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Identifying the Financial Cycle in Slovakia

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Identifying the Financial Cycle in Slovakia *

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Abstract

The concept of a financial cycle has become a matter of immediate concern for central bankers. The aim of this paper is to construct an aggregate indicator of the financial cycle from input indicators such as credit growth, house prices, debt burden, credit standards, interest rate spreads, and current account deficit-to-GDP ratio. We contribute to the literature with additional evidence on the financial cycle for small open economies with shallow financial markets. Expansionary and contractionary periods of a financial cycle identified by the indicator can be a valuable source of information for policy makers.

Keywords: financial cycle; credit growth; house prices; small open economy

JEL-Codes: E30, E44, E51, G10

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1. INTRODUCTION

After the Global financial crisis, the concept of a financial cycle has become a matter of immediate concern for central bankers. This topic is not relevant only for the major central banks but also for a growing number of other central banks as well.

The literature uses two concepts to model a financial cycle. First concept relates to the empirical work on early warning indicators ([Shin \(2013\)](#)) or financial markets stress indicators ([Holló et al. \(2012\)](#) or [Giglio et al. \(2016\)](#)). [Červená \(2011\)](#) and [Rychtárik \(2014\)](#)'s indicators developed at the National Bank of Slovakia belong to this category. Second modelling concept handles primarily the financial cycle and its interactions with the economy and monetary policy ([Borio et al. \(2012\)](#) and [Borio \(2014\)](#)). Financial cycle is often extracted using the turning point analysis, statistical filters, or unobserved components models.

Despite the indisputable usefulness of the financial cycle monitoring, number of issues arise in the case of economies with shallow financial markets. Evidence on the financial cycle for advanced economies is well-documented ([Borio \(2014\)](#)), however, for emerging and especially small open economies, evidence is scarce. The literature more or less settles on the input indicators for both developed and emerging economies, but not on how to extract the financial cycle in a short sample with many structural breaks.

This study tries to address these problems and identifies the financial cycle in Slovakia. We contribute to the current state of the financial cycle modelling at the National Bank of Slovakia in two ways: (i) we model endogenous co-movement between input indicators, and (ii) we solely focus on indicators which monitor the build-up phase of risks. Results point to an expansionary phase of the financial cycle from 2005 to the peak at the end of 2008, followed by a trough at the end of 2009. Currently, the financial cycle has been at an expansionary phase which started roughly at the end of 2013.

The rest of the paper is organised as follows. Section 2 provides a brief overview of the relevant literature. Section 3 discusses the construction of an indicator. Section 4 evaluates the results and checks their robustness. Finally, section 5 concludes.

2. REVIEW OF THE LITERATURE ON THE FINANCIAL CYCLE

The concept of a financial cycle, pioneered by [Borio \(2014\)](#) after the Global financial crisis, has become a matter of immediate concern for central bankers. Despite its indisputable usefulness, quite a number of practical modelling issues arise, notably in the case of small open economies with a shallow financial market.

Two modelling concepts have been identified¹. The first concept relates to the empirical work on early warnings indicators (EWI) (e.g. [Kaminsky et al. \(1998\)](#), [Shin \(2013\)](#), and [Giordani et al. \(2017\)](#)). This approach combines a number of financial, real, institutional, political, and a variety of ad-hoc variables in the construction of an early warning indicator. Rather on its theoretical and methodological justification, the early warning indicators primarily focus on their empirical performance.

A subsection in this category are pure financial market stress or systemic risk indicators (FSI). An important measure of financial stress is the Composite Indicator of Systemic Stress (CISS) in the financial system (see [Holló et al. \(2012\)](#) for the euro area, [Louzis and Vouldis \(2012\)](#) for Greece, [Johansson and Bonthron \(2013\)](#) for Sweden, [Iachini and Nobili \(2014\)](#) for Italy, and [Wen \(2015\)](#) for Norway). [Giglio et al. \(2016\)](#) evaluate in total 39 measures of financial stress for the euro area, the United Kingdom, and the United States. They conclude that the analysed systemic risk indicators provide significant predictive information out-of-sample for the lower tail of future macroeconomic shocks.

There are a few attempts to construct in a sense similar measures in Slovakia. The first attempt is the Stress indicator for the economy and financial system developed by [Červená \(2011\)](#). It uses 11 variables covering the macro, price, and banking sector. According to the results, the economy and the financial system were the most stable from the end of 2005 to the end of 2008. Subsequently, stress increased and peaked during 2009 and slowly faded later on to the end of the sample in 2011. The need to implement macroprudential policies led to the development of a new indicator called the Cyclogram ([Rychtárik \(2014\)](#)) in addition to the standard credit-to-GDP gap measure. The Cyclogram is constructed using 13 indicators covering three major categories: business and financial cycle, banks, and customers. According to the results it identifies the excessiveness in 2005-2008, abrupt drop in 2009, and a slight recovery in 2010-2013.

¹Literature on the financial cycle has foundations in a general literature on systemic boom and bust patterns in the financial system and their interactions with the real economy. Initial work in the field consists of [Fisher \(1933\)](#), [Minsky \(1986\)](#), and [Kindleberger and Aliber \(2011\)](#).

Second modelling concept targets the financial cycle (FCI). In this case credit, credit-to-GDP, house prices, equity prices, credit spreads are viewed as endogenous and are interrelated with the aggregate economic activity, monetary policy, and financial stability (e.g. [Lowe and Borio \(2002\)](#), [Detken and Smets \(2004\)](#), [Goodhart and Hofmann \(2008\)](#), [Gerdesmeier et al. \(2010\)](#), [Edge and Meisenzahl \(2011\)](#), [Schularick and Taylor \(2012\)](#), [Taylor et al. \(2015\)](#),). In practice, however, the distinction between early warning indicators and the financial cycle indicators is not so clear cut. Authors often refer to these concepts interchangeably due to the specifics of analysed economies and used indicators.

With respect to the financial cycle concept, the literature recognises three approaches to measure (extract) the financial cycle. The first is the turning point analysis ([Claessens et al. \(2011\)](#) and [Claessens et al. \(2012\)](#) in the sense of the [Burns et al. \(1946\)](#) methodology. Second approach uses statistical or frequency-based filters ((e.g. [Hodrick and Prescott \(1997\)](#), [Baxter and King \(1999\)](#) or [Christiano and Fitzgerald \(2003\)](#))) to identify the financial cycle as in [Aikman et al. \(2015\)](#). [Borio et al. \(2012\)](#) in an influential paper combine both aforementioned approaches. Finally, third approach employs the Kalman filter ([Durbin and Koopman \(2012\)](#)) to extract the unobserved medium-term financial cycle using multivariate time series models ([Koopman and Lucas \(2005\)](#) and more recently [Galati et al. \(2016\)](#)). All three approaches identify a common medium-term component which they relate to the financial cycle.

Evidence on the financial cycle for advanced economies is well-documented, however for emerging and especially small open economies, evidence is scarce. The literature more or less settles regarding the input indicators, but not how to extract the financial cycle in short samples with many structural breaks. Using the set of standard tools is at least problematic. This study build on the previous work of [Plašil et al. \(2015\)](#) and tries to fill this gap in the literature using a more robust approach when identifying the financial cycle.

3. CONSTRUCTION OF THE FINANCIAL CYCLE INDICATOR

3.1. FINANCIAL CYCLE FROM THE PERSPECTIVE OF A SMALL OPEN ECONOMY

In the literature, there is no straightforward definition of the financial cycle. In this paper we use the generally accepted definition proposed by [Borio \(2014\)](#). He sees the financial cycle as self-reinforcing *interactions* between perceptions of value and risk, attitudes towards risk and financing constraints, which translate into booms followed by busts. To put it simply, the financial cycle can be seen as fluctuations in market participants' attitude to financial risks ([Plašil et al. \(2015\)](#)). Also, there is not a univariate single measure that would capture the financial cycle ².

Slovak economy is a small open economy with a relatively shallow financial market. The capital market with a small number of stock-exchange listed financial and non-financial corporations is dominated by local universal banks focused on retail business with simple and standardised credit products in the domestic currency. Given the absence of a deep and liquid financial markets, the residential property market (especially the one with apartments) is the market with the most liquid asset prices ([Červená \(2011\)](#) and [Rychtárik \(2014\)](#)).

Financial cycles in emerging and advanced economies are becoming more and more synchronised. Empirical investigation by [Rey \(2015\)](#) suggests that financial cycles share common features across advanced economies, led by the FED and other main central banks' monetary policy decisions, especially after the early 2000s economic slowdown. Both the general high degree of openness and the high level of foreign ownership of systemic banks ³, mean almost immediate transmission of the so-called global financial cycle into emerging economies ([Bauer et al. \(2016\)](#), [Rey \(2015\)](#)).

²The problem is not so pronounced for the business cycle. Institutions and organisations like the National Bureau of Economic Research's Business Cycle Dating Committee, the Conference Board's Business Cycle Indicator, the Euro Area Business Cycle Network, The Centre for Economic Policy Research's Business Cycle Dating Committee, or the Banca D'Italia's €-coin indicator publish synthetic measures of the business cycle. These measures aggregate several leading (e.g. surveys, expectations, confidence), coinciding (e.g. GDP, consumption, exports), and lagging (e.g. unemployment, labour volume) sub-indicators. Nevertheless, deviations of the GDP from its trend are often considered as a simple measure of the business cycle.

³Notably the influence of Western European banks over the Eastern European banks. The share of the foreign capital in the Slovak banking sector is higher than 90 percent. It is mostly from the EA/EU countries like Austria, Belgium, Italy, Luxembourg or Czech Republic.

Thus, the general stylised facts about the financial cycle are more than useful for modelling and understanding the financial cycle in emerging countries, such as Slovakia. These facts are gathered from recent empirical studies considering countries around the globe (Borio et al. (2012), Borio (2014)) and EU/EA countries (Hiebert et al. (2014), Comunale and Hessel (2014), Stremmel (2015), Galati et al. (2016)) and can be summarised as follows:

#1: The most parsimonious description of the financial cycle is in terms of credit and property prices, equity prices can be a distraction.

#2: The financial cycle has a much lower frequency and a larger amplitude than the traditional business cycle. For seven industrialised economies across the globe the average duration is around 16 years, for the EU/EA countries around 13 years. Evidence suggests that the amplitude of the financial cycle ranges between 10 to 20 percent while the amplitude of the business cycle is roughly around 5 percent. However, these findings are regime-dependent, see the stylised fact #5.

#3: Peaks in the financial cycle are closely associated with financial crises. Financial crises could originate home, be imported or both. Recessions that coincide with the contraction phase of the financial cycle are especially severe.

#4: Financial cycle helps detect financial imbalances with a good lead in real time. Financial cycle constructed from the cross-border credit flows in addition to the indicators in #1 is a good leading measure of the build-up phase of financial crises.

#5: Both the length and the amplitude of the financial cycle are regime-dependent. Three factors and their interplay are important: (i) financial liberalisation weakens financing constraints, (ii) monetary policy frameworks focused on (near-term) inflation provides less resistance to build-up, and (iii) positive supply side developments provide fuel for financial booms and at the same time downward pressure on inflation.

3.2. SELECTION OF THE INPUT INDICATORS

First of all, as it is mentioned both in Červená (2011) and Rychtárik (2014), there are some data issues which limit our analysis. Data series for lending market are distorted by past structural changes in the Slovak economy and especially in the Slovak banking sector. The bad loans write-offs in corporate sector loan portfolio inhibits any serious

trend analysis until 2004. In addition, development of the household debt started in 2003 with the mortgage market expansion. On top of that, the house price data series is available only from 2002. Thus, the analysed sample is 2003Q1-2019Q3 with 67 observations for each variable.

Regarding the financial cycle definition, the measure should include indicators which are forward-looking in nature and are relevant for future financial crises (see the stylised fact #4). Details about the raw indicators are presented in Table 1.

Credit to households and non-financial corporations (I1),(I2): The literature broadly agrees that credit booms tend to sow the seeds of crises. A great number of studies (Borio et al. (2012),Schularick and Taylor (2012), Borio (2014), Giese et al. (2014), Galati et al. (2016), Červená (2011), Rychtárik (2014), among others) consider the excessive credit growth essential in boom-bust cycles.

Property prices (I3): Giese et al. (2014) argue that credit growth may be less of a concern for financial stability if it is used to finance investment projects that enhance the economy's capacity to produce output, R&D activities, or start-ups than if it is used to buy (and subsequently to sold) existing assets. Typical example are real estate prices (Borio et al. (2012), Claessens et al. (2012), Borio (2014), Plašil et al. (2015), Červená (2011), Rychtárik (2014), among others).

Households and non-financial corporations' debt burden (I4), (I5): Potential borrowers normally do not only need to meet a leverage constraint but their future expected income flows have to be sufficiently high to service future interest payments. Moreover, debt service costs enter their budget constraint and affect their expenditure. Economic agents tend to overestimate their ability to repay future debts, especially in good times. Should a recession occurs, they have to cut back expenditure spending to avoid default (Giese et al. (2014), Juselius and Drehmann (2015), Rychtárik (2014)).

Financing conditions for households and non-financial corporations (I6), (I7), (I8), (I9): Financing conditions represent financial risk attitude on the credit supply side and help differentiate between the credit supply and credit demand forces. According to ECB's Bank lending survey, financing conditions can be divided into two categories: (i) credit standards which are internal guidelines or loan approval criteria (set prior to the negotiation), and (ii) terms and conditions which are related to the borrower's characteristics (result of the negotiation). Furthermore, the second category consists of non-interest and interest terms and conditions. Recent empirical evidence (Köhler Ulbrich et al. (2016)) shows that banks tend to change more intensively their interest terms and conditions than their, closely related, non-interest terms and conditions and credit standards. Next, developments in interest terms and conditions are

closely associated with developments in actual bank lending spreads, calculated as the difference between the composite lending rate and a relevant market reference rate (Köhler Ulbrich et al. (2016) and Giese et al. (2014)). In this paper, financing conditions consist of both the non-price component modelled by credit standards and the price component modelled by bank lending spreads.

Aforementioned indicators (credit, house prices, debt burden, and financing conditions) are heavily interrelated. In Beneš et al. (2016)'s words, this relationship is called a *deadly embrace* which we can relate to the financial cycle. Starting from the equilibrium, an initial move for the financial cycle can originate from a positive shock to the economy (demand side), easing financing conditions (supply side), or both. Demand for housing and/or lending to the housing sector will start rising relative to the initial equilibrium. As a result, now slightly inflated house prices encourage households to increase their demand for credit and banks to lend more, mainly due to positive expectations about the future growth. This loop reinforces the upward pressure on house prices, demand for credit, financing conditions, and growth of debt. Slowdown in credit expansion, correction in house prices, process of deleveraging, and/or banks' reassessing of their exposures can then lead to a severe financial crisis.

Current Account Deficit (I10): Borio and Disyatat (2011) argue that the role of the current account is often overestimated and miscast the resulting imbalances in the crisis. Based on additional evidence, Borio (2014) argues that credit and asset price booms go hand-in-hand with a deterioration in the current account. Giese et al. (2014) and Plašil et al. (2015) also point out that large and persistent current account deficits could be seen as a warning sign of building vulnerabilities, especially in small open economies.

Non-included variables: Borio et al. (2012) include equity prices in their analysis of the financial cycle, but they conclude that equity prices can be a distraction. They co-vary with the aforementioned variables far less. At the same time, much of their variability concentrates at comparatively higher frequencies (Borio (2014), Giese et al. (2014)). Moreover, given the nature of the Slovak capital market, this variable is not very suitable for the financial cycle modelling.

Business cycle measures such as GDP, output gap, consumption, investment, unemployment rate, and consumer confidence are used in Červená (2011) and Rychtárik (2014) and only for comparison in Borio et al. (2012). According to Borio et al. (2012) and Borio (2014) these measures are different phenomena and their importance lies in higher frequencies.

Some authors (Borio et al. (2012), Stremmel (2015), Červená (2011), Rychtárik (2014)) see the credit-to-GDP gap as an important indicator for the financial cycle. However, we

have decided to not include it. The reasoning is as follows: (i) the credit-to-GDP gap is a stand-alone macroprudential tool in Slovakia; (ii) HH and NFC debt burdens are in a sense quite similar measures; (iii) [Giese et al. \(2014\)](#) recognise that the gap measure is not a timely indicator in all circumstances, because the stock of credit is more persistent than the GDP which may lead to an increase in the gap in an economic downturn; (iv) this measure does not distinguish between good (enhancing productivity) versus bad (inflating asset bubbles) credit expansions ([Beneš et al. \(2016\)](#)); and (v) the unreliability of the estimated real-time trend ([Edge and Meisenzahl \(2011\)](#) in contrast to [Giese et al. \(2014\)](#)).

[Červená \(2011\)](#) and [Rychtárik \(2014\)](#) use a number of variables that characterise the banking sector including capital adequacy ratios, return on equity, return on assets, and loan-to-value ratios. [Stremmel \(2015\)](#) considers bank funding ratio, bank-net-income-to-total-assets ratio, loans-to-total-assets ratio for EU economies and concludes that a medium-term cycle in bank variables is somewhat lagging with respect to other financial variables. The problem is also the banking data availability.

Another considered variable ([Červená \(2011\)](#), [Rychtárik \(2014\)](#)) are non-performing loans. A non-performing loan is a legacy of the past (potentially excessive) credit expansion and the current state of a business cycle. Moreover, as research in [Berti et al. \(2017\)](#) suggests, the evolution of NPLs in the euro area is a more structural problem and relates to the real economic development. Thus, by our definition of the financial cycle, non-performing loans are lagging behind the financial cycle and are more related to the business cycle.

It would be possible to include other variables that would capture the attitude towards risk, such as credit spreads, risk premiums, or default rates but there is a problem with data availability.

Table 1: Raw data

ID	Raw Data	Frequency	Source
(R1)	Loans to HH, mil. EUR	Monthly	NBS
(R2)	Loans to NFC, mil. EUR	Monthly	NBS
(R3)	House Price, EUR/m ²	Quarterly	NBS
(R4)	Nominal GDP, SA, mil. Eur	Quarterly	SO SR
(R5)	Credit standards on loans to HH, %	Semiannually	NBS/ECB
(R6)	Credit standards on loans to NFC, %	Semiannually	NBS/ECB
(R7)	IR on loans to HH, %	Monthly	NBS
(R8)	IR on loans to NFC, %	Monthly	NBS
(R9)	Interbank Rate 3MEURIBOR (3MBRIBOR), %	Daily	NBS
(R10)	CA-deficit-to-GDP, %	Quarterly	OECD

We convert loans to HH and NFC to quarterly frequency using the sum over the period method. Credit standards on loans to HH and NFC using the original value for all periods. Finally, the interest rate on loans to HH, NFC, and the 3 month-interbank rate

using the average value over the period method.

We use annual growth rates of relevant variables (see Table 2 and Figure 1). These growth rates capture different movements of acceleration and speed of indicators (Stremmel (2015)) and, at the same time, capture the medium-term component better (Comin and Gertler (2006)).

Table 2: Input indicators (x_t)

ID	FCI Input Indicator	Transformation
(11)	Change in the stock of loans to HH	yoy change of (R1)
(12)	Change in the stock of loans to NFC	yoy change of (R2)
(13)	House Price Inflation	% yoy change of (R3)
(14)	HH Debt service ratio	yoy change of (R1)/(R4)
(15)	NFC Debt service ratio	yoy change of (R2)/(R4)
(16)	Credit standards on loans to HH	(R5)
(17)	Credit standards on loans to NFC	(R6)
(18)	IR Spread on loans to HH	(-1)*((R7) - (R9))
(19)	IR Spread on loans to NFC	(-1)*((R8) - (R9))
(I10)	CA-Deficit-to-GDP	(-1)*(R10)

Source: Authors' own computations.

3.3. TRANSFORMATION OF INPUT INDICATORS

Construction of a univariate cycle indicator from a group of input indicators requires both cycle extraction and aggregation. Moreover, which phase should come first is a matter of further debate (Stock and Watson (2014)).

The cycle extraction is usually carried out by time series models of trends, statistical filters, unobserved components models, turning point analysis, demeaning, or as it becomes clear later, by empirical cumulative distribution function.

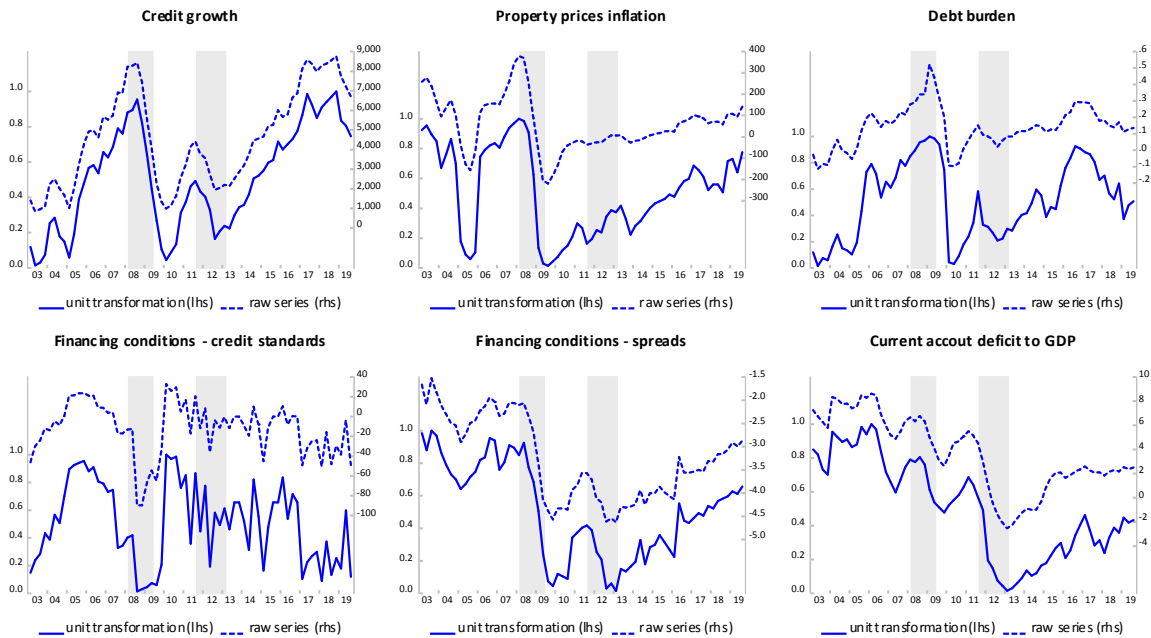
Input indicators are often aggregated using averaging, principal component analysis, common cycle restrictions in unobserved components models, weighted empirical cumulative distribution function, or using a portfolio theory.

In the financial cycle literature it is common to first extract cycles and then combine this information into an indicator (Borio et al. (2012)). Červená (2011) among others uses standardisation of input indicators and then averaging which is the most common way. However, this method implicitly assumes that the underlying series are normally distributed, which is not always the case, especially with financial data. Similar problem emerge with principal component analysis, since it is sensitive to outliers (Holló et al. (2012)). Other aforementioned aggregation methods are not suitable for a small open economy with many structural breaks. Modelling trends, setting the length of a financial cycle, estimating unobserved components models, or identification of turning

points would be rather arbitrary in Slovakia with experience of only one and possibly incomplete financial cycle.

Rychtárik (2014) similarly admits incapacity to set an ad-hoc threshold of excessiveness or other equilibrium levels for a small open economy and proposes a different approach⁴. Every input indicator should be compared to its own history only. If actual level of input indicators has already been observed before, and this period has later proved to be sustainable, we can get a reasonable feeling about the current development and vice versa. A number between 1 and 9 is then assigned to the actual value of the variable depending on its position in respective percentiles of its historical distribution.

Figure 1: Raw and transformed input indicators.



Note: Shaded areas are recessions in the Eurozone dated by CEPR.

Source: NBS, Eurostat, ECB, OECD, authors' own computations.

In this paper we use a similar approach and transform input indicators using their empirical cumulative distribution functions (1), involving the computation of order statistics (Holló et al. (2012), Wen (2015), Plašil et al. (2015)). In other words, this transformation replaces each value of raw data x_t by its ranking number r , scaled by the sample size T :

$$s_t = F_T(x_t) := \begin{cases} r/T & \text{for } x_{[r]} \leq x_t < x_{[r+1]}, \quad r = 1, 2, \dots, T - 1 \\ 1 & \text{for } x_t \geq x_{[T]}, \end{cases} \quad (1)$$

which yields a set of standard distributed indicators $s_t \sim U(0, 1)$. This transformation

⁴In contrast, Juselius and Drehmann (2015) use a VAR model in the error correction form to estimate the equilibrium paths for leverage and debt service burden in the United States.

makes their values mutually comparable and ready to aggregate. The lowest value of the transformed variable indicates a potential trough of the cycle and the highest value its potential peak (see Figure 1).

A few issues arise regarding this approach. This transformation is based on historical distributions; therefore it is sample dependent and estimates might change as new data arrived (Plašil et al. (2015)). However, this may not be a big issue for identifying the position in the cycle as it is for the amplitude. Moreover, as we are observing more data, potential problems from this transformation will matter less and less.

3.4. PORTFOLIO THEORY AND SYSTEMIC RISK

Partial indicators are aggregated into a univariate indicator of the financial cycle based on the portfolio theory. This theory was introduced by Markowitz (1952) and applied into the macro-prudential context by Holló et al. (2012), Wen (2015) or Plašil et al. (2015).

In the simplest possible case assume that we have only two assets. Let w denotes a vector of portfolio asset weights which sum to 1 such as $\sum_{i=1}^2 w_i = 1$, σ_i to be a vector of asset return variances and ρ is the correlation between the two. Then the risk of the whole portfolio is $\sigma_p^2 = w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + 2w_1w_2\rho\sigma_1\sigma_2$. The key point from this theory is that the more asset's return variance co-move (is correlated) with the rest of the portfolio, the more risk it adds to the portfolio in addition to its individual risk.

Applying these ideas to model a financial cycle indicator as in Holló et al. (2012) or Plašil et al. (2015) we end up with the following formula:

$$FCI_t = (w \circ s_t)' C_t (w \circ s_t) \quad (2)$$

where a vector of weights $w = (w_1, w_2, \dots)$ indicates the relative importance (systemic importance) of the individual input indicator, $s_t = (s_{1,t}, s_{2,t}, \dots)$ is the vector of transformed input indicators at time t , $(w \circ s_t)$ represents the element-by-element multiplication of these vectors. Finally, matrix C_t contains pairwise correlation coefficients $\rho_{ij,t}$ determining the relationship between the input indicator i and j at time t (interconnectedness). The result is the financial cycle indicator defined on the interval $(0; 1)$. The higher the indicator, the higher is the degree of financial risk tolerance among market participants in the economy. In other words, low values indicate high risk aversion while high values indicate low risk aversion.

In the two-variable example, the FCI at time t would look like:

$$FCI_t = w_1^2 s_{1,t}^2 + w_2^2 s_{2,t}^2 + 2w_1 s_{1,t} \rho_{12,t} w_2 s_{2,t} \quad (3)$$

Impact of an individual indicator consist of two parts: (i) the weight and the value of the indicator, and (ii) the indicator correlation with all other indicators. While the interpretation of the first part is straightforward, the effect of correlation needs a little more attention.

If the correlation is zero, then the FCI is simply a sum of squared products. Contrary, if the correlation is perfect, then the FCI attains its theoretical maximum. First derivative of the FCI in (3) w.r.t. correlation is $2w_1 s_1 w_2 s_2$. This means that the higher (lower) the input indicators, the bigger (smaller) the effect of their correlation on the final value of the FCI. To illustrate this point, let us assume that both input indicators are historically on elevated levels at .95. Then the effect of a unit change of their correlation on the FCI will be around .45. On the other hand, if the input indicators are on their historical lows at .10, the effect of a unit change of their correlation on the FCI is below .01.

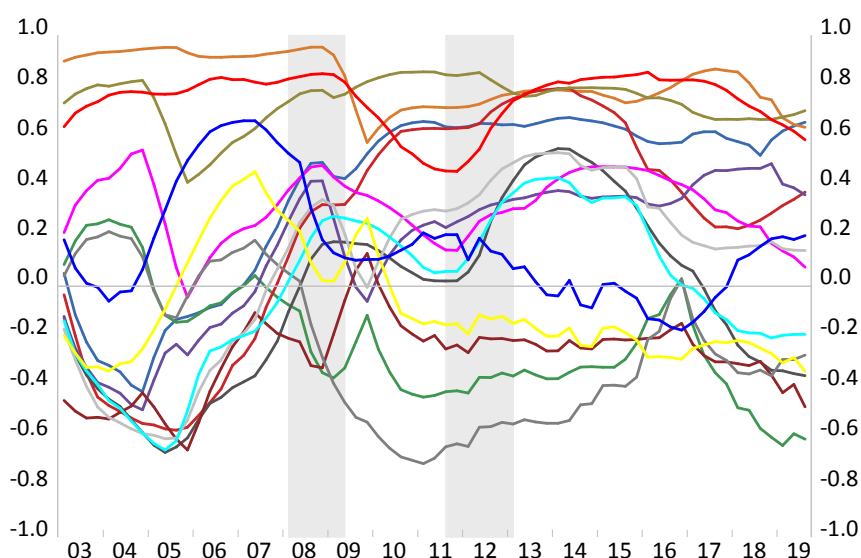
3.5. WEIGHTS AND TIME-VARYING CROSS-CORRELATION

The aggregation of input indicators is done in two stages. In the first stage the input indicators are aggregated across sectors (households and non-financial corporations) using the arithmetic average with time-varying weights. These weights reflect the relative share of each subsector in total loans to the private sector. For instance, the share of households loans to total loans was 0.3 in 2004 while this ratio more than doubled in 2016.

We are well aware that there exists many possible approaches of choosing input indicators weights. For example, [Holló et al. \(2012\)](#) select the weights for subindicators in their CISS index based on their average relative impact on industrial production growth measured by the cumulated impulse responses from different VAR models (for illustration, 0.15 for money market, 0.15 for bond market, 0.25 for equity market, 0.30 for financial intermediaries, and 0.15 foreign exchange market). In their robustness checks, they also try equal weights (0.2) for each subindicator and the results were almost identical. [Plašil et al. \(2015\)](#) in a similar indicator to ours use a different approach. At first, they *a priori* set the constraints on weights to reflect their expert knowledge on importance of individual input indicators. In the next step, they select the weights which give the best predictions of non-performing loans. In their case, only credit growth alone has weight of 0.62, while house prices only around 0.10. Lastly, many authors favour

equal weights for all input indicators to ensure the robustness of results. As was argued earlier, the financial cycle is best described in terms of credit and property prices, therefore we assign them more than 50% in the financial cycle indicator. We set the vector of weights in (2) as $w = (0.3; 0.3; 0.1; 0.1; 0.1; 0.1)$ for aggregate credit, property prices, aggregate debt burden, aggregate non-price financing conditions, aggregate price financing conditions, and current account deficit. We will later also check different set of weights.

Figure 2: Time-varying cross-correlations



Source: Authors' own computations.

Time-varying correlation coefficients (see Figure 2) were estimated using the exponentially weighted moving average (EWMA) method:

$$\begin{aligned}
 \sigma_{ij,t} &= \lambda\sigma_{ij,t-1} + (1 - \lambda)\tilde{s}_{i,t}\tilde{s}_{j,t} \\
 \sigma_{i,t}^2 &= \lambda\sigma_{i,t-1}^2 + (1 - \lambda)\tilde{s}_{i,t}^2 \\
 \rho_{ij,t} &= \sigma_{ij,t} / \sigma_{i,t}\sigma_{j,t},
 \end{aligned} \tag{4}$$

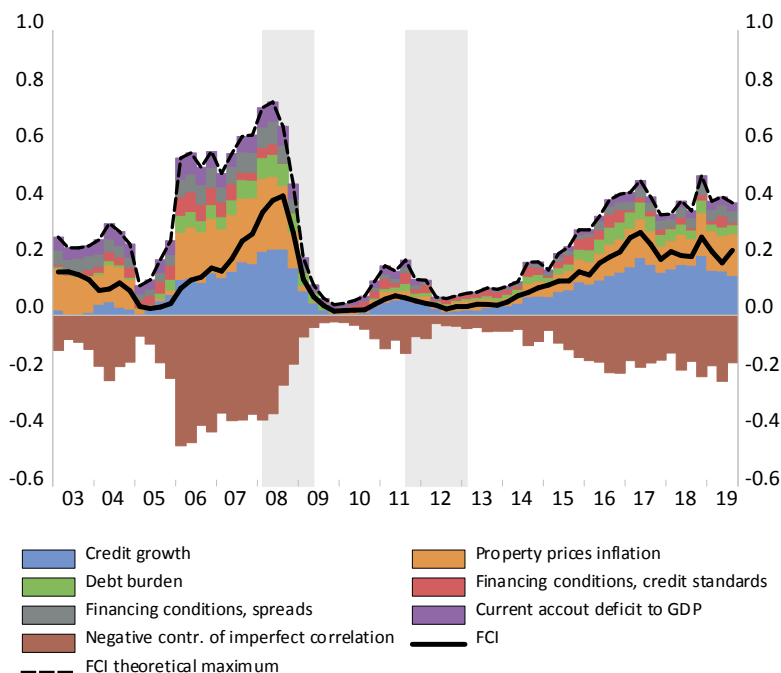
where $\lambda = 0.93$ is a smoothing factor⁵ and $\tilde{s}_{i,t} = (s_{i,t} - 0.5)$ denotes the values of individual subindicators after subtracting their "theoretical" median. Based on Plašil et al. (2015), the initial values of the correlation coefficients at time $t = 1$ were estimated using the EWMA method applied in reverse order from the most recent observations to the start of the sample.

⁵Setting the smoothing factor is rather arbitrary. The higher the smoothing factor the more stable and smoother the estimated correlations coefficients are. In the macroprudential context it is common to set the value at 0.93 (Holló et al. (2012)) or at 0.94 (Plašil et al. (2015)).

4. EVALUATION

Figure 3 shows the evolution of the FCI from 2003 to 2019. Starting in 2005, there is clear evidence of an expansionary phase of the financial cycle. During this period all input indicators showed strong dynamics. Intense credit growth accompanied with rising house prices, loose financing conditions and external imbalances led to the peak of the financial cycle in the second half of 2008. It is worth noting that in the upward phase of the financial cycle not all variables peak at same time (Borio et al. (2012) point to a similar problem in advanced economies). High negative contribution of the imperfect correlation, especially in 2006-2007, could be explained by this observation.

Figure 3: FCI and its decomposition



Note: Financial cycle indicator takes values from the interval $[0,1]$. Low values of the FCI indicates high risk aversion in the economy or the through of the financial cycle, high values of the FCI point to low risk aversion or to the peak of the financial cycle. Figure 3 shows the estimated evolution of the FCI (black line), its theoretical maximum (black dashed line), decomposition (bar chart), and the negative contribution of the imperfect correlation between indicators; 2003Q1-2019Q3.

Source: Authors' own computations.

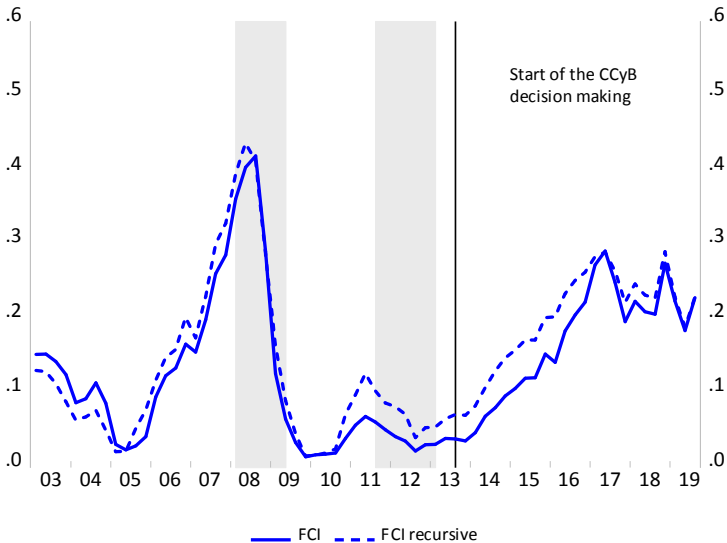
Global financial crisis hit the global economy at the end of 2008 which translated almost immediately into extremely high risk aversion. Through of the financial cycle is identified at the end of 2009. It seems that in the downward phase of the financial cycle all variables are falling rapidly and usually at the same time (note the almost zero negative contribution of the imperfect correlation in 2009-2010). Minor recovery in risk tolerance in 2011 was further depressed by the European debt crisis.

Risk appetite was again continuously rising from the end of 2013 until the mid 2017, mainly due to the credit and property prices growth. This expansionary phase of the financial cycle has been constantly suppressed by the macro-prudential measures, however, the FCI remains high.

4.1. QUASI REAL-TIME PERFORMANCE

The signal issued by the FCI should be stable over time. As it was mentioned in section 3.3, unit transformation of input indicators is sample dependent and, therefore, the historical distributions may change as new data arrives. To test this dependency, we split our sample in two parts to recursively evaluate the FCI. The part from the beginning of the sample until 2013Q3 will be the base period for recursion. We have set 2013Q3 as the last data point in our recursion, because at that time the macro-prudential policy tools had been introduced into the toolkit of the National Bank of Slovakia more systematically and the concept of a financial cycle had become more relevant. Every point in the recursive FCI from 2003Q1 to 2013Q3 uses all available information up to 2013Q3. In the second part of the sample, for example for 2013Q4, we use all available information up to 2013Q4, but only the FCI in 2013Q4 is saved. This quasi real-time evaluation runs quarter-by-quarter until the end of the sample. In Figure 4 we compare the FCI from section 4, which uses whole sample for all data points, with the aforementioned recursive FCI. It can be seen that these two give us qualitatively similar information with minor discrepancies around the European debt crisis.

Figure 4: Quasi real-time performance of the FCI

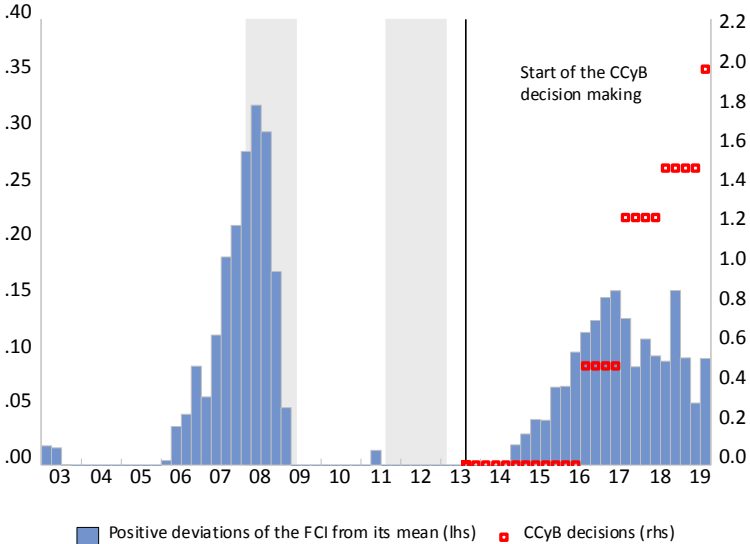


Source: Authors’ own computations.

National Bank of Slovakia, as an institution responsible for the conduct of macro-prudential policy, has been employing a set of tools starting roughly in 2013. These tools range from soft measures like stability reports, inspections, meetings with institution representatives, recommendations to more hard measures and legislative instruments, notably, capital buffers.

To evaluate the real-time policy relevance of the FCI, we have computed deviations of the quasi real-time FCI, computed as in previous paragraph, from its quasi real-time mean and compare it with the counter-cyclical capital buffer (CCyB) decisions (not the dates of implementation) by the National Bank of Slovakia (see Figure 5).

Figure 5: FCI and the CCyB decisions



Source: Authors’ own computations.

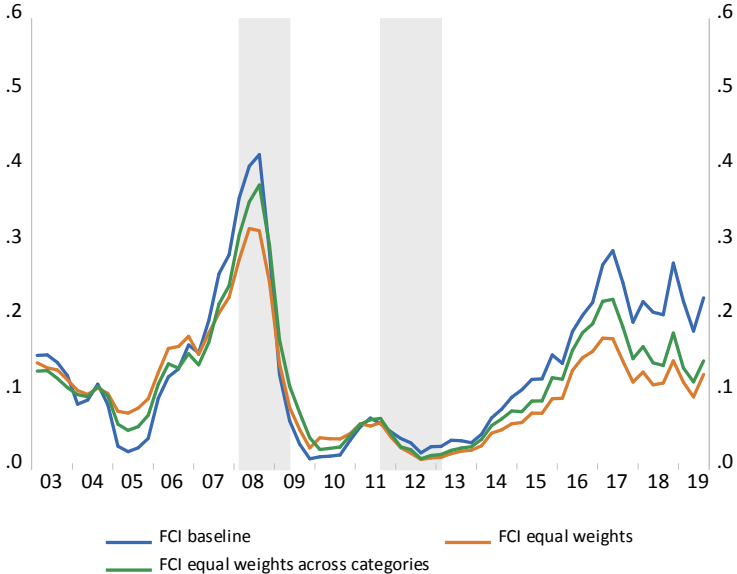
FCI started giving positive signals about the build up phase of the financial cycle in late 2014. From there, the signals grew stronger and in 3Q of 2016 the National Bank of Slovakia decided to rise CCyB to 0.50%. However, there were not any signs of stabilisation and the FCI continued to grow. In 3Q of 2017 the National Bank of Slovakia took another decision and lift the CCyB to 1.25%. This increase was followed by a brief dip in the FCI. As the FCI has been still elevated, there were one more lift in 3Q 2018 to 1.50%, and more recently, more pronounced lift to 2.00% in 2019 Q3.

4.2. DIFFERENT WEIGHTS AND DECAY FACTORS

Holló et al. (2012) select the weights based on the input indicators impact on industrial production growth. Plašil et al. (2015) use a different approach and choose the weights

which give the best predictions of non-performing loans. Lastly, many authors favour equal weights for all input indicators to ensure the robustness of the results.

Figure 6: FCI w.r.t. different weights



Source: Authors’ own computations.

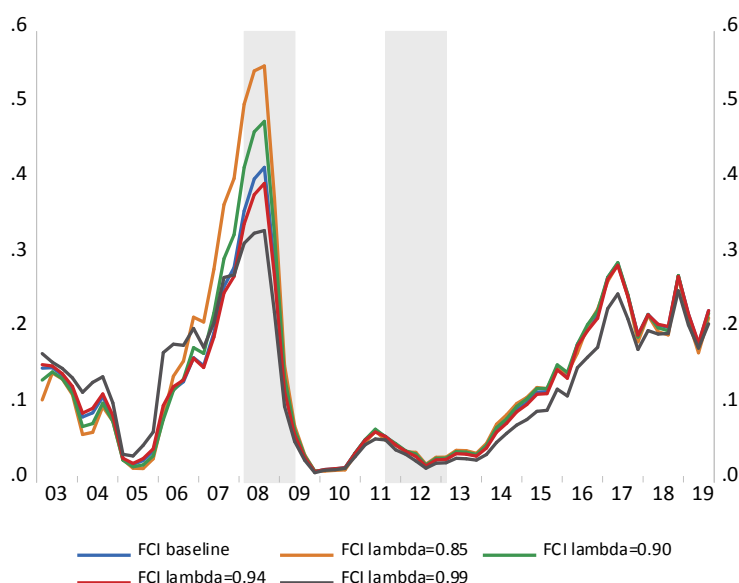
None of the aforementioned approaches is preferred in the literature. Figure 6 compares our baseline FCI indicator with the indicator with equal weights⁶ and with the indicator with equal weights across input indicators categories attached in the second stage of aggregation⁷. Although the compared indicators have different amplitudes, they all tell the same story. They point to an expansionary phase of the financial cycle during the 2005-2008 period, peak at the end of 2008, through at the end of 2009, and elevated levels currently.

Smoothing factor in equations (4) is usually set according to the methodology developed by Riskmetrics (1996). Higher (lower) values produce more stable (volatile) estimates of time-varying correlation coefficients. Discussed smoothing factor values in Riskmetrics (1996) range from 0.85 to 0.99, but the most common values in the literature are either 0.93 or 0.94. Figure 7 illustrates all these cases. Similarly to the previous robustness check, amplitude of the indicators is different, but their relative performance is analogous.

⁶w=(0.167;0.167;0.167;0.167;0.167;0.165).

⁷w=(0.2;0.2;0.2;0.1;0.1;0.2).

Figure 7: FCI w.r.t. different smoothing factors



Source: Authors' own computations.

4.3. COMPARISON OF THE FCI, STRESS INDICATOR, CREDIT-TO-GDP GAP, AND CYCLOGRAM

As was mentioned in the beginning, there has been a number of quite similar indicators developed at the National Bank of Slovakia. Specifically, a stress index (Figure A.1) by Červená (2011), credit-to-GDP gap (Figure A.2) and cyclogram (Figure A.3) by Rychtárik (2018). Despite their different methodologies, their results are consistent with our proposed indicator of the financial cycle. Of course, partly due to the fact that they use some common input indicators.

In any case, somewhat stressed period is identified at the beginning of the stress index sample. This was related to the modest loan growth as described by the credit-to-GDP gap. The period roughly between 2005 and 2008 was characterised by favourable financing conditions mirrored in improved overall macroeconomic outlook with early signs of overheating. Stress values reached a peak in 2009, followed by a credit crunch and economic slowdown. Post crisis recovery was halted by the European debt crisis. Starting in 2014, credit has been continuously growing, jointly reinforcing with improving broad economic conditions. All indicators are approaching to levels seen before the Global financial crisis.

5. CONCLUSION

This study has proposed a financial cycle indicator for the Slovak economy. It contributed to the limited literature on the financial cycle modelling in small open economies with additional evidence. At the same time we contributed to the current set of tools developed and used at the National Bank of Slovakia, essentially in two ways: we have (i) taken into account endogenous co-movement between input indicators, and (ii) focused solely on the build-up phase.

Results are quite robust with respect to different robustness checks and in a sense similar to other indicators as well. Moreover, policy prescriptions implied by the financial cycle indicator broadly collides with the macro-prudential decisions undertaken by the National Bank of Slovakia. The financial cycle indicator implies an expansionary phase of the financial cycle from 2005 to its peak at the end of 2008, followed by a rapid reversal in the risk attitude at the end of 2009. Currently, the financial cycle has been at an expansionary phase which started roughly at the end of 2013.

This indicator may serve as an input indicator for different kinds of macroeconomic models. For example as a proxy for time-varying risk aversion or a financial cycle. How to exactly use this indicator for macro-prudential purposes is a matter of further debate and research.

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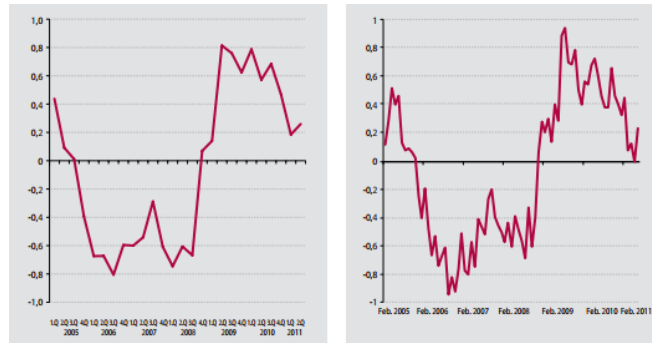
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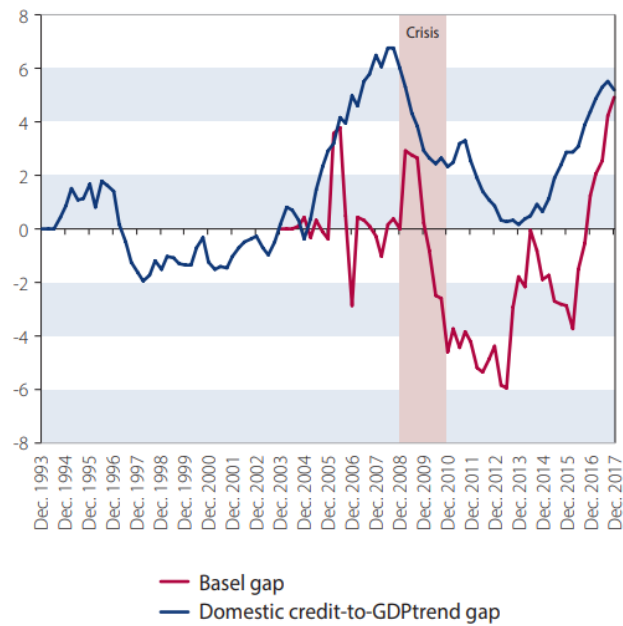
6. APPENDIX

Figure A.1: Červená (2011)'s stress indicator



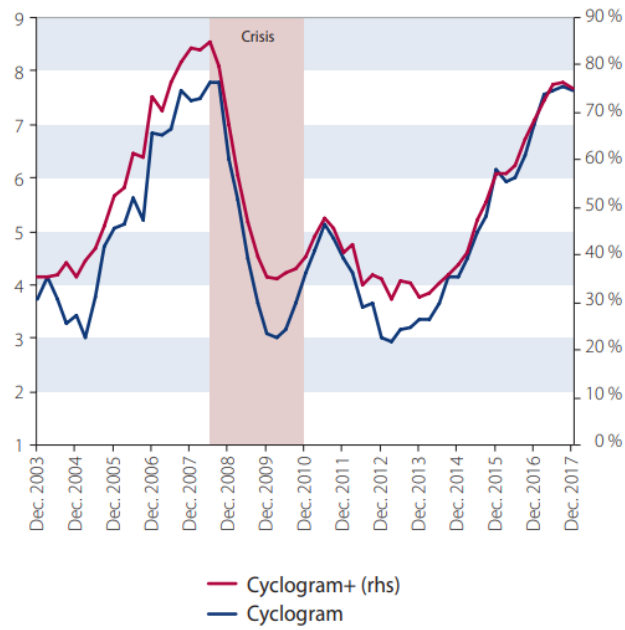
Source: Červená (2011).

Figure A.2: An updated version of Rychtárik (2014)'s credit-to-GDP gap



Source: Rychtárik (2014).

Figure A.3: An updated version of Rychtárik (2018)'s cyclogram



Source: Rychtárik (2018).