ORIGINAL ARTICLE

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Tracking financial cycles in ten transitional economies 2005–2018 using singular spectrum analysis (SSA) techniques

Abstract

Research background: Financial cycles are behind many deep financial crises and it closely connects them with the business cycles, showing long memory properties and effects. Being closely connected with the business cycles, we must first explore the true nature of the financial cycles to understand the nature of the business cycles. Financial cycles are real, they have long memory properties and long-lasting effects on the economy.

Purpose of the article: This study investigates the use of (SSA) in tracking and monitoring financial cycles focusing on ten (10) transitional economies 2005–2018.

Methods: Singular spectrum analysis isolate significant oscillatory patterns (cycles) on housing markets with an average 4-years length. We isolate credit cycles just for Bulgaria, implying long memory properties of the cycles since this study investigated medium term (2–5 years) oscillations.

Findings & Value added: The results prove the importance and advantages of using (SSA) in the study of financial cycles attempting to reveal the true nature of financial cycles as the principal component behind business cycles. Financial cycles show longer oscillations in the credit and property price series, which can explain 37.7%–49.9% of the variance of the total financial cycle fluctuations. Study results are of practical importance, particularly to policy-makers and practitioners in former transitional economies being vulnerable to adverse shocks on the financial markets. The results should assist policy-makers and financial practitioners in building and maintaining a sound financial policy needed to avoid future financial "bubbles".

Introduction

Business cycles have always attracted a large interest in the body of literature on economics. This is because of large negative effects that volatility in economic activity can cause. Volatility in real economic activity is a significant headwind to economic growth. Financial cycles have always been in the shadow of business ones. The crisis of 2008 brought them to light, but after the recovery the world forgot about financial cycles once again. Financial cycles are, therefore, studied randomly and mostly for most developed economies. Other economies, like transitional economies, lack a body of literature on financial cycles. We cannot identify the true nature of the business cycles before looking at the financial cycles, since they are intrinsic to business cycles Borio (2017), Antonakakis *et al.* (2015). In this study, we track financial cycles in ten (10) transitional economies using singular spectrum analysis (SSA) as a potential tool for tracking business cycles efficiently.

We can find a body of literature targeting financial cycles in Drehmann *et al.* (2013), Borio (2014), Drehman *et al.* (2012). Drehmann *et al*. (2013) find movements in the credit and property prices to be principal components behind the financial cycles. Financial cycles are closely connected to financial crises and show high synchronicity with the business cycles. A strong link exists between financial cycles and various economic policies, monetary policy (Borio, 2014) and fiscal policy (Borio *et al.,* 2019). Financial cycles present a long memory nature, lasting longer than business cycles, sixteen or more years according to the study by Drehman *et al*. (2012).

Successfully tracking financial cycles involves the need of choosing the best empirical technique. The task becomes even more arduous under limited data constraints as with a particular group of countries (transitional economies). Empirical, non-parametric methods in frequency domain seems to offer advantages over the time series methods (Burns & Mitchell, 1946), frequency-based filters (Christiano & Fitzgerald, 2003) and turning point analysis (Don & Adrian, 2002) in the quest for financial cycles. Without a proper tool for tracking and monitoring financial cycles, we can't understand the business cycles' nature.

The purpose of this research is the affirmation of the (SSA) technique as an efficient instrument in tracking and monitoring business cycles. Extensive research of the frequency domain technique in studying business cycles exists in the work of Vautard and Ghil (1989), Ghil *et al*. (2001), Vautard *et al.* (1992), Sella *et al.* (2010), Iacobucci (2005). Our study is among

the few (if any) to apply (SSA) technique in the study of financial cycles and in transitional economies.

This research attempts to identify the key advantages of using (SSA) techniques in tracking financial cycles. Essentially, this research responds to the demand of studying financial cycles nature more deeply and discovers the connection with the business cycles. Time domain (time series) methods, frequency-based filters and tuning point analysis show significant limitations compared to (SSA). In addition, we target this research to transitional economies with significant data constraints and volatility on credit and property markets.

We expect the findings of this research to assist policy-makers in designing efficient economic policies and researchers to motivate them to use (SSA) in their study of financial cycles. Study results are of practical importance also to the financial sector and managers working on the credit and property markets. In section 2, we review relevant literature on financial cycles. We present data and research method in the section 3, while in section 4 we summarize and discuss empirical findings. We offer implications, limitations and suggestions for future research in the conclusion of this paper.

Literature review

Financial cycles, their nature, duration dependence and inherited mechanism attract researchers' attention, but lack a more general approach to studying them. There is a gap in the literature studying financial cycles as phenomena similar to the body of literature we have on business cycles. Financial cycles miss thorough investigation as business cycles. Not only, studies on financial cycles take a principal component approach trying to isolate different components in the financial cycles to research. There is a lack of empirical studies taking a more holistic approach to financial cycles. Study of Drehman *et al*. (2012) attempts to identify the turning points in financial time series and develop a measure of financial cycles. To identify financial cycle in Australia, Germany, Japan, Norway, Sweden, United Kingdom and USA, they isolate medium-term cycles in credit and property prices. From the set of five financial variables, they select credit, credit to gross domestic product (GDP) and property prices as the main components of the financial cycle.

Adjusting the method from Harding and Pagan (2016) to best fit the medium term cycles in selected components, they develop an algorithm to construct a financial cycle indicator. They find the average duration of the

financial cycle is 16 years with large amplitudes, and they strongly coincide with banking crises and connection to business cycles. The same line of approach is followed in different studies on financial cycle Drehmann *et al.* (2013). The authors also explore in more details the connection of the financial cycle with business cycle and economic policies Borio and Drehmann (2011), Borio (2014; 2017), Borio *et al.* (2019), Borio *et al.* (2017). In Drehman *et al.* (2012), the study authors find a close connection between shocks in economic activity and financial cycles. The link is difficult to observe since financial cycles frequencies deviate from the traditional business cycles. Financial cycles depend on movements on the housing and credit markets and increased in volatility since mid80's. Study results warn on "unfinished recession" of 2008 and monetary policy focused on target inflation and not financial cycles' inherited instability. Financial repression policy can be an adequate solution in time of financial crisis, but only under certain conditions (Yülek, 2017).

Antonakakis *et al.* (2015) study the dynamics between credit growth and output growth for G7 countries during 1957–2012. They find evolving dynamics for credits and real output to be heterogeneous with bidirectional shocks spillovers. They also find a close/strong connection between credit growth and real output dynamics during financial crisis episodes. Corporate governance model and associated bank risks show a close connection with the financial crisis (Felicio *et al.*, 2018).

In conclusion, all points to the fact of credit growth as the dominant transmitter of financial shocks. The magnitude (force) of the transmission depends on the strength/importance of (globalized) financial markets from which credit growth shock started (ground zero market). Their study uses the spillover index approach developed by Diebold and Yilmaz (2009, 2012) to measure total and directional volatility spillovers for the four key US asset classes: stocks, bonds, foreign exchange and commodities. A later study examines seven (7) developed stock markets (US, UK, France, Germany, Hong Kong, Japan and Australia) and twelve (12) emerging markets (Indonesia, South Korea, Malaysia, Philippines, Singapore, Taiwan, Thailand, Argentina, Brazil, Chile, Mexico and Turkey). Both studies show the connections of stock markets' volatility spillovers with different markets (particularly in time of financial distress). Chorafas (2015) point out the importance of studying financial cycles along with classical business cycles. Financial cycles in modern economies have a great impact on economic activity. Fundamental factors behind financial cycles are long term in nature (longer in relation to business cycles) and so failure to account for them while studying business cycles leaves important economic forces out of sight. His study defines financial cycles as periods of boom and busts

that include interactions among profit, risks, value observation and financial markets constraints. Economic forces behind the financial cycles which dictate the dynamics of the financial cycles present a combination of movements in credit aggregates and property (assets) prices. Nolan and Thoenissen (2009) use the financial accelerator model of Bernanke *et al.* (1999) and find financial shocks closely connected with business cycles. Miranda-Agrippino and Rey (2018) find evidence of large financial spillovers from the (US) world most important financial market. US monetary policy in the form of FED interest rate targeting is a driver of a global financial cycle. Tightening or lengthening monetary policy by the FED through the interest rate channel causes large spillovers from the US on the international level. Financial crisis thus not only became global, but also a driving force behind business cycles. Kunovac *et al.* (2018) find strong empirical relation between real bank loans to non-financial corporations and economic activity in six countries (Belgium, Germany, Spain, France, Italy and the Netherlands. Business cycles, credit cycles and financial cycles show a large level of synchronization Chang (2016) with Taiwan. Firms' performances show a strong connection with the financial crisis regimes (Lee *et al.*, 2017).

Studies on financial cycles and financial cycles interactions with business cycles lack in numbers. The paper from Bongini *et al.* (2017) on the link between financial development and economic growth in Central, Eastern and South-Eastern European (CESEE) countries find new evidence of bank credit cycles affecting economic growth. We reach the same conclusion with the financial system efficiency accounting for foreign-owned bank asset on the financial market in (CESEE). In their study, they use two proxies for financial development; credit to private sector to GDP and stock market capitalization to GDP. Contrary to their results, a study of Škare *et al.* (2019b) find a positive and statistically significant link between credit dynamics and economic growth in Croatia 1990– 2018. The same authors show evidence of the existence of strong empirical link between financial development and economic growth in Poland 1990–2018 (Škare *et al.*, 2019a). The paper of Globan (2018) use the financial supply index (FSI) that measures the level of supply of foreign capital in a small open economy. The author provides empirical evidence that the foreign capital flow in the 11 EU new member states depends on financial variables' intrinsic conditions and economic factors (economic sentiments and business environment).

Data and research method

In this study, we use quarterly data for ten (10) transitional economies; Bulgaria, Croatia, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, Russia. For each country we analyze house price index (property prices 2015=100), credit to private non-financial sector (from all sectors, chained 2010 Euro), credit to private non-financial sector (share in a percentage of GDP) over the period 2005: Q1–2018Q2. We express property prices in house price index 2015=100, credit to private non-financial sector in EUR (millions of chained 2010 Euros), and percentage points for credit to private non-financial sector share in the GDP. We express the quarterly series in constant prices; real gross domestic product, millions of chained 2010 Euros, credit to private non-financial sector from all sectors in millions of chained 2010 Euros, percentage points (credit to private non-financial sector from all sectors, share in the GDP), house and seasonally adjusted with X-3ARIMA-SEATS Seasonal Adjustment Program — US Census Bureau in Eviews 10.0. For details on variables' description, data sources, see the sources in the appendix. The data cover the period from first quarter 2005 to second quarter 2018 for all countries. To extract the data for the Singular Spectrum Analysis (SSA), we extract the trend and the cyclical (residual) component from the series by applying a Hodrick-Prescott filter (HP) following the study of Hodrick and Prescott (1997). We standardize the series (by taking logarithm) and normalize by dividing residuals got after HP filtering (cyclical component) by the extracted trend from the series. Large trend magnitudes can distort cross-correlation in frequency domain. Singular spectrum analysis helps us isolate dominant periodicity (oscillatory patterns) and doing it with precision requires having series pre-processed before comparing them to white or red noise spectrum.

Figure 1 and Figure 2 show interesting patterns in the cyclical components of credit to private non-financial sector, real GDP and house price index in selected transitional economies. In Bulgaria, financial cycles (extracted cyclical component of credit to private non-financial sector and property prices) move closely with cycles in real economic activity (business cycles). Credit dynamics (credit cycles) closely connected to the business cycles while property prices high volatility. The same conditions apply to Croatia with credit cycles coinciding with business cycles. House prices also closely follow credit and business cycles with high volatility regimes. Property prices in the Czech Republic show a higher volatility when compared to Bulgaria and Croatia. House prices also follow a different dynamics, diverging from the credit and real economic activity dynamics. Therefore, volatility in the property prices in the Czech Republic is driven by

some other endogenous/exogenous (fundamental) factors and not by changes in the real GDP and credit cycles. Business and credit cycles in the Czech Republic show high synchronicity and convergence. In Estonia, until 2010, house price dynamics show coincident behavior with credit and business cycles, but not a convergence. After the financial crisis of 2008, property prices in Estonia show coincident and converging dynamics with credit and business cycles. Coincident and converging dynamics between credit and business cycles hold for Estonia, like for the previously mentioned economies. Property prices in Hungary show diverging behavior in relation to the business cycles and coincident behavior with credit cycles. Credit cycles show a high volatility in the series with diverging behavior in relation to business cycles. Thus, loan supply is not crucial for economic growth in Hungary. Since 2011 credit and business cycles show more coincident and converging behavior than it was the case prior to the 2008 financial crisis.

From the Figure 2, in Latvia we can observe a similar behavior between financial and business cycles as with Hungary, Croatia, the Czech Republic and Estonia. Credit cycles show high synchronicity (coincident and converging) with the business cycles in Latvia. Property prices in Latvia also show high volatility regimes with a high coincidence and convergence with credit and business cycles after 2011. The same conclusions hold for Lithuania, with an even higher level of synchronicity between credit and business cycles and property prices. House prices in Lithuania after the financial crisis of 2008 move closely together with credit and business cycles. Almost perfect synchronicity between credit and business cycles exist in Lithuania after the crisis. Poland shows, among all the countries in the sample the highest level of coincident behavior between credit cycles, property prices and business cycles (series move closely together). Credit and business cycles, together with house prices, move in perfect synchronicity after the financial crisis of 2008. This is interesting since Poland did not experience recession during the financial crisis period. Russia, like Hungary shows the highest volatility in the property prices in the sample of observed countries. Credit cycles in Russia show more diverging dynamics in relation to the real economic activity when compared to other observed countries in this study. Monetary policy in Russia (same as in Hungary) is not closely connected with the business cycles as it is the case in other observed transitional countries. In Russia, like in Hungary house prices are driven by some other fundamental factors and not credit/business cycles. Slovakia shows similar behavior between financial and business cycles as in other transitional economies we analyze in this study. We can see that house prices show higher volatility in relation to credit and business cycles

dynamics. After the crisis of 2008, property prices show more coherent and move along with credit and business cycles than before 2008. Credit and business cycles move together showing a high level of synchronicity.

From Figure 1 and 2 we see there is close, joint, movement between credit and business cycles and property prices in the observed transitional economies. While credit and business cycles show a high coincidence and convergence, house prices show more fluctuations and divergence. Financial and business cycles in transitional economies share a similar dynamics with financial cycles affecting real economic activity. To track financial cycles, we isolate the oscillatory patterns in the original financial series and reconstruct them (in time domain) using univariate SSA.

In this study, we use univariate singular spectrum analysis as developed by Allen and Smith (1996), Groth and Ghil (2015), Vautard and Ghil (1989), Vautard *et al.* (1992) Ghil *et al.* (2001) to identify and isolate the dynamics in the financial cycles using short and noisy quarterly time series data for transitional economies from 2005 to 2018. First, we decompose variance in our series in eigenvalues λk and eigenvectors Ek, following the study of Vautard and Ghil (1989), Ghil *et al.* (2001) using

$$c_{ij} = \frac{1}{N - |i - j|} \sum_{t=1}^{N-i-j} x(t)x(t + |i - j|) \qquad (1)$$

where:
c_{ij} – lag covariance matrix;
N – number of data points in a time series;
i, j – time indices;
t – continuous time $t \in R$;
x_t – observed time series.

Equation (1) allowed us to isolate the underlying patterns in the series (trend, cycle, random noise). In this paper we isolate cycles (oscillatory patterns) in the financial (credit, house price) and real economic activity (GDP) series. (SSA) as discussed in Ghil *et al.* (2001) is a suitable tool for analyzing chaotic (series under exogenous shocks), short and noisy time series as present in the financial time series for transitional economies. We decompose the observed series into corresponding principal components (identified eigenvalues and eigenvectors) of the variance matrix Vautard and Ghil (1989), Mañé (1981), Takens (1981).

$$X = \begin{bmatrix} x(1) & x(2) & ... & x(M) \\ x(2) & x(3) & ... & x(M+1) \\ .. & ... & ... & ... \\ x(N-M+1) & x(N-M+2) & ... & x(N) \end{bmatrix} \qquad (2)$$

where:
M – embedded dimension;
X – univariate time series.

and the corresponding principal components (PCs).

$$A_k(t) = \sum_{j=1}^{M} X(t+j-1)\rho_k(j) \qquad (3)$$

with
ρk – kth eigenvector.

To capture the phase of the financial and real economic activity of the time series we analyze, we use identified principal components (PCs) to reconstruct the original time series and calculate the series' reconstructed components (RCs) using Ghil *et al*. (2001)

$$R_\kappa(t) = \frac{1}{M_t} \sum_{k \in \kappa} \sum_{j=L_t}^{U_t} A_k(t-j+1)\rho_\kappa(j) \qquad (4)$$

where:
$R_K(t)$ – reconstructed components for all set of indices used in the data series reconstruction;
K – set of indices;
M_t – normalization factor;
L_t and U_t – lower and upper summation bound;
ρ_k, EX – kth eigenvector and eigenvector matrix of CX.

Following the research of Drehmann *et al*. (2013), we set the window length for the (SSA) to identify possible financial cycles of M=11,20,27,32. There is no general rule or procedure for the optimal window selection, so we combine several approaches to determine the best window length. First, we follow theoretical dimensional window width with financial cycles last-

ing around 9–20 quarters (so we want to capture a periodicity (cycle) between 9–20 years. Ghil *et al*. (2001) suggest a window selection to be based on expected periodicity we are searching for and a trade-off between too small (fail to capture dynamics) or too large window (lack of statistical confidence). According to their study, a possible optimal window selection procedure should follow M=N/5, in our case this is M=54/5=10.8 or around 11. Nina *et al.* (2001) suggest a general rule of thumb for selecting window length M = N/2 (half the length of the time series data). In our study this is M=54/2, M=27. Another approach is to apply a window-closing procedure (moving from a narrow window selection to the best spectral stability) as suggested in Jenkins and Watts (1968), Iacobucci (2005). We use window-closing procedure to select the window length in our study.

Results

A summary of empirical results of the (SSA) analysis for credit, GDP and house price index for ten transitional economies is visible in Table 1.

Before we analyze and explain the results of the (SSA) for the financial series, we explain the result for the GDP series. From Table 1 we can observe that (SSA) did not detect medium or longer fluctuations (business cycles) for a majority of the countries in the study except for the Czech Republic, Estonia, Latvia and Lithuania. With Latvia, we detect a business cycle of longer duration (2 years) at 5% significance level. For Lithuania, we detect the same oscillation of about 2 years at 10% significance level. In all other cases, Bulgaria, Croatia, Hungary, Poland, Russia and Slovakia we find no evidence of business fluctuations under the embedded dimension. For the Czech Republic, we isolate 4-year business cycle (at 10% significance level) and Estonia also with a 4-year cycle (at 5% significance level). Isolated oscillations in the GDP series for the Czech Republic (4 years) cycle explains about 37.7% of the variance in the GDP series and 41.4% for Estonia. In the cases of Latvia and Lithuania isolated oscillations explain only a small part of the identified variance in the GDP series. This was, however, expected, since previous similar studies Sella *et al.* (2010) using (SSA) to detect business fluctuation in the GDP series find evidence of a 5-year medium oscillation. In our study, to isolate longer business cycles the selected window length (M) should be 36 and more, which results in low statistical significance (lack of statistical confidence). We calibrated our (SSA) model to search for expected periodicity between 2–5 years in the financial series. In fact, we can observe from Table 1 that (SSA) for the

credit to private non-financial sector detects 4 years periodic oscillations (cycles) for Bulgaria at 5% significance level.

The isolated pattern in the credit series (credit cycle) shows that identified cycle can explain 45.3% of the fluctuations (variance) in the credit series. For Hungary, we detect a credit cycle of 2 years with (SSA) at 10% significance level. We do no isolate oscillations in the credit series (credit cycles) for all other countries in the sample in between 2–5 years. This points to the conclusion that credit cycles in these countries are longer than 5 years supporting the results from the study Drehmann *et al*. (2013). Credit cycles dynamics in most of the transitional economies under study here are longer oscillations (>5 years) not isolated in this study (because of disposable time series data for credit series).

For the housing prices series, we isolate oscillating pattern of about 4 years, which differs significantly from Monte Carlo simulated red noise (95% confidence level band). Identified principal components in the house price series got from (SSA) explains fluctuations in the property price series ranging from 37.3%–49.9% (see summary results in Table 1 for the house price series). Four-year (financial) cycle in the house price series is identified for Bulgaria, Croatia, the Czech Republic, Estonia, Latvia, Lithuania, Poland, Russia and Slovakia. In data series for Credit and House price in Bulgaria using (SSA) we isolate a four (4) year oscillating pattern (cycle).

Figure 3 shows the (SSA) for the Credit series in Bulgaria with eigenvalues (dots in Figure 3) and corresponding errors bars (grey) from the Monte Carlo test Allen and Smith (1996). Eigenvalues (dots) outside of the error bars show variance in the Credit series is not a consequence of red-noise process. Therefore, we reject the null hypothesis of variance in the Credit series as results of red-noise process. Variance in the Credit series was results of an oscillatory pattern (4-year cycle) identified (at 5% significance level) with the eigenvalues which are divergent from the simulated red noise realization. Isolated (financial) cycle in the Credit series correspond to 4 years (see Figure 3). Isolated principal components (eigenvalues) explain partial variance of the total variance in the Credit series of 45.4%. (SSA) performed on the House price series for Bulgaria show results in Figure 4.

From Figure 4 we can see the same 4-year cycle (oscillatory pattern) isolated in the House price series for Bulgaria at 10% significance level. Identified cycle is significant against the null hypothesis of the red-noise process at 90% confidence level. Using Equation (4) on the isolated patterns, we reconstruct both Credit and House price series in the time domain using (SSA). We plot reconstructed series in the figures below.

Figure 5 show the 4-year (financial) cycles in Bulgaria for credit and property price cycles. We can observe that both credit cycle and property cycle share the same 4 years cycle dynamics. Principal components (eigenvalues) in the credit series explain 45.3% of the total variance in original credit data series for Bulgaria. In 2008, we notice a large increase in the variance of the oscillatory pattern (cycle) because of the world financial crisis. Reconstructed credit cycle for Bulgaria fit the original credit data series well. During 2012–2016, we observe another credit cycle, but this time with a smaller increase in the amplitude (variance) when compared to the 2008. Property cycle in Bulgaria follows closely the same dynamics in 2008. Increase in the variance of property price series is visible during the 2008 financial crisis. We isolate the same 4-year cycle as in the credit's case series. Effects of the property price shocks are larger in variance (bigger increase in the amplitude), but with more stable behavior after the crisis. After the 2008 shock, credit dynamics still show more volatile behavior in relation to the property prices. Therefore, credit cycle shows a trace of a long memory properties while property prices follow more mean reversion path.

(SSA) reconstruction for all the countries in the sample exhibit different behavior (not presented here because of space constraint). For Bulgaria, we detect a 4-year fluctuation (cycle) in the credit series while for the other countries in the sample we do not detect fluctuations (cycles) in between 2–5 years. Different results hold for the property series, with all countries (except for Hungary) share the same 4-year oscillation pattern (property price cycle). Oscillatory patterns in the reconstructed property price series explain from 37.3% to 49.9% of the total variance (amplitude) in the original property price series. Therefore, a clear and statistically significant 4-year property price cycle is identified for the transitional economies in this study.

Conclusions

Using (SSA) we isolate a 4-year oscillatory pattern in the credit data series (Bulgaria) and in the housing price data series (nine countries except for Hungary). Therefore, we conclude that credit cycles in transitional economies follow larger (>4 years) oscillatory path (cycles — see Figure 5). Housing markets in transitional economies follow a clear, statistically significant 4-years oscillatory path (cycle) which is visible from the Figure 5. Business cycles were not tracked since the (SSA) window filter was set to trace oscillatory patterns up to 5 years due to a limited time series data at

our disposition. This is in line with previous studies of Drehmann *et al*. (2013), Drehman *et al*. (2012) suggesting business cycles ranging from 5 to 9 years and financial cycles from 12 to 16 years. House market price dynamics show only shorter, 4-year oscillation, while we expect credit cycles to show long memory behavior (>10 years of length).

Combining both (SSA) results for the credit and housing cycle to isolate a unique financial cycle in transitional economies we would find support for the thesis of financial cycles lasting around 16 years. The research undertaken in this paper suggest housing cycles do not show long memory properties while credit cycles do. These conclusions are of importance to the policy-makers and economic agents on the financial market. They should expect large volatility (bubbles) on the housing markets following 4 years of volatility-stability interchanging regimes. Credit cycles show more stable behavior in the medium-term fluctuations (5–10) years, but highly volatile and divergent behavior under longer oscillations' regime (12–16 years).

This study investigates and track potential financial cycles in ten (10) transitional economies from 2005 to 2018. To our knowledge, is among few studies researching financial cycles in transitional economies and possibly among a first to track financial cycles using Singular spectral analysis techniques (SSA). Cycles in the credit and housing price series explain a large part of the oscillations in the financial cycles (around 37%–49%) supporting thesis of Drehman *et al*. (2012), Drehmann *et al*. (2013) that dynamics on the credit and housing markets drive financial cycles. Because of the (objectively not available data) a few time series data (only 54 quarters) and a medium sample (ten countries) we cannot isolate a full credit cycle and a full financial cycle of the expected 16 years' length. We hope this study will encourage further research in this direction by deriving a longer time series (1990–2018) database for the transitional economies.

Our results reveal credit and housing markets as primary factors behind financial cycles in the transitional economies with housing markets being 4-year and credit cycles expected to be between 12–16 years. Credit and housing markets data can explain a large variance (oscillations) in the financial cycle dynamics making possible to study them in more details for the purpose of tracking and forecasting financial cycles. Behind a single financial 'bubble', one should always look for a credit and housing 'bubble' first because that is from where the air to pump the 'bubble' is coming.

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Annex

Table 1. Univariate Singular Spectrum Analysis Results

Series	5 years	4 years	2 years
Bulgaria			
Credit	46.70%	**45.3%****	7.50%
GDP	40.60%	39.20%	8.50%
House price	48.30%	**43%***	6%
Croatia			
Credit	46.40%	31.60%	6.70%
GDP	42.80%	38.60%	6.20%
House price	43.20%	**41%***	5.90%
Czech Republic			
Credit	32.50%	28.10%	13.20%
GDP	41.70%	**37.7%***	9.50%
House price	51.90%	**39.7%***	7.50%
Estonia			
Credit	42.80%	35%*	11.50%
GDP	48.20%	**41.8%****	3.20%
House price	43.40%	**43.5%***	6.10%
Hungary			
Credit	26%	19.50%	**15.2%*(5)**
GDP	38.70%	33.90%	13.90%
House price	62.80%	28.70%	3.30%
Latvia			
Credit	41.60%	31.50%	9.60%
GDP	45.60%	47.70%	**2.3%****
House price	44.20%	**48.5%****	4.70%

Table 1. Continued

Series	5 years	4 years	2 years
Lithuania			
Credit	45.30%	38.5%*	6.60%
GDP	47.30%	40.80%	**5.0***
House price	45.80%	**41.1%****	5.00%
Poland			
Credit	35.10%	31.60%	10.70%
GDP	37.60%	31.50%	8.80%
House price	39.60%	**44.2%****	12.10%
Russia			
Credit	49.30%	38.40%	2.70%
GDP	39%	48.10%	7.70%
House price	40.70%	**37.3%***	10.80%
Slovakia			
Credit	36.80%	26.50%	7.90%
GDP	34.50%	43.20%	9.10%
House price	39.40%	**49.9%***	6.90%

Notes: *, ** at 5% and 10% significance level under Monte Carlo simulation for red noise components at the 95% confidence level.

Table 2. Variable list and data sources

Country	Variables and data source
Bulgaria	Credit (loans to non-financial corporations, households and NPISHs, (Euro/ECU series), Millions of Chained 2010 Euros, Quarterly, Not Seasonally Adjusted, Bulgarian national bank).
	GDP (Eurostat, Real Gross Domestic Product (Euro/ECU series) for Bulgaria [CLVMEURSCAB1GQBG], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CLVMEURSCAB1GQBG (Accessed on January 10, 2019).
	House price (House price index, 2015 = 100, quarterly data, Eurostat housing price statistics, http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=prc_hpi_q&lang=en (Accessed on January 10, 2019).

Table 2. Continued

Country	Variables and data source
Croatia	Credit (Loans non-financial private sector, in millions, NCU, Croatian national bank).
	GDP (Eurostat, Real Gross Domestic Product (Euro/ECU series) for Croatia [CLVMEURNSAB1GQHR], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CLVMEURNSAB1GQHR (Accessed on January 10, 2019).
	House price (residential property prices, all dwellings, pure prices, 2015=100, Bank for international settlement, https://www.bis.org/statistics/pp.htm and Croatian statistical office www.dzs.hr (Accessed on January 10, 2019).
Czech Republic	Credit (Czech Republic - Credit to Private non-financial sector from All sectors at Market value - US dollar - Adjusted for breaks, billions, Bank for international settlements)
	GDP (Eurostat, Real Gross Domestic Product for Czech Republic [CLVMNACNSAB1GQCZ], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CLVMNACNSAB1GQCZ (Accessed on January 10, 2019).
	House price (Real house prices, 2015=100, Q1 2001 – Q2 2018, OECD (2019), Housing prices (indicator). doi: 10.1787/63008438-en (Accessed on January 10, January 2019).
Estonia	Credit (Credit to Private non-financial sector from All sector, EUR millions, Estonian national bank).
	GDP (Eurostat, Real Gross Domestic Product for Estonia [CLVMNACSCAB1GQEE], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CLVMNACSCAB1GQEE (Accessed on January 10, 2019).
	House price (Real house prices, 2015=100, Q1 2001 – Q2 2018, OECD (2019), Housing prices (indicator). doi: 10.1787/63008438-en (Accessed on January 10, 2019).
Hungary	Credit (Hungary - Credit to Private non-financial sector from All sectors at Market value - US dollar - Adjusted for breaks, billions, Bank for International Settlements).
	GDP (Eurostat, Real Gross Domestic Product (Euro/ECU series) for Hungary [CLVMEURNSAB1GQHU], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CLVMEURNSAB1GQHU, January 10, 2019).
	House price (Aggregated real MNB House Price Index, 2015=100, deflated by CPI, Magyar Central Bank, https://www.mnb.hu/en/statistics/statistical-data-and-information/statistical-time-series/vi-prices/mnb-house-price-index (Accessed on January 10, 2019).
Latvia	Credit (Credit to Non-financial corporations from All sectors at Market value - millions of EUR, Bank of Latvia).
	GDP (Eurostat, Real Gross Domestic Product for Latvia [CLVMNACNSAB1GQLV], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CLVMNACNSAB1GQLV (Accessed on January 10, 2019).
	House price (House price (Real house prices, 2015=100, Q1 2001 – Q2 2018, OECD (2019), Housing prices (indicator). doi: 10.1787/63008438-en (Accessed on January 10, 2019).

Table 2. Continued

Country	Variables and data source
Lithuania	Credit (Credit to Private Non-financial Sector from All sectors at Market value - millions of EUR, Bank of Lithuania).
	GDP (Eurostat, Real Gross Domestic Product for Lithuania [CLVMNACSCAB1GQLT], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CLVMNACSCAB1GQLT (Accessed on January 10, 2019).
	House price (residential property prices, all dwellings, pure prices, 2015=100, Bank for international settlement https://www.bis.org/statistics/pp.htm (Accessed on January 10, 2019).
Poland	Credit (Poland - Credit to Private non-financial sector from All sectors at Market value - US dollar - Adjusted for breaks, billions Bank for International Settlements).
	GDP (Eurostat, Real Gross Domestic Product (Euro/ECU series) for Poland [CLVMEURNSAB1GQPL], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CLVMEURNSAB1GQPL, January 10, 2019).
	House price (House price (House price index, 2015 = 100, quarterly data, Eurostat housing price statistics http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=prc_hpi_q&lang=en (Accessed on January 10, 2019).
Russia	Credit (Russia - Credit to Private non-financial sector from All sectors at Market value - US dollar - Adjusted for breaks, Billions Bank for International Settlements).
	GDP (Organization for Economic Co-operation and Development, Gross Domestic Product by Expenditure in Constant Prices: Total Gross Domestic Product for the Russian Federation [NAEXKP01RUQ652S], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/NAEXKP01RUQ652S (Accessed on January 10, 2019).
	House price (House price (Real house prices, 2015=100, Q1 2001 – Q2 2018, OECD (2019), Housing prices (indicator). doi: 10.1787/63008438-en (Accessed on January 10, 2019).
Slovakia	Credit (Credit to Private non-financial sector from All sectors at Market value, millions of EU, Slovakia national bank).
	GDP (Eurostat, Real Gross Domestic Product for Slovakia [CLVMNACNSAB1GQSK], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CLVMNACNSAB1GQSK (Accessed on January 10, 2019).
	House price (Real house prices, 2015=100, Q1 2001 – Q2 2018, OECD (2019), Housing prices (indicator). doi: 10.1787/63008438-en (Accessed on January 10, 2019).

Figure 1. Extracted Cyclical Components of Credit to Private Non-Financial Sector, Real GDP and House Price Index (Bulgaria, Croatia, Czech Republic, Estonia, Hungary)
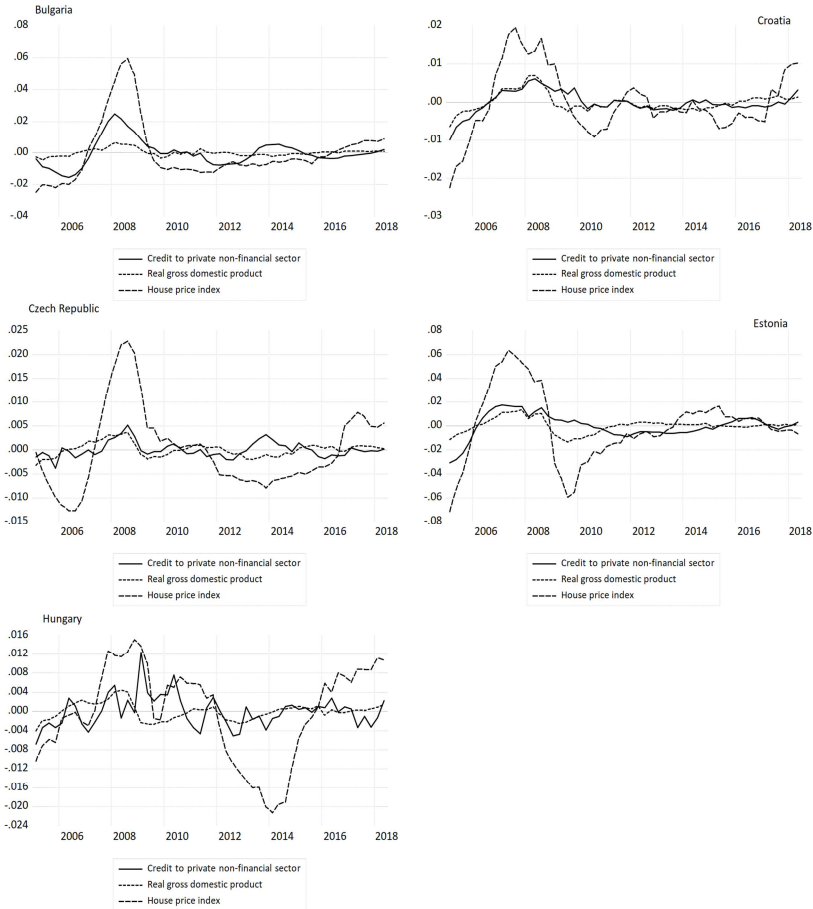
Figure 2. Extracted Cyclical Components of Credit to Private Non-Financial Sector, Real GDP and House Price Index (Latvia, Lithuania, Poland, Russia, Slovakia)
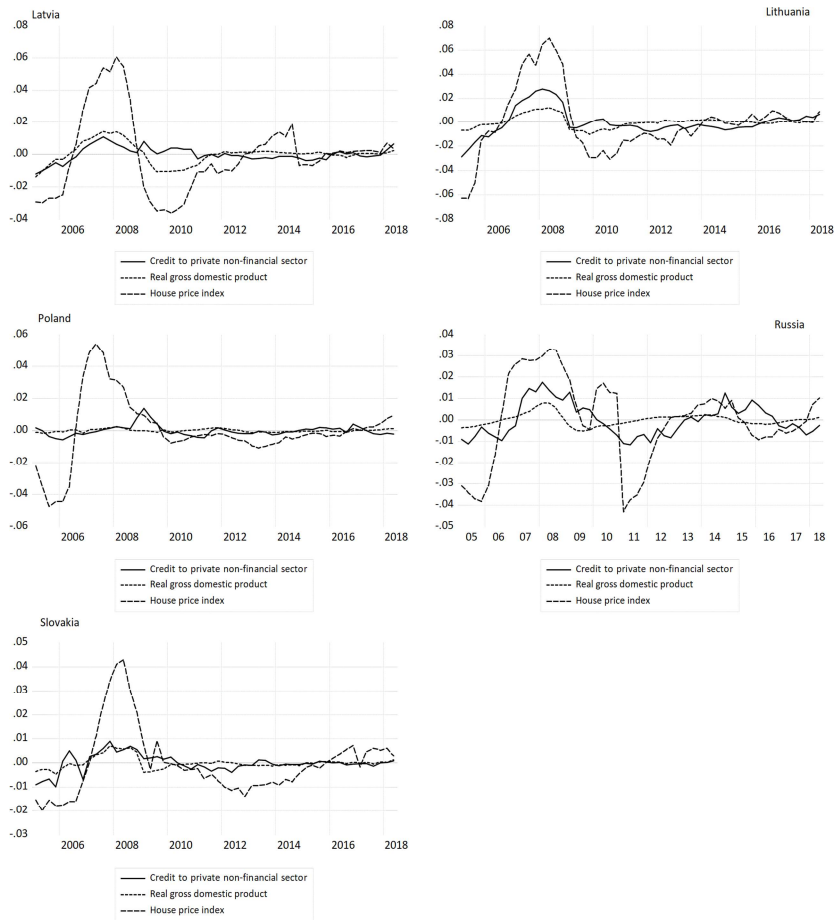
Figure 3. Singular Spectrum Analysis (SSA) of Credit series