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Cyclicality in lending activity of Euro area in pre- and post- 2008 crisis: a local-adaptive-based testing of wavelets

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ABSTRACT
The paper deals with the identification of time-frequency regions describing cyclicality of bank loans before, during and after the 2008 crisis via wavelets. We bring new methods and findings about the short and medium cycles of loans provided to corporates and households in the Euro Area in 2000–2017 using seasonally unadjusted monthly data. We have recognized an impact of the crisis on data volatility which further influences the type of significance testing of wavelet spectrograms. To avoid this influence we propose: (1) an adaptive spectrogram testing based on Torrence and Compo approach and (2) robustness analysis via enhanced spectrogram modelling tested by the MC simulations. Both cross-checked approaches prove the sensitivity of standard wavelet tests on data volatility. The results confirm the usability of the new approaches and show that the crisis in 2008 influenced the cyclical behaviour of both categories of economic sectors, but in a different way.

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1. Introduction

The banking sector plays a special role in the monetary transmission mechanism and produces waves of cyclical behaviour with a strong propagation in the real economic sector. Bernanke and Gertler (1989) discuss the idea that economic booms improve the borrowers' balance sheets and net worth and support the lending activities of banks and thus spending, investment and as such the output of the growing economy. On the other hand, recessions bring the opposite transmission with a negative impact on the economy in distress. Discussions about fluctuations in lending activity and factors causing these fluctuations have been quite frequent since the financial crisis of 2007 and 2008 during which the world economy faced a drastic drop in the lending activity, particularly in the case of large loans (most of which are syndicated loans). The drop was caused by a worsened access of banks to deposit financing, as documented by Ivashina and Scharfstein (2010).

It is a well-known fact that banks tend to behave pro-cyclically and reinforce the credit and economic cycle, i.e. they lose their credit underwriting practices and massively provide loans in the period of economic growth and severely tie the practices and limit their

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lending activities just before and in crisis times. The extreme case when banks limit providing loans is called a credit crunch. Also, in times of globally integrated financial markets, a negative economic shock can be very quickly transmitted to other countries and may produce negative spill-over effects and a financial crisis in the world economy. Therefore, the analysis, identification and recognition of cyclical behaviour and changes in lending activity in the economy are in the forefront of economic research and policy makers can thus adjust policy measures not only to economic cycles but also to credit cycles. This can reveal how quick and flexible short-, medium- and long-term reactions of banks and economic sectors to a shock in the economy can be. In our paper, we do not study factors influencing the behaviour of banks (i.e. supply and demand factors). We focus on the development of methods which could give us an information about the time and the frequency behaviour of the selected economic time series representing the volume of loans provided to basic economic sectors.

In this context, such fluctuations in lending activity can be generally defined as credit cycles, or more generally as financial cycles. However, financial cycles have not been satisfactorily defined and identified in empirical research so far. Borio (2014) states that it is possible to describe the financial cycle using quantity (the volume of credit) and price (residential property prices, equity prices, risk premia etc.) variables. According to Drehmann, Borio, and Tsatsaronis (2012), the character of a financial cycle has changed since the early 1980s and was caused particularly by financial liberalization and less strict monetary policy after leaving Keynesian stop-go macroeconomic policy. While financial cycles have an impact on economic cycles (see Claessens, Kose, & Terrones, 2012), traditional macroeconomic policy is not able to address them.

As pointed out by Aquiar-Conraria and Soares (2014), '*economic time series are an aggregation of components operating on different* frequencies'. Galati, Hindrayanto, Koopman, and Vlekke (2016, p. 5) wrote and proved that as for the financial cycle, '*there is not consensus in the literature on which variables to include in the analysis*'. Further, as documented by Kunovac, Mandler, and Scharnagl (2018, p. 16) wavelets allow to '*distinguish the case that a series is the sum of several cycles at different frequencies from the case that the series is characterized by structural changes*'. The time-frequency (TF) modelling allows the investigation of the spectral character of time series with respect to time. In this way, we can analyze how various cyclical components, i.e. long, medium and short cycles, as well as seasonal component (a very short cycles), of a particular time series evolve through the time (Aloui, Hkiri, & Nguyen, 2016).

The early methodology of financial cycle analyses contains filtering and decomposition methods from the simplest to more advanced, turning point analysis, and the combination of both. Consequent approaches include frequency domain methods for an identification of hidden cyclical components. One group of researchers who used the early methods states that financial cycles are longer than business cycles (Drehman et al., 2012; Claessens et al., 2012; Aikman, Haldane, & Nelson, 2014). Talks about 5–20 years with a cross-country median around 15 years. Contrary to this group of researchers, another group proved that in a certain small group of countries (Germany, the Czech Republic, Hungary or the Netherlands), there are shorter financial cycles which are close to the business cycle frequencies (Galati et al., 2016; Gonzalez, Lima, & Marinho, 2015; Rünstler & Vlekke, 2018). The third group of researchers make their findings more general (Galati et al., 2016; Hiebert, Klaus, Peltonen, Schüler, & Welz, 2014; Rünstler et al., 2018) as they see the variation of the financial cycles' length at the country level which reflects heterogeneity between countries. Hiebert et al. (2014) point out the facts that financial cycles tend to differ from the business cycle counterparts, and that the identified length of financial cycles differs according to the definition of financial cycles which is given by the used methodology.

The last current group of scientists provide more complex results related to cyclical properties of time series by investigating the issues by early methods as well as by the use of wavelets. Altar, Kubinschi, and Barnea (2017) measure the financial cycle length using quarterly data via wavelets in the case of developed and emerging economies. Their results show that in developed countries financial cycles are longer than business cycles. Verona (2016) uses power wavelet spectrum (PWCS) to estimate three types of time series, i.e. three types of quarterly data, and identifies several cyclical regions across all frequency range. Similarly, Rünstler et al. (2018) use PWCS on several type of quarterly data for European countries and also identify a wide range of time-frequency regions differing across countries and indicators. Their findings, using wavelets, confirm the statements of Aquiar-Conraria and Soares (2014) and Kunovac et al. (2018), and the conclusion of Hiebert et al. (2014).

Applications of TF analyses, where wavelets belong, have been so far limited by the fact that it was impossible to draw any implications on the statistical significance. The original contribution in the spectrogram testing was provided by Torrence and Compo (1998) (TC98), followed by Ge (2007, 2013) (Ge07). Both TC98 and Ge07 assume the fixed variance during all-time range of data. We use a modified form of this test considering that the variance in time series may vary for a certain sub-period, even for a short duration. Then strong events, such as the 2008 crisis, may cause a change in the data volatility. This may suppress the significance of other events which have a lower level of the data volatility and thus may suppress the importance of other cyclicality behaviour in a specified time range. If there are no changes in the data variance, both (standard and modified) forms of the test produce the same results.

The paper deals with the identification of the time-frequency regions describing cyclical behaviour of the bank loans with a special attention to the pre-, post- and 2008 crisis. The paper focuses on evaluating how the specific shock, i.e. the financial crisis in 2007 and 2008, could affects the cyclical behaviour of given indicators. We found an important impact of the crisis on data volatility which may further influence the significance of wavelet spectrograms estimates. Therefore, keeping in mind this volatility influence, we propose: (i) testing of wavelet spectrogram via standard Ge07 test and its robustness check via Monte Carlo (MC) simulation; (ii) testing of wavelet spectrogram via modified form of Ge07 called local-adaptive-based testing; and (iii) robustness analysis of wavelet testing via enhanced spectrogram modelling also tested by the MC simulations. We show that Continuous Wavelet Transform (CWT), i.e. wavelet spectrogram, compared to the Short-Term Fourier Transform (STFT), i.e. STFT spectrogram, is much more influenced by the data volatility during the standard Ge07 testing. To demonstrate the newly proposed method, we use the monthly data of bank loans provided to corporates and households in the Euro Area in 2000–2017.

Presented paper investigates an application of proposed methods only on unadjusted monthly data. Therefore, the results obtained via presented methodology is interpreted from the cyclical point of view where the seasonal component (i.e. very short cycles) is taken as a part of cyclical behaviour.

While many authors focus on the medium and long cycles of selected price- and volume-based measures of financial or credit cycles and use quarterly data, we bring new methods and findings about the short and medium cycles of loans provided to corporates and households in the Euro Area in 2000–2017. By using seasonally unadjusted monthly data, we were able to identify time-frequency regions for higher frequencies. Moreover, we distinguish between the sector of corporates and households as the lending activity is motivated by different factors. Borio (2014) calls for new modelling strategies and adequate reactions of macroeconomic policies to the changes of financial cycles. Alcidi (2017) emphasizes the role of empirical research for the purpose of describing the features of financial cycles and designing macro-prudential policies. In this way, we propose a method of identifying mostly short and medium lending cycles of corporates and households, which is quite important for prompt reactions of policy makers and proper implementation of economic policies.

We aim to answer, by applying the cross-checked approaches (i–iii) described above, the following economic questions: Did the shock, represented by the financial crisis of 2007 and 2008, influence the cyclical behaviour of lending activity in the Euro Area and if so in which lengths of the cycles (i.e. in which frequencies) were the reactions the strongest? Was the character of the cyclical behaviour different before, during and after the crisis? Are there any differences in the character of cyclicality in the two analyzed sectors? Does our approach bring new possibilities for modelling strategies of policy makers? The results confirm the usability of the newly proposed approaches in our case (the research was conducted only on seasonally unadjusted data), particularly in the short cycles and show that the crisis in 2008 had an important impact on the cyclical behaviour of corporates and households, but in a different way. Moreover, the most remarkable influence of the crisis on the cyclicality was identified in the case of households.

The paper is organized as follows: Section 2 provides a literature review. Section 3 presents the methodology of the testing approaches and the enhanced spectrogram modelling. Section 4 describes the data and the settings of the TF methods. Section 5 presents the obtained results via CWT and STFT tested by Ge07. Section 6 describes the obtained results via an alternative form of spectrogram modelling and testing. Section 7 discusses the results from the economic and methodology point of view. Section 8 concludes the paper.

2. Literature review

The cyclical behaviour of lending activity has been analyzed in a wide range of empirical studies. In their paper, Bernanke and Gertler (1989) study the credit channel of monetary transmission and state that the demand side (i.e. the demand for credit) influences the lending activity and creates lending fluctuations. Asea and Blomberg (1998) study the relationship between the bank lending activity and unemployment in the USA using a wide dataset of provided loans in 1977–93 and they conclude that banks change their credit underwriting practices over the economic cycle and as such, this behaviour has a strong impact on economic fluctuations. Bassett, Chosak, Driscoll, and Zakrajšek (2014) study the role of bank lending standards in the US economy in 1991–2012 and identify a negative impact of tight lending standards on the credit availability and thus on the output of the economy.

Some authors try to identify factors which have an impact on the behaviour of banks. Berger and Udell (2004) formulate the institutional memory hypothesis using data from the US banks in 1980–2000. The hypothesis assumes that bank officers tend to ease lending standards during the era of economic growth as they forget about the crisis times connected with the deterioration of the quality of bank loans. The authors confirm the existence of pro-cyclical lending behaviour of banks for both the analyzed time period and all groups of a bank size. Bouvatier and Lepetit (2008) examine the impact of loan loss provisions on the changes in the lending behaviour of European banks for the period 1992–2004, i.e. before the financial crisis, and find out that banks with a low level of capital reserves tend to impose constraints on their lending activity during crisis times as they did not create a capital buffer for these times. Using the data for G7 countries in 1988–2009, Helbling, Huidrom, Kose, and Otrok (2011) assess to what extent credit markets can influence global economic fluctuations. In the first step, they try to identify a common component in the analyzed macroeconomic variables. Then, they estimate the impact of credit markets on these variables and confirm that credit shocks have a significant effect on these variables.

The impact of bank activities on the real economy is connected to the particular type of financial system. In market economies, banking institutions (in a bank-based financial system) and financial markets (in a market-based financial system) are considered to be the most important sources of liquidity. Particularly in the Euro Area, banks play a significant role as a financial intermediator and a source of funding for economic agents because there exists a traditional bank-based financial system. When this source of liquidity dries up, nonfinancial firms must enter capital markets (see e.g. Kaya & Wang, 2016). Moreover, the reaction of bank-based economies to shocks or economic crises is longer and less flexible, as Gambacorta, Yang, and Tsatsaronis (2014), Mavrotas and Vinogradov (2007) or Allard and Blavy (2011) argue.

The procyclical behaviour of bank lending activities was confirmed in many studies (Bassett et al., 2014; Becker & Ivashina, 2014; Drehmann et al., 2012; Helbling et al., 2011; Ivashina & Scharfstein, 2010; Kaya & Wang, 2016, etc.). Because of the limited credit supply or even a credit crunch during the times of economic crisis, businesses start to look for new funding sources (Becker & Ivashina, 2014). Becker and Ivashina (2014) use firm-level data of US nonfinancial firms for a long period of 1953–2013 and find out that businesses can substitute loans and bonds, and conclude that this substitution is the strongest during the period of tightened lending standards and limited supply of loans, i.e. during the times of economic recession. The same effect is verified by Kaya and Wang (2016) who test Eurozone nonfinancial firms in the period 2003–2013; the effect is the strongest in the case of the core Eurozone countries with developed capital markets. As the literature review shows, bank loans can amplify credit fluctuations in the economy and thus exacerbate the economic cycle.

The evolution of methodological approaches analysing credit and financial cycles and its characteristics reflects the development of business cycle[1] analysis. As many authors agree (Hiebert et al., 2014; Rünstler et al., 2018; Verona, 2016), the literature on financial cycle analysis remains nascent. The methodological approaches started with (i) time domain analysis of turning points identification (Claessens et al., 2012) and was followed by (ii) detrending via frequency-based filtering (Drehmann et al., 2012; Aikman et al., 2014). Several authors use more sophisticated models such as unobserved component models

(Rünstler et al., 2018) or structural models (Galati et al., 2016; Gonzalez et al., 2015). The next step was (iii) the application of frequency domain methods which allows the identification of spectral components, i.e. periodicities hidden in the data. Currently, (iv) the time-frequency methods, especially wavelets (Kunovac et al., 2018; Rünstler et al., 2018; Verona, 2016), which combine both time and frequency points of view and allow us to describe the cyclical behaviour of data with respect to the time, are at the forefront of methodological approaches.

The methods of identification of turning points, mostly based on Bry-Boschan or a similar algorithm, describe the cyclical character of data via calculating the distance between two peaks (local maxima) of an unobserved time series however, the methods suffer from the fact that the data may consist of several cyclical components, i.e. hidden periodic component. This insufficiency was partially solved by applying detrending methods such as frequency-based filters (high-pass or band-pass filters) (Drehmann et al., 2012) which allow the selection of pre-defined frequency range from the data, or multivariate model-based filters (Galati et al., 2016; Rünstler et al., 2018). Some authors (Drehmann et al., 2012; Galati et al., 2016; Hiebert et al., 2014) combine both filtering and dating approaches to improve the achieved results and bring more robust conclusions. Gonzalez et al. (2015) use alternative methods, i.e. the combination of Bayesian model and singular decomposition followed by Fourier spectral analysis.

An extension of the frequency domain methods is allowed by the identification of spectral components, i.e. periodicities hidden in the data. Both approaches (detrending/filtering and dating) fight the problems concerning statistical character, e.g. resulting from assumptions for dating methods application (sensitivity for trend extraction), or expected frequency range for the financial cycles filtering (no consensus for frequency range of financial cycles), or application of filtering methods themselves (ideal filter approximation, edge effect problem) (Drehmann, 2012; Galati et al., 2016; Gonzalez et al., 2015; Hiebert et al., 2014; Rünstler et al., 2018). Even if the frequency techniques highlight the cyclical behaviour of data, they, unfortunately, are not able to describe the temporal character of identified cyclical behaviour.

An alternative approach is the time-frequency methods, especially wavelets, which become a current method for the financial cycles analysis. The well-known TF methods include Short-Term Fourier Transform (Gröchenig, 2013), or Time-Frequency Autoregressive Process (TFAR) (Box, Jenkins, Reinsel, & Ljung, 2015). While turning point approaches require pre-specified rules or mathematical apparatus to identify the local extrema of time series, even if the frequency domain techniques have no prior assumptions for the financial cycles frequency range, their combination does not bring information of the time localization of the frequency. This can be easily proposed by the wavelets (Verona, 2016). As Aquiar-Conraria and Soares (2014) write, contrary to the time representation of time series, wavelets map the original time series as a function of time and frequency revealing how each periodic component of the time series changes over time. As we can study in Yogo (2008), Crowley (2005) or Conway and Frame (2000), the wavelet analysis allows a decomposition of even non-stationary economic time series into different frequencies which, after the summation, constitute the original series. Via this approach, we can assess the relative importance of a different frequency component trough time and see how such relationship changes over the time, which makes wavelets a very useful tool for analysing financial cycles. As many researchers agree, the main advantages of wavelets are their applicability on non-stationary time series, flexible settings of parameters reflecting data character, ability to uncover unique complicated patterns over the time and good time resolution (Aloui et al., 2016; Aquiar-Conraria & Soares, 2014; Berdiev & Chang, 2015; Fidrmuc, Korhonen, & Poměnková, 2014; Ftiti, Tiwari, Belanès, & Guesmi, 2014; Crowley, 2005; Tiwari, Mutascu, & Albulescu, 2016, etc.). Therefore, it is worth investigating their use in financial cycle analyses.

3. Methodology

We use CWT, TFAR, STFT (Proakis et al., 2002) for the TF modelling of input time series. Since these techniques are well known, we will not provide their description. For the significance testing of TF transform, we use the standard test according to TC98 (Torrence & Compo, 1998) improved by Ge07 (Ge, 2007, 2013). Additionally, we propose a local-adaptive-based testing for the cases when the variance in the time domain may vary over the time. For the robustness check of Ge07 on the CWT and STFT results, we use Monte Carlo simulations and local-adaptive-based testing. For the cross-check of previous results we propose the robustness enhanced spectrogram modelling tested for its robustness by MC simulations.

3.1. Standard testing

The standard significance test for the wavelet power spectrum (PWS) with the Morlet wavelet (and complex Morlet wavelet) is proposed by TC98. Ge07 showed that TC98 results are numerically accurate when adjusted by the factor of the sampling period. This testing statistic is for the wavelet spectrogram coefficients $W_n(a)$ (with use of complex Morlet wavelet) with respect to the Gaussian White Noise (GWN) type of the background noise

$$\frac{|W_n(a)|^2}{\sigma^2} \sim \frac{1}{2}\chi_2^2 \tag{1}$$

at each time n, for the variance σ^2 of the time series $s(n)$ and scales a is χ_2^2 distributed with two degrees of freedom. For the Fourier power spectrum, the testing statistic and its distribution for spectrogram coefficients $S_{FT}(f)$ is

$$\frac{N|S_{FT}(f)|^2}{2\sigma^2} \sim \frac{1}{2}\chi_2^2 \tag{2}$$

where N is the number of points, σ^2 is the variance of the time series $s(n)$. This testing statistic is distributed as χ_2^2 distribution with two degrees of freedom. Thus, we can assume that the feature with the confidence of a certain percentage can be taken as true when the peak in the power spectrum is significantly above the background noise spectrum (in our case GWN).

3.2. Local-adaptive-based testing (LAB)

Both testing statistics presented in Equations (1) and (2) are formed as the power value of the spectrogram of a noise signal normalized by the signal variance in the time domain. In the case of an input signal with strongly localized fluctuations of the signal strength, the total variance may not sufficiently describe the character of the data. It is, therefore, not surprising that events, such as the 2008 crisis, may have a strong impact causing a suppression of other events. To avoid this problem, we propose an adaptive form of Ge07 testing named a local-adaptive-based testing (LAB). In the case when the data does not have this problem, the Ge07 and LAB testing produce the same results.

The LAB testing is based on the evaluation of significance via Ge07 in each time n with respect to the sliding window l. Let us have the time series s(n), $n = 1, \ldots, N$ and set up the time window length l, l is an odd number. The vector of local variances $\sigma_n^2,\ n = 1,\ \ldots, N$ of the same length as the time series s(n) is calculated on the sliding window l with the sliding one step ahead (Figure 1). In the border regions, the edge effect may occur, caused by a limited number of observations available for the calculations. In these cases, we use the first and the last l observations of the $s(n)$ for border variances σ_n^2 calculation. In the middle region, we use l observations of the $s(n)$. Then we use this vector for thresholds calculation

$$\frac{|W_n(a)|^2}{\sigma_n^2} \sim \frac{1}{2}\chi_2^2 \tag{3}$$

The localization allows us to assess the spectral components with reference to its surrounding events. The range/scope of these events is selected by the length l of the sliding window. To set an appropriate time window length, we must take into account the requirement for at least 35 points (approx. 3 years for monthly data) to ensure that the local variances have a descriptive character. To maintain sufficient adaptability to rapid signal fluctuations, we set the window length to $l = 49$ (i.e. approx. 4 years window).

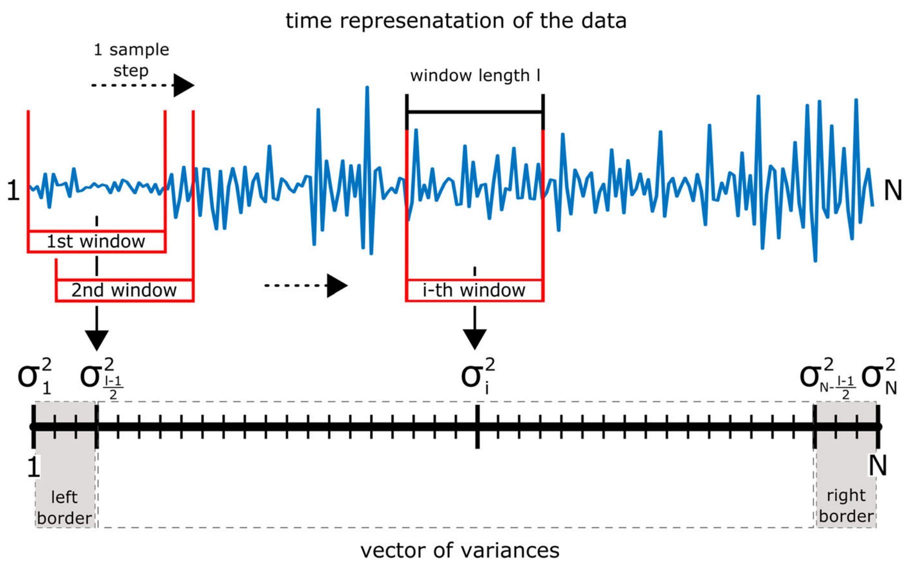

Figure 1. LAB testing diagram.

3.3. An enhanced spectrogram modelling

For the significance testing on the basis of TC98 and Ge07, we have to know the character of background noise. When analysing economic indicators, we can assume that the background noise is GWN. In some cases (the application of pre-filtering, heteroscedasticity in the data etc.) this assumption need not to be satisfied. To avoid such a case, we suggest the combination of several TF approaches and in the following we call the resultant TF transform 'enhanced'. The enhanced transform is a display of the CWT, TFAR and STFT spectrograms of one-time series in one chart for obtaining the best possible TF representation. We investigate mainly the amplitude part of the spectra. The phase part of complex spectra S_{CWT} and S_{STFT} is not investigated.

Firstly, we align the time axis of all obtained spectra S_{CWT}, S_{AR} and S_{STFT} to match each other. Since all three time vectors are linearly increasing, it is sufficient to adjust the starting and ending point for each method. We omit the first and the last 15 columns of S_{CWT}, we denote the remaining matrix as S'_{CWT}. Hereby we ensure the correspondence of the time axes for all three methods since S_{AR} and S_{STFT} use a window function leading to the shrinkage in the time dimension. Secondly, we align the frequency/scale axis of S'_{CWT}, S_{AR} and S_{STFT}. The frequency range of S_{AR} and S_{STFT} is cropped to correspond with the range of S'_{CWT}, which was 6–192 months (0.5–16 years) cycles. The resulting frequency cycles vectors $\overline{f_{AR}}$ and $\overline{f_{FT}}$ have a linearly increasing trend, however, the trend of $\overline{f_{CWT}}$ is non-linear. To obtain the corresponding vectors we match each point of $\overline{f_{CWT}}$ with one value of $\overline{f_{AR}}/\overline{f_{STFT}}$ with 1.4% tolerance:

$$|f_{CWT} - f_{STFT}| \leq 0.014 \max\left(\overline{f_{CWT}};\ \overline{f_{STFT}}\right), \quad |f_{CWT} - f_{AR}| \leq 0.014 \max\left(\overline{f_{CWT}};\ \overline{f_{AR}}\right) \tag{4}$$

With this step, we obtain the adjusted TF matrices S'_{AR} and S'_{FT} by making all three methods aligned. The combination of methods is done by a simple multiplication (Klejmova & Pomenkova, 2017) and is called the 'enhanced TF picture'

$$S_{TF} \leq S'_{CWT} S'_{AR} S'_{STFT}. \tag{5}$$

3.4. Monte Carlo (MC) simulations

The MC simulations are used to model the probability of different outcomes. This idea is based on the repetition of a process. In each iteration, random samples are selected from the input probability distribution. The results from these inputs are recorded and the process is repeated numerous (hundreds, thousands) times. Because of the law of large numbers, we can identify an empirical distribution close to the probabilistic distribution and identify empirical statistics, such as quantile or percentile. MC simulation can be summarized into following steps (Robert & Casella, 2004): (i) the definition of the model to be simulated, (ii) generating random values of predefined distribution, (iii) the calculation of model for each iteration, (iv) analysis of results, quantiles identification. In our case:

(1) GWN with variance corresponding to the data series
(2) 1000 realizations of GWN time series with the corresponding length

(3) Corresponding CWT, STFT and TFAR transformation
(4) Calculation of 95% quantile

4. Application

4.1. Data

In order to identify the cyclical behaviour of financial data, we use the seasonally unadjusted real monthly data of bank loans provided to corporates (Corporates) and households (Households) in the Euro Area in 2000/M1–2017/M05 (Millions of Euros) (ECB, 2017). To be more precise, we focus on the credit cycle as we use the level of provided credit as one possible approach of how to measure the financial cycle, i.e. we use a quantity-based measure and not a price-based measure of the cycle. As proved by relevant empirical studies, the chosen methodology is applicable to our date range (see Aloui et al., 2016; Altar et al., 2017; Berdiev & Chang, 2015; Fidrmuc et al., 2014; Ftiti et al., 2014; Galati et al., 2016 or Kunovac et al., 2018). From the first overview of an input time series in Figure 2a–b, we can see that the time series of Households and Corporates contain a long-term trend which goes through visible expansion and recession phases. In both cases, we can see several structural breaks.

In our analyses we use seasonally unadjusted data, because the aim of the paper is focused on the cyclical behaviour of financial data (lending activities) where the seasonal component is taken as part of cyclical behaviour. The information about cyclical character containing seasonal behaviour is valuable, because the analysis of unadjusted data: (i) better reflects the real behaviour of subjects (households and corporates) which can be influenced by seasonality; (ii) it can bring more valuable information to policy makers than adjusted data: they can react better to prevent disruptions of the economic cycle because of seasonality or they can reduce its possible negative effect. The use of adjusted time series may lead to losing some information, which could reduce the efficiency of monetary policy and limit the achievement of the objectives.

There are also methodological aspects (Astolfi et al., 2018) to use unadjusted data: (i) the seasonal component is not independent from the cyclical component and can change in time; (ii) '*the evaluation of the seasonal component provided by an adjustment method is hampered by the fact that the true seasonal component remains a theoretical and imprecise concept, never liable to direct observation*'; (iii) '*the objectives of seasonal adjustment appear multiple and implicit. Is it to obtain the best estimate of the trend-cycle*

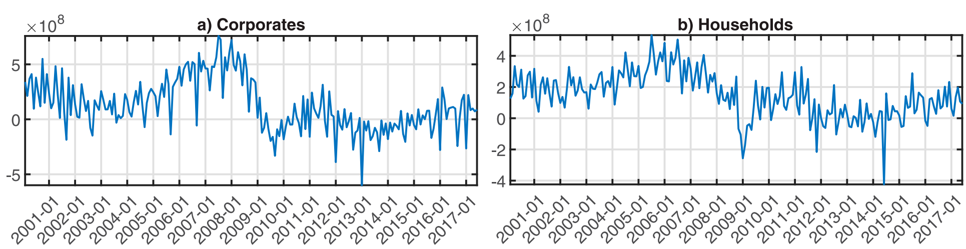

Figure 2. a–b. Input data for Euro area. Source: ECB (2017).

component, the best estimate of the seasonal component itself? Each objective will generate its own quality criteria'; (iv) '*the expected content of a quality report usually differs according to the user*'. That is, the different adjusting method can produce different adjusted time series which can adjust more or less than a seasonal component and that seasonal and other cyclical components can interact.

Generally, in the case of monthly data we can expect that the seasonal component will range in frequencies up to 12 months. With respect to the ability of wavelets to model the time-frequency behaviour of the time series, we can consider that the wavelet spectrogram in the range of 2–12 month length cycles (in our paper short-run cycles) can contains in the case of seasonally unadjusted time series seasonal and some cyclical component. Our complementary analysis confirm an interaction of both cyclical components in the frequency range 6–12 month in our figures and that the seasonal component changes during time. This fact will be kept on mind during interpretation of the results.

Therefore, because we aim to identify the time-frequency regions describing mainly short- and medium-term cyclicality of bank loans before, during and after the financial crisis in 2008 and with respect to the ability of wavelets to model time-frequency character of the data it is worth to leave from economic as well as methodology point of view seasonal effect in the data.

4.2. Settings of TF methods

In the case of the TF estimation via the TFAR, we use the Burg approach for coefficient estimates on 40 samples with 39 samples overlay, and the Hann window. The optimal value of the lag order is based on AIC criteria. The parameters of the STFT are set to correspond to the TFAR settings (40 samples, 39 samples overlay, Hann window) to simplify the process of the methods combination.

For the CWT transform calculation, we set the scales corresponding to the range of half a year to 16 years, with 388 individual scales. We select the complex Morlet wavelet with the centre frequency $f_b = 1.5$. That is, for the time vector with $N = 209$ samples $t = 2000/M1 - 2017/M5$, we set the vector of the period T to be equidistantly distributed between maximal ($T_{\max}$) and minimal ($T_{\min}$) length of the period $T_{\max} = 16$ years (192 months), $T_{\min} = 0.5$ years (6 months) corresponding to the vector of frequency f with minimum and maximum of:

$$f_{\min} = 1/T_{\max} = 0.0625\,\text{year}^{-1}, \quad f_{\max} = 1/T_{\min} = 2\,\text{year}^{-1}. \tag{6}$$

For the number of scales 388, we can set the vector of scales s

$$s = \frac{f_b}{f\,\delta_t}; \quad s_{\min} = \frac{f_b}{f_{\max}\,\delta_t} = 9, \quad s_{\max} = \frac{f_b}{f_{\min}\,\delta_t} = 288, \tag{7}$$

for $f_b = 1.5$ and $\delta_t = 1/Fs = 1/12$ (for monthly data).

In the case of the TF estimation via the TFAR, we use the Burg approach for coefficient estimates on 40 samples with 39 samples overlay, and the Hann window. The optimal value of the lag order is based on AIC criteria. The parameters of the STFT are set to correspond to the TFAR settings (40 samples, 39 samples overlay, Hann window) to simplify the process of the combined methods.

5. Empirical results

After the preliminary analysis, we follow these steps: (i) we perform the CWT and STFT modelling of each series to obtain the spectrograms; we use the significance testing via Ge07. For the robustness check of the results, we apply MC simulations; (ii) we perform adaptive LAB testing of the wavelet spectrograms; (iii) we do the cross-check of the (i)–(ii) results via enhanced spectrogram transform tested for its robustness by MC simulations; (iv) we compare and discuss the achieved results.

Although the TF method, especially the CWT, allows the modelling of a non-stationary time series, we decide to transform all input time series via the first order difference (FOD), because it can easily remove the long-term trend. Moreover, it is not possible to do the standard logarithmic transform before FOD for scattering reduction of the data, i.e. we can expect the persistence of a long-term component in CWT as an edge effect. Additionally, we check the results for both series, with and without a long-term trend. In accordance with the graphical processing and to insure a better visibility of detected areas, we decide to use detrended data via FOD. The long-term trend (i.e. cycles from 48 to 192 months) in TF transform of all indicators was present during all time. To make the orientation in the description of the results easier, we are going to divide the cyclical behaviour into three basic regions: the short-run cycles (SR–C) of duration <12 months, the short cycles (S–C) of duration 12–20 months and the medium cycles (M–C) of duration 20–48 months. Denote that the wavelet spectrogram in the short-run cycles in our paper can contains seasonal and some cyclical component.

5.1. CWT and STFT spectrograms tested by Ge07 test

In our empirical analysis, we focus on the CWT modelling mainly due to its wide range of economic applications and its popularity among economists. Further, the CWT has a better time resolution compared to the STFT and the TFAR (Aloui et al., 2016; Ftiti et al., 2014; Marsalek, Pomenkova, & Kapounek, 2013) which is important for economic applications in general. To confirm the CWT results, we use the STFT method which estimates the spectrogram in the moving time window, therefore, it can differ in low frequencies (due to the window used). Both CTW and STFT transforms are tested by standard Ge07 test. For the robustness of the results both transforms (CWT and STFT) are also tested by MC simulations.

Comparing the CWT (Figure 3a, c) and the STFT spectrograms (Figure 3b, d), we can find two differences in the significance areas: (i) using the CWT transform, we identify a long-term trend component covering cycles of the approximate length of 48 months during the time range, while in the case of the STFT it is not present; (ii) the significant areas for the CWT and the STFT are different. While for STFT, Ge07 and MC simulations identify similar significant regions, in case of CWT, MC simulations show a wider and also an additional area of significance.

The first difference mentioned above can have several reasons. It can be caused be the existence of the edge effect of the CWT transform called the cone of influence (COI). As Torrence and Compo (1998) wrote, the COI is a usual problem for finite-length time series and may occur at the beginning and at the end of the spectrogram or the PWS representation. The second reason is the nature of the Fourier transformation (Ftiti et al., 2014). The persistence of a long-term trend component could be also expected with

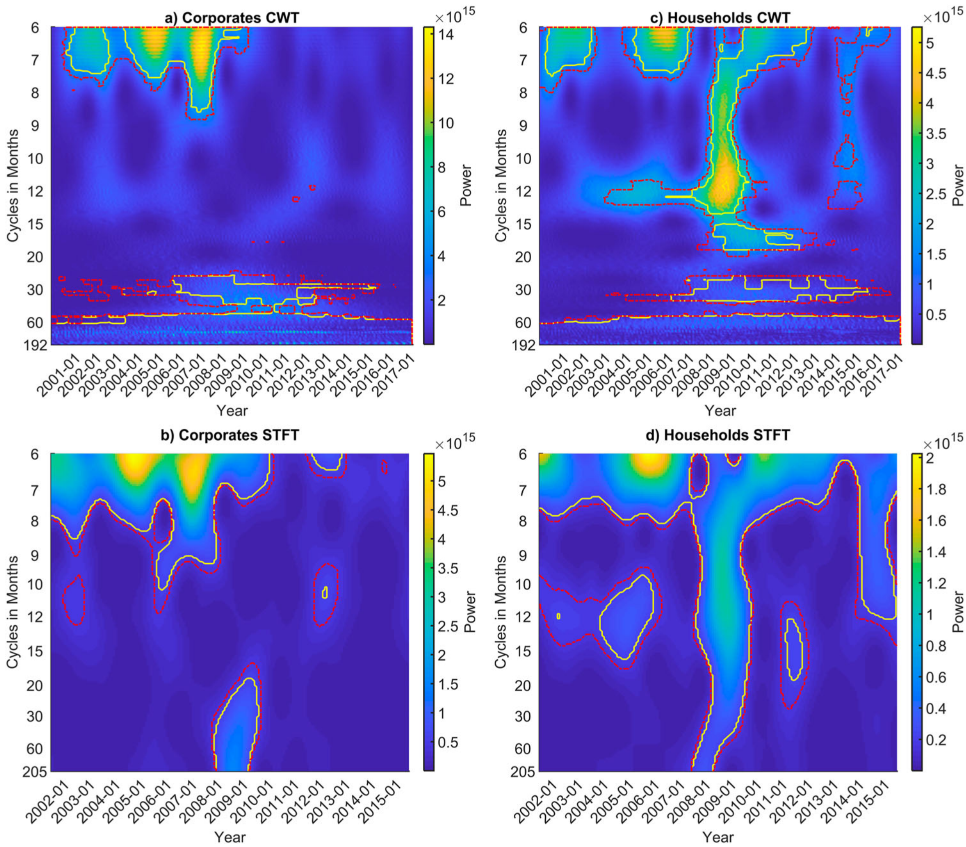

Figure 3. a–d. CWT and STFT spectrogram tested by Ge07.

Notes: *x*-axis represents time, *y*-axis represents specific periods (cycles in months) and *z*-axis represents values of spectrogram. The figures show a two-dimensional projection of three-dimensional charts. The intensity of each contour represents the relative importance of the different periodicities and time, i.e. from dark blue (low amplitude) to yellow (high amplitude) colour. The yellow (full line)/red (dotted line) curves in all figures indicate a significant area found by Ge07/MC simulations.

respect to the FOD transform, as we mentioned at the beginning of the Results section. Such an assumption is partially confirmed by the results of the STFT which is not so sensitive to the long-term trend. In other words, if the data contain the long-term trend component represented by the long cycles (low-frequency component) occurring in the time period shorter than the moving window part (which is 40 samples in our case, i.e. approximately 36 months), the STFT will not identify it. Despite the fact that STFT has this limitation, we can identify the existence of the long-term trend component in the subperiod of Households and Corporates. Then, we can admit the existence of cycles of 30–48 months duration despite the existence of the CWT edge effects.

In the case of the second difference (except the long-term trend component explained above) we assume that it is caused by Ge07 testing which evaluates the significance with respect to the fixed variance calculated in all-time range and does not consider the data character, i.e. the volatility of the values. Then, an event (such as the 2008 crisis) may suppress the significance of other events. It is also important to note that for the STFT results, the resultant figures have a shorter time axis caused by the STFT methodology. Thus, CWT transform tested by classical Ge07 approach can lead to misleading results. Therefore, the Ge07 test seems to be insufficiently adaptable to the volatility changes.

5.2. LAB significance testing

As the next step to adapt to the volatility changes in CWT testing, we proceed with an adaptive form of Ge07 testing, i.e. local-adaptive-based testing. Comparing Figure 3a,c and Figure 4 and taking into account the adaptive nature of LAB testing, we can conclude that the LAB testing of PWS spectrograms generally confirms the CWT spectrogram tested by MC simulations. The differences in the significant areas identified via Ge07 and the LAB testing in CWT figures is caused by the changing volatility in the data. This fact should imply that Ge07 approach may not be able to find all significant regions. That is, the denominator of the testing statistic given in Equation (2) is a constant value and it is the total variance for the time series (i.e. one fixed number). Therefore, in this case we prefer the results of the LAB testing of CWT due to its adaptability.

6. Robustness analysis via enhanced transform and MC simulations

6.1. Enhanced spectrogram modelling

As an alternative approach which considers data volatility we propose the enhancement spectrogram modelling tested via MC simulations. The enhanced transform is the display of the CWT, TFAR and STFT spectrograms of one-time series in one chart for obtaining the best possible TF representation. Since the CWT has a better time resolution compared to the STFT and TFAR (they are better in the frequency resolution) (Aloui et al., 2016; Ftiti et al., 2014), we decide to use the combination of the TF results via simple multiplication. This method is based on a simple idea that important components in the same positions

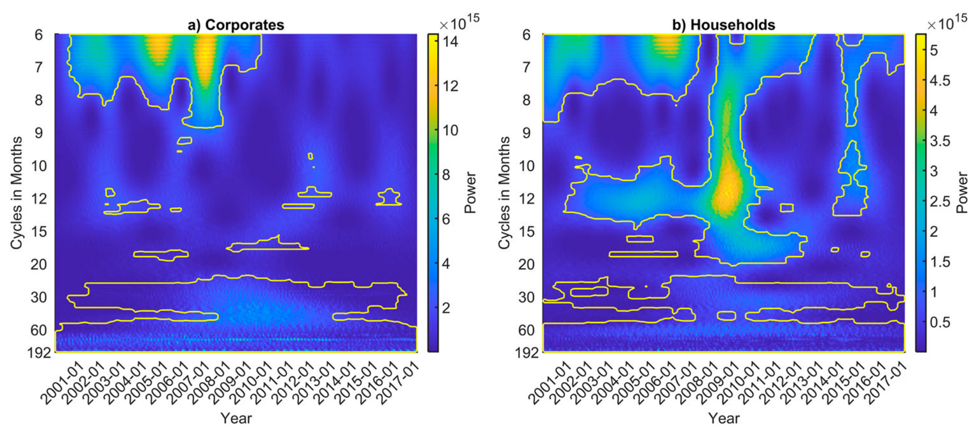

Figure 4. a–b. Wavelet spectrograms tested by LAB test.

Notes: *x*-axis represents time, *y*-axis represents specific periods (cycles in months) and *z*-axis represents values of spectrogram. The figures show a two-dimensional projection of three-dimensional charts. The intensity of each contour represents the relative importance of the different periodicities and time. The yellow curves in all figures indicate a significant area found by LAB testing.

(time and frequency) will be strengthened and methodical residues should be suppressed. The resultant spectrograms according to Equation (4) have been called 'enhanced' and are presented in Figure 4a–b. Due to the STFT and TFAR limitations we expect a worse ability to capture the long-term trend component. Since the application of STFT and TFAR causes the shortening of the sample size, all figures below (Figure 4) are in the shorter time range 2001/9–2015/9 compared to the CWT (Figure 3a–d). Further, the comparison of CWT and enhanced spectrograms is evaluated in this shortened time range. All enhanced spectrograms are tested via Monte Carlo (MC) simulations.

Comparing Figure 3a, c, Figures 4 and 5, and taking into account the methodology nature of individual approaches, we can conclude that the enhanced approach generally confirms the influence of data volatility on the CWT spectrogram testing. That is, we confirm that it is important to take into account the data character during the TF significance testing.

6.2. Comparison of achieved results

Since the results show that the enhanced spectrograms and LAB testing of CWT spectrograms generally provide the same results, we will demonstrate the difference between Ge07 testing and the LAB testing of CWT spectrograms. The summary of the significant regions is shown in Table 1.

For Households and Corporates, both testing approaches for the short-run cycles have, in general, similar results till 2013. In 2013–2017 there is the difference in case of Household, where the LAB approach identify additional cyclicality (i.e. seasonal or cyclical component). In the short cycles, the LAB testing identified additional significant cyclical behaviour compared to Ge07. In the case of medium cycles, the LAB testing identified a wider time-region with a significant cyclicality. Such similarities are possible because, analysing Figure 2, we can see that the Households and Corporates time series do not show a serious problem with the data volatility. The bigger differences occur when comparing

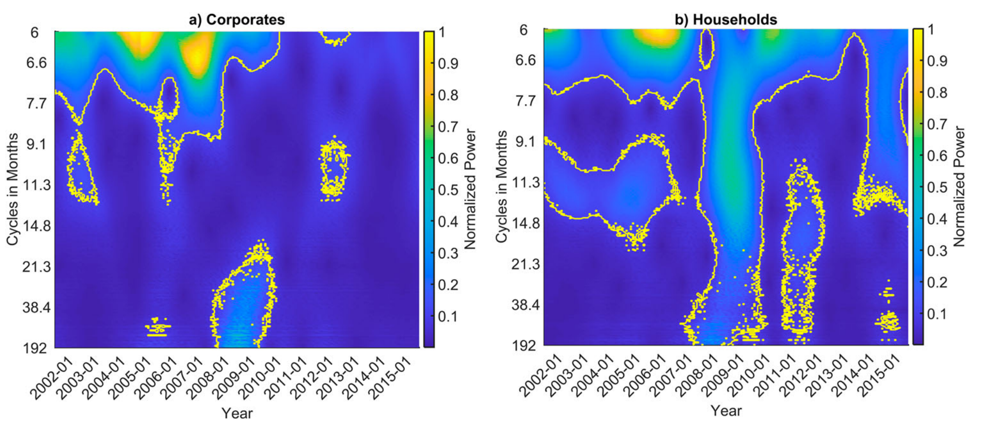

Figure 5. a–b. Enhanced TF pictures.

Notes: *x*-axis represents time, *y*-axis represents specific periods (cycles in months) and *z*-axis represents values of spectrogram. The figures show a two-dimensional projection of three-dimensional charts. The intensity of each contour represents the relative importance of the different periodicities and time. The results were tested by MC simulations.

Table 1. Significant area of wavelet spectrogram over frequency intervals.

	Test	Short-run cycles (<12 months)	Short cycles (12–20 months)	Medium cycles (20–48 months)
Corporates	Ge07	2001/Q1–2002/Q3 2003/Q3–2009/Q1	–	2004/Q3–2015/Q1
	LAB	2000/Q4–2010/Q1	2002/Q1–2004/Q3 2008/Q2–2011/Q1 2012/Q1–2013/Q2 2015/Q2–2016/Q3	2001/Q1–2016/Q2
Households	Ge07	2000/Q4–2002/Q2 2004/Q4–2007/Q1 2008/Q2–2013/Q1 2014/Q2–2016/Q1	2007/Q1–2012/Q2	2006/Q1–2016/Q3
	LAB	2000/Q1–2007/Q3 2008/Q2–2013/Q1 2014/Q2–2017/Q1	2001/Q2–2012/Q2 2014/Q1–2015/Q2	2000/Q1–2017/Q2

both testing approaches. Ge07 was not able to reveal any cyclicality (i.e. seasonal or cyclical component) in the short-run cycles and any cyclicality in the short cycles in Households after 2013. In case of Corporates Ge07 was not able to reveal any cyclicality in short term cycles. In the case of the medium cycles, the identified areas via Ge07 are smaller. Such a shortcoming of Ge07 testing was expected also from the comparison with the STFT results.

As we stated in the sections above, the significance via Ge07 does not consider variation in the data variability and takes a fixed variance for all data samples. Therefore, this testing indicates the significant areas of the cyclicality with respect to the all-time range. This leads to the suppression of other possible significant areas by the biggest shocks (the financial crisis). Moreover, the identified areas are smaller or are not even identified. On the other hand, using the LAB testing uncovers and confirms the existence of previously omitted areas. In this way, we are able to evaluate the cyclical behaviour of lending activities in the time window with a higher precision.

Based on the performed analyses and after a detailed examination of the results, the methodological findings can be summarized in the following recommendations. In the case of constant volatility in the data, Ge07 testing approach is plausible. We can also recommend and use this test if we want to evaluate any event in the time series with respect to the all-time range. In cases of increasing or decreasing volatility in the data, the overall variance can be affected. In this case, we recommend LAB testing, due to its adaptability, or enhanced spectrogram modelling.

7. Discussion

In our paper, we have presented and compared the results of three approaches (CWT and STFT tested by Ge07 and MC simulations, LAB testing of CWT, enhanced spectrogram modelling) applied to the cyclicality description of bank loan activities. We recognized that the volatility in the data influences the type of testing and we, therefore, recommend using the LAB testing of CWT or enhanced approach. In this section, we discuss interpretations of achieved results in the economic context.

First, the general results given by CWT with the Ge07 testing (Figure 3a–d, Table 1) show that the financial crisis was reflected in both economic sectors, but in a different way. We found the most extensive reaction to the crisis in the behaviour of Households.

The reactions were strong particularly in the years around the crisis across all frequencies (from short-run to long cycles), and in the years just before and after the crisis in the quick movements represented by the short-run cycles (i.e. in seasonal and some cyclical components). In the case of Corporates, the financial crisis did not cause any significant reactions during and after the crisis. We can find only one reaction, i.e. the disappearance of short-run cyclicality.

Next, due to new approaches, i.e. adaptive LAB testing or enhanced spectrogram modelling, we can evaluate the above-mentioned general results with a better precision. In the case of Corporates, there is an important area in the short-run cycles which covers seasonal and cyclical components and during the crisis. After the crisis, there is no significant area, probably as a result of the credit crunch. The LAB testing for Corporates (Figure 5a, Table 1) reveals the important pre-crisis and crisis period 2002–2010 in the short-run frequencies (up to 12 months; i.e. seasonal and some cyclical components) and the unique short cyclicality (12–20 months). Thus, we can see that the reaction of Corporates to the crisis was very limited without any strong impact on the post-crisis time.

At the same time, the situation for Households is different; the financial crisis of 2008 can be taken as an important factor having a strong impact on cyclicality. The new approaches (Figure 4b and 5b, Table 1) show several important areas: (i) the first area can be identified in the time 2000–2016 in the short-run cycles (up to 12 months; i.e. in the seasonal and some cyclical components); (ii) the second in the time 2001–2012, 2014–2015 in the short cycles (12–20 months); (iii) the third in the medium cycles in the time 2006–2012. We can see a very strong reaction to the crisis, which was reflected across all frequencies around and after the year 2008. Before 2008, a significant area lies (similarly as for Corporates) in the short-run cycles which covers seasonal and some cyclical components. After the crisis, we can find an important area in the short-run and the medium cycles. Therefore, we can confirm our previous results that the cyclical movement of loans to Households during the financial crisis was the most significant. In the case of both sectors, we can also see the medium cycles (12–20 months), but due to the COI (discussed in the previous sub-section), we can admit its existence in 2007–2011, i.e. shortly before, during and after the crisis.

Overall, our results can be summarized as follows. The financial crisis of 2007 and 2008 had a significant impact on the cyclical behaviour of both categories of economic sectors analyzed in our paper, but in a different way and with a different intensity. Moreover, the character of the cyclical behaviour was different before and after the crisis. In the case of Corporates, we do not see any significant cyclical behaviour after the crisis. This fact could be caused by a stronger position of large firms which have more financing possibilities than small firms and both banks and nonbanks provide short-term financing to large firms rather than smaller firms (Gertler & Gilchrist, 1993). Small firms are also connected to small banks (Holod & Peek, 2013) and this may influence the lending activity of small banks as they are more influenced by economic distress and information asymmetries compared to large banks (Kashyap & Stein, 1995). However, the ongoing banking consolidation and a reconstruction of internal organization of banks in recent years have caused the fact that the bank size is not as important for small business lending as before (Takáts, 2004). As such, this sector could be presented as a relatively stable sector with the least volatile lending activities. On the contrary, in the case of Households sector, the crisis was a very important event causing changes in the volume of lending activity and thus economic or financial distress may cause huge fluctuations in the spending of households which are also substantial for the economic growth of a country. This fact is documented in Gertler and Gilchrist (1993) who argue that banks tend to limit lending to households while they may rise loans to firms at the same time. However, Beck, Büyükkarabacak, Rioja, and Valev (2012) state that it is lending to firms, and not lending to households, that has a positive impact on economic growth and limits income inequality through the financial development, better capital allocation and economic transformation. Therefore, the lending activities in the sector of Households showed the most extensive cyclical behaviour and this sector could be characterized as the sector which was influenced by the financial crisis most significantly. In this context, it would be advisable to stabilize these fluctuations in lending activities of households using various economic policy measures. Many studies confirmed the existence of the cyclical behaviour of the lending activities (see Berger & Udell, 2004; Bernanke & Gertler, 1989; Bouvatier & Lepetit, 2008; Helbling et al., 2011 and others). However, we bring new findings about the short- and medium-term cyclicality in these two economic sectors via the TF transform.

8. Conclusion

The paper deals with the identification of the time-frequency regions describing the cyclicality of bank loans activity before, during and after the financial crisis in 2008. We proposed the local-adaptive-based testing and the so-called enhanced time-frequency spectrogram modelling and compare them with standard classical testing of CWT and STFT spectrogram. The demonstration of the methods was proposed only on seasonally unadjusted monthly financial data of bank loans provided to two categories of economic sectors in the Euro Area in 2000–2017. We identified areas of cyclicality in the lending activities and found an important impact of the crisis on data volatility which further influenced the type of significance testing of wavelet spectrograms. The results confirmed the usability of the newly proposed approaches, i.e. LAB testing of CWT spectrogram and enhanced spectrogram modelling, in those case the data have a changing volatility. In the case of constant volatility, the Ge07 testing approach of TF transform gave the same results.

The proposed approaches extend the methodology related to studying short and medium cycles as they can be applied also in the case of volatile data. Applying the methods, which were conducted only on seasonally unadjusted monthly data, enables us to detect a faster reaction to a specific change, which further enables a faster response from the economic policy makers.

From the economic point of view, the results show that the crisis in 2008 had an impact on the cyclical behaviour of corporates and households, but in a different way. The most remarkable influence of the crisis was identified in the households. Here, the reaction was relatively strong during and after the crisis. Therefore, we can identify Households as a more sensible sector reacting to changes, such as the 2008 crisis. At the same time, the less dynamics is apparent in Corporates, with severe fluctuations mainly in the period before the financial crisis. Therefore, Corporates seems to be less affected by the crisis compared to Households and this finding may be of high importance for policy makers when formulating and implementing their economic policy measures in a period of crisis.

On the other hand, the cyclicality of Corporates was mainly dominated by the short-run cycles (which includes seasonal components) and the medium cycles. Therefore, Eurozone policy makers should take this information into account. We need to point out that the presented research did not distinguish between the supply and the demand factors of lending activities, i.e. whether the movement was caused by banks or by economic agents. In this context, we bring interesting findings showing the cyclicality in economic sectors of corporates and households.

Note

1. Business cycle is defined by Burns and Mitchell (1946).

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