the window length showed on second line, this means that we are actually using only Basic SSA, grouping additional eigentriples for periodicities detection with TLS-ESPRIT.

Credit/GDP gap	Brazil	Canada	France	Germany	Turkey	UK	US	Australia	Austria
Window length (L) no. of quarters	33	65	84	60	50	75	61	75	35
Trend Grouping	1, 2	1	1, 3	1	1	1	1	1	1
Smoothed Periodogram	6*	15	15*	18*	27	22.5	20.8*	18*	10*
	9	20	22.5	13.5*	13.5	15*	15.6*	27	12.5
F-test	8	16	18.3	16	16	21.3	21.3	21.3	10.7
	7.1	1.3	16	1	12.8	18.3	18.3	18.3	9.8
Sequential *L*	33	118	84	104	50	83	122	105	96
Residuals Grouping	3, 4, 5, 6	1, 2, 3, 4	2, 4, 5, 6	1, 2	2, 3	1, 2	1, 2	1, 2	1, 2
SSA - ESPRIT	9.4	15.4	9.2	17.5	17.6	18.2	17.9	19	10.3
	3.7	10.1	17.1	NA	NA	NA	NA	NA	NA

Table D1: Financial cycle periodicities estimated on credit/GDP gap.

Credit/GDP gap (cont.)	Belgium	South Africa	Indonesia	Italy	Japan	Netherlands	Norway	Spain	Sweden
Window length (L) no. of quarters	25	98	12	40	75	40	92	84	64
Trend Grouping	1	1, 2, 3	1	1	1, 2	1	1	1, 2, 3	1
Smoothed Periodogram	8.4*	16.7	3.4*	16.9	16.7	12	16	9*	16.9
	11.2	12.5	4.5	33.8	25	18	24	7.5*	11.2*
F-test	9.8	18.3	4	16	21.3	18.3	21.3	8.5	18.3
	9.1	16	3.6	14.2	18.3	11.6	18.3	8	16
Sequential *L*	64	98	26	64	95	70	92	84	64
Residuals Grouping	1, 2	4 a 14	1, 2	1, 2	1, 2	1, 2, 3, 4, 5, 6, 7, 8	2, 3, 4, 5	4, 5	2, 3, 4, 5
SSA - ESPRIT	9.5	9.4	4	15.8	19	3.8	10.8	8.8	9.5
	NA	19.8	NA	NA	NA	18.7	18.4	NA	19.1

Table D2: Continuation of table D1.

Credit/GDP gap (cont.)	**Czech Republic**	**Denmark**	**Finland**	**Hungary**	**Ireland**	**Korea**	**Mexico**	**Poland**	**Portugal**
Window length (L) no. of quarters	38	108	86	20	85	88	66	20	108
Trend Grouping	1, 2, 3	1	1, 2, 3	1, 2, 3	1, 2, 3	1, 2	1, 2, 3	1	1, 2, 3
Smoothed Periodogram	4	18*	11.2*	1.4*	9	11.2*	8.4*	0	13.5*
	2.9	27	9*	1.3	7.5	15	6.8*	0	10.8*
F-test	3.8	18.3	11.6	2.9	9.1	14.2	9.1	9.1	14.2
	0.8	1.9	10.7	2.8	8.5	12.8	8.5	8	12.8
Sequential *L*	38	128	86	20	85	88	66	20	108
Residuals Grouping	4, 5, 6, 7, 8, 9	2, 3, 4, 5, 6, 7	4, 5, 6, 7, 8, 9	4, 5, 6, 7	4, 5, 6, 7	3, 4	4, 5	2, 3	4, 5
SSA - ESPRIT	3.9	26.4	8.4	3.3	13.5	13.5	10	8	16.7
	1.9	10.7	12.7	1.4	4.2	NA	NA	NA	NA

Table D3: Continuation of table D1.

Credit/GDP gap (cont.)	**Switzerland**
Window length (L) no. of quarters	108
Trend Grouping	1, 2, 3
Smoothed Periodogram	10.8*
	9*
F-test	11.6
	10.7
Sequential *L*	108
Residuals Grouping	5 a 14
SSA - ESPRIT	11.3
	NA

Table D4: Continuation of table D1

Appendix E – Tables STM

Country	*Length*	*Zeta Var*	*Kappa Var*	*Eps var*	*Rho*	*Lambda*	*log m(Y)*	*Psi Var*	*Q ratio*	***HPD (10%)***	***Period***	***HPD (90%)***
Australia	217	19	341	286	0.57	0.3	628.406	1,603	0.01	3.72	5.68	7.95
Austria	105	40	46	1	0.73	0.479	383.939	1,870	0.23	2.46	3.56	5.09
Belgium	77	38	91	6	0.70	0.366	257.341	1,943	0.28	3.05	4.71	6.90
Brazil	73	51	731	223	0.51	0.368	175.416	2,889	0.03	2.95	4.75	7.12
Canada	213	36	268	60	0.59	0.293	679.484	1,619	0.04	3.79	5.83	8.13
Czech_Republic	73	255	80	23	0.54	0.36	216.448	2,367	2.79	2.96	4.86	7.32
Denmark	97	105	228	447	0.48	0.345	248.825	1,280	0.13	3.10	5.07	7.46
Finland	97	319	200	255	0.48	0.348	250.273	91,264	0.58	3.07	5.03	7.47
France	217	28	145	444	0.47	0.333	631.862	560	0.04	3.16	5.26	7.76
Germany	93	53	267	85	0.63	0.303	269.303	3,095	0.13	3.70	5.64	7.94
Hungary	77	189	153	36	0.59	0.364	223.621	2,017	0.93	2.99	4.80	7.23
Indonesia	97	460	983	303	0.54	0.346	218.347	6,737	0.25	3.05	5.06	7.49
Ireland	69	311	671	1364	0.33	0.369	134.832	111,126	0.14	2.86	4.79	7.32
Italy	133	47	114	59	0.64	0.31	434.088	1,454	0.18	3.60	5.52	7.77
Japan	81	77	515	139	0.57	0.342	209.316	3,324	0.08	3.16	5.09	7.46
Korea	177	47	962	368	0.64	0.297	441.227	7,792	0.01	3.82	5.71	8.01
Mexico	85	153	742	60	0.63	0.343	213.602	7,606	0.10	3.15	5.06	7.48
Netherlands	105	88	95	45	0.48	0.352	337.458	577	0.53	3.02	4.97	7.38
Norway	145	53	366	480	0.31	0.372	387.27	613	0.05	2.86	4.75	7.24
Poland	77	99	226	296	0.41	0.359	199.39	1,023	0.16	2.98	4.89	7.34
Portugal	77	95	190	121	0.45	0.357	215.334	852	0.25	3.01	4.91	7.38
South_Africa	217	36	165	265	0.70	0.282	643.84	2,671	0.04	3.95	6.00	8.16
Spain	77	64	10	11	0.54	0.352	276.404	807,160,000	2.43	3.08	4.95	7.28
Sweden	85	120	147	169	0.64	0.327	233.484	5,232	0.35	3.37	5.26	7.53
Switzerland	137	55	100	25	0.60	0.323	469.414	938	0.26	3.28	5.41	7.89
Turkey	65	702	1930	624	0.55	0.361	118.346	203,211	0.21	3.01	4.86	7.29
United_Kingdom	237	47	167	264	0.66	0.279	706.003	2,282	0.06	3.99	6.11	8.32
United_States	269	17	333	93	0.70	0.263	837.597	4,177	0.01	4.43	6.34	8.41

Cross-country Mean	**Min**	**Mean**	**Max**
	3.56	**5.17**	**6.34**
HPDs [0.1-0.9] Mean	**3.27**	**5.17**	**7.50**
HPDs [0.1-0.9] Median	3.09	5.06	7.47

Table E1. Business Cycles estimates, order 2, wide prior

Country	*Length*	*Zeta Var*	*Kappa Var*	*Eps var*	*Rho*	*Lambda*	*log m(Y)*	*Psi Var*	*Q ratio*	***HPD (10%)***	***Period***	***HPD (90%)***
Australia	216	156	976	240	0.49	0.198	556.963	3,793	0.06	3.96	13.00	28.42
Austria	216	67	599	511	0.50	0.173	566.845	6,857	0.04	4.36	14.88	30.92
Belgium	173	272	1528	975	0.55	0.187	374.919	10,600	0.06	4.15	13.83	30.20
Brazil	73	207	166	220	0.40	0.257	189.412	74,929	0.45	3.37	8.08	14.67
Canada	216	136	1627	412	0.64	0.138	514.532	19,081	0.02	5.84	16.73	32.14
Czech_Republic	76	345	1254	545	0.55	0.241	157.775	18,373	0.15	3.67	8.53	15.37
Denmark	216	406	2433	1215	0.55	0.178	438.511	15,072	0.05	4.41	14.08	30.17
Finland	173	866	3140	313	0.55	0.194	352.228	21,669	0.11	3.82	13.66	29.43
France	177	127	362	352	0.57	0.17	480.543	6,083	0.12	4.47	14.77	30.52
Germany	216	44	458	572	0.60	0.154	573.695	3,907	0.02	5.34	15.17	30.50
Hungary	76	2482	23499	6365	0.50	0.254	67.6696	108,466	0.05	3.45	8.20	14.91
Indonesia	56	151	252	301	0.41	0.274	133.125	16,695,600	0.24	3.34	7.07	11.80
Ireland	171	2302	3621	9516	0.49	0.198	222.023	351,430	0.13	3.86	13.43	29.77
Italy	216	100	517	1015	0.52	0.193	527.571	3,210	0.04	4.10	13.11	28.13
Japan	197	178	3188	520	0.43	0.19	415.066	7,995	0.03	4.11	13.34	28.16
Korea	176	463	2405	685	0.65	0.145	369.255	43,544	0.07	5.41	16.32	32.34
Mexico	133	126	54	75	0.45	0.212	429.753	759,790	0.75	3.70	11.56	23.94
Netherlands	212	109	1564	347	0.41	0.198	511.552	3,640	0.03	3.94	12.90	27.91
Norway	216	387	7845	507	0.55	0.171	382.433	38,104	0.02	4.62	14.43	29.92
Poland	76	415	914	156	0.56	0.241	174.642	13,662	0.30	3.57	8.65	15.52
Portugal	216	744	2096	2152	0.45	0.199	408.936	16,523	0.12	3.82	13.28	29.09
South_Africa	196	88	630	343	0.64	0.139	520.17	11,934	0.05	5.60	17.12	32.58
Spain	176	384	285	762	0.42	0.213	427.725	3,444,750	0.30	3.56	12.58	27.85
Sweden	212	798	1782	2478	0.67	0.15	393.895	88,692	0.12	5.18	15.89	31.62
Switzerland	216	129	1269	634	0.54	0.191	511.921	6,358	0.03	4.11	13.52	29.60
Turkey	105	145	1181	1013	0.41	0.224	226.241	4,736	0.05	3.65	10.15	20.05
United_Kingdom	204	396	1685	906	0.52	0.171	440.966	13,697	0.10	4.60	14.54	30.44
United_States	248	113	182	214	0.66	0.157	743.231	11,258	0.17	4.83	15.85	31.92

Cross-country Mean	**Min**	**Mean**	**Max**
	7.07	**13.02**	**17.12**
HPDs [0.1-0.9] Mean	**4.24**	**13.02**	**26.71**
HPDs [0.1-0.9] Median	**4.10**	**13.47**	**29.52**

Table E2. Financial Cycles estimates, order 2, wide prior