EXPLORING LEADING INDICATORS OF BANKING CRISIS IN CASE OF ALBANIA

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Abstract

This paper investigates several macro-financial indicators as possible leading indicators of systemic banking crisis in the case of Albania. We test various credit related indicators using the *single extraction approach* and *loss function minimization approach,* on various leading horizons (from 7 quarters to 13 quarters ahead of the crisis). We use quarterly data and find that the *trend deviation of total credit to private sector–to-GDP ratio*, using one sided HP filter (λ of 100.000 and 400.000), and within the thresholds of 2-3 percentage points, performs as a good leading indicator of impending crises.

Keywords: leading indicators, banking crisis, signal extraction.

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Introduction

The late financial crisis (2007-2008) and the large economic costs associated with it, highlighted the need for an effective set of policy tools that can be used to mitigate systemic risk and prevent the recurrence of crises. On this content, many central banks and other institutions have already engaged in building macro-prudential frameworks and policies in order to detect and discourage the build-up of macro-financial vulnerabilities and risks that might set the path of future crisis.

The ultimate aim of macroprudential policies and instruments is to prevent the financial crises in advance. But the activation of such policies takes time, so the policymakers need to be aware of the risks and vulnerabilities that are building-up at an early stage. On the other hand, the implementation of these policies might be costly, so it is important to take into account these costs before taking unnecessary preventive actions. On this regard, a crucial part of the macroprudential framework is the identification/construction of a reliable set of "leading indicators" of crises that can detect on time the emerging vulnerabilities and have the best balance between false alarm and missed crisis.

Despite the various methods and instruments built to monitor systemic risk, the identification of a unified set of reliable indicators that can serve as "predictors" of possible banking crisis, is quite difficult. This because the ability of one or more macro-financial indicators to detect the accumulation of macroeconomic imbalances, is closely related to a number of factors that vary significantly from one country to another, such as: the structure of the economy and/or the financial system, the characteristics of the banking sector, crisis complexity, length and accuracy of the data series etc. For this reason, an indicator that may result efficient in predicting the crisis in a particular country or during a particular time may not result as such if these conditions change. However, among various indicators tested for their ability to detect past crises episodes, most authors agree that the indicators related to credit (such as: credit to GDP gap, credit growth, loan/ deposit ratio, etc.), are the most efficient one and as history tend to repeat itself, they can be used to signal future episodes of distress as well.

Taking guidance on the existing literature addressing the issue, this paper investigates various macro-financial factors as possible leading indicators of systemic banking crisis in the Albania. Since Albania has never experienced a banking crisis according the standard definitions[2], the selected indicators are tested over past moments of strong systemic stress, which we agree to consider as "crisis episodes". To determine the beginning and the ending of these "crises", we rely on the information provided by the Financial Systemic Stress Index for Albania, developed by Kota and Saqe (2013), as well as on the relevant literature (such as BoA Financial Stability Report, IMF Report etc.)

We make use of two methodologies to test the selected indicators:
(1) *the signal extraction approach*, originally developed by Kaminsky and Reinhart (1999) and used in other well-known studies about financial and banking crises (Borio and Lowe (2002 a, b); Borio and Drehman (2009) etc.). This is a non-parametric method which classifies the observations as being either in a tranquil or a vulnerable (or crises) state according to certain critical threshold for each indicator taken into analysis: if the indicator value is above this threshold value, the indicator "issues a signal" of a possible future crises which might or might not happen during a fixed time window. This time window usually defers from 1 to 4 years after the signal is issued. 2*) the minimization of the loss function*
The paper is organized as follows: *Section 2* reviews the existing literature on various leading indicators of systemic financial/banking crisis and the main findings about their performance; *Section 3* explains the "signal extraction approach" by Kaminsky and Reinhart (1999) which is used to test the selection of possible leading indicators; *Section 4* discuses past episodes of systemic stress experienced by the Albanian banking sector, considered as "crisis episodes"; *Section 5* presents the selection and construction of leading indicators in the Albanian context; *Section 6* presents the main results of the analysis and *the last section* summarizes the conclusions of the paper.

[2] We define systemic banking crises as the "simultaneous failures in the banking sector that significantly impairs the capital of the banking system as a whole, which mostly results in large economic effects and government interventions" (Laina et al., 2014).

2. Literature Review

The literature on leading indicators on crisis, particularly banking crisis, has been significantly active in the late '90s and mid '00s. The most popular works in this period focus on issues related to banking crisis and the exchange rate crisis in developing countries. After the 2007-2008 global crisis, the issue of leading indicators received renewed attention both from the academics and institutions such as central banks and international institutions (IMF, BIS, ECB, etc.), especially in the view of constructing macroprudential policies.

According to Borio and Lowe (2002 a,b) and later Borio and Drehmann (2009), the idea of leading indicators is based on the view that banking crises often result from growing financial vulnerabilities on private sector balance sheet (individuals, non-financial and financial corporations) during benign economic conditions. These vulnerabilities, known as "financial imbalances", are often associated with aggressive risk taking by banks and also economic agents (such as individuals and companies), which is driven but also feed an unsustainable economic expansion through a feedback effect. It is widely accepted that at a certain point in time, triggered by various domestic or external events, these accumulated imbalances will unwind, potentially causing widespread financial distress in the banking sector (Borio & Drehmann, 2009). The deeper the imbalances the higher the level of stress that may materialize in a systemic banking crisis, with serious economic and financial consequences. While the exact timing of the crisis may be unpredictable, the symptoms of the build-up of the imbalances might by detected ahead in time through the behavior of certain macro-financial indicators around the crisis, allowing this way the authorities to take preventive actions.

Referring to Borio and Lowe (2002), a good leading indicator should: first, be able to predict a high percentage of crises that occur within a certain period of time, and second, it should not signal very often causing false alarms or "noise". In more technical terms, an effective indicator should provide a low rate between false alarms and correct predictions. In a later study by Drehmann and Juselius (2013), the authors propose three criteria for selecting the leading indicators in the context of macroprudential policies. The first is the *time criterion*, which relates to the fact that a good leading indicator should signal ahead in time enough for the policymakers to take preventive measures. Basel III guidelines on this issue,

recommends that "the leading indicator must signal at least 2-3 years before the crisis" (BCBC, 2010, p 16). The second is *the stability criteria,* which means that the indicator should be consistent in issuing signals and not fluctuate from one period to another inducing uncertainty. The third criteria relates to the *interpretation* of the indicator's behavior. The signals that are difficult to interpret by policymakers are likely to be ignored. In this regard, a simple indicator might be preferred.

In an effort to find the best leading indicator or (set of indicators) for financial or banking crises, different authors have selected/tested various categories of indicators, generating different results, depending on the economic characteristics of the country/countries taken into analysis, timing and types of crises, data availability etc. However, most authors focus on the study of credit aggregates, such as credit to households, corporate, mortgage, total credit to private sector etc. Many authors in the late '90 that studied various crisis mostly on emerging markets (such as Detragiache Demirguç-Kunt (1998) and Kaminsky and Reinhart (1999)), argue that the banking crises are usually preceded by credit booms. Subsequent works from Borio and Lowe (2002, 2004) and especially the after crisis literature on leading indicators (Alessi and Detken (2009), Borgy et al. (2009)), Drehman et al. (2010, 2011)), also conclude that the behavior of credit indicators can provide useful early signals of future crises. Dell'Ariccia et al. (2012) in their study about the credit booms[3], found that one third of the credit booms in their sample were followed by a banking crisis within three years of its end, and three-fifths by a weak economic period. Giese et al. (2012), review the performance of credit-to-GDP gap for the case of UK, which is also recommended by Basel III to be used as a reference guide indicator (alongside judgment) in detecting the emergence of vulnerability and therefore activating the countercyclical capital buffer. The authors find that this indicator works well in providing early signals of the past episodes of financial stress in the UK banking system, but it does not guarantee that it will be successful in detecting potential future episodes. Therefore, the authors suggest some additional complementary leading indicators. Laina et al. (2014) investigate the leading indicators of systemic banking crises in a panel of 11

[3] The authors classify an episode as "credit a boom" if either of the following two conditions is satisfied: (i) the deviation from trend is greater than 1.5 times its standard deviation and the annual growth rate of the credit-to-GDP ratio exceeds 10 percent; or (ii) the annual growth rate of the credit-to-GDP ratio exceeds 20 percent.

EU countries, focusing particularly in the case of Finland. The authors find loans-to-deposits and house price growth to be best leading indicators for their case. Growth rates and trend deviation of loan stock variables are also useful in signaling impeding crises. Table 1 below, is taken from this study and summarizes the selection of indicators in terms of broad categories and their performance (significance) proposed by various authors. It shows that credit-related indicators have been included in all studies and most of them are found to be successful in detecting future crises.

Table 1. Categories of leading indicators in literature.

Source	Credit aggregates	Asset prices	Financial regulative framework	Monetary aggregates	Interest rates	Exchange rate	GDP	Current account
Demirguc-Kunt & Detragiache (1998)	(X)		X	X	X	-	X	
Kaminsky & Reinhart (1999)	X	(X)		X	(X)	X	X	X
Eichengreen & Arteta (2000)	X		-		-		X	
Borio & Lowe (2002 a,b)	X	X					X	
Borio& Drehmann (2009)	X	X						
Alessi & Detken (2011)	X	X		X	X	(X)	X	
Drehmann & Juselius (2013)	X	X					X	X
Lo Duca & Peltonen (2013)	X	X				-	X	(X)
Laina et al.(2015)	X	X						

Source: Laina et al (2014).

X= significant; (X) – partly significant; - = not significant

Beside the credit-related indicators, different authors have tested a selection of other macro-economic variables as possible leading indicators of crisis, as well as combinations of two or more of them. They rely on the idea that the financial system is complex, interconnected and time-varying, and thus a single indicator may be insufficient to warn a potential crisis in the future. Thus policymakers may need to monitor a wide and time-varying set of indicators depending on the emerging risks in the country. Relying on the view that the behavior of credit, asset

prices and possibly the exchange rate, contain useful information about the development of financial imbalances, Borio and Lowe (2002 a)[4], statistically assess the predictive performance of three core indicators: the ratio of private sector credit to GDP, equity prices (deflated by the price level) and real effective exchange rate (REER). The authors also test various combinations of the above indicators. In Borio and Lowe (2002b)[5], beside the indicators of credit and asset prices, the authors consider also GDP growth and investment, as well as various combinations of the indicators. They find that when considered separately, the credit to GDP gap is without doubt the best leading indicator for banking crisis. On the other hand, when indicators are combined, the combination of credit gap to asset price gap, displays the best forecasting powers. Some years later, Borio and Drehman (2009) assessed the out of sample performance of the leading indicators of banking system distress developed in their previous abovementioned works, but over the period of 2004-2008 and in the light of the late financial crisis. They extended their previous analysis by incorporating an indicator the property prices and considered three different combinations of the variables where all of them include a credit gap, but differ in the terms of asset prices included. They find most of the indicators to be fairly successful in providing early signal for several banking crises considered in the analysis. Other categories of indicators, such as money aggregates, financial regulation and financial sector size, have also been accounted in some studies, while indicators such as interest rate, exchange rates and current account deficits have rarely been used or found significant.

3. Methodology

In this paper, we choose to use two well-known approaches to define the optimal indicator: the 'signal extraction approach' and the 'loss function minimization approach".

3.1 The signal extraction approach

This is a non-parametric approach firstly developed by Kamminsky and Reinhart (1999) and subsequently developed by many other authors who have addressed the issue of banking crises (such as Borio and Lowe (2002a, b), Borio and Drehmann (2009), Lo Duca and Petronen, (2011); Drehmann et al. (2011), Laina et al. (2014) etc.

[4] "Assessing the risk of banking crisis", BIS Quarterly Review, December 2002.
[5] Asset prices, financial and monetary stability: exploring the nexus.

This approach is based on the view that crises are preceded by accumulation of imbalances and that the movements of some macro-financial indicators beyond certain critical levels, can help to detect them ahead in time. Technically, the methodology developed by Kaminsky and Reinhart (1999) runs in four main steps: *First*, one must define what events can be classified as a banking crisis and then identify its starting and ending points. Kaminsky and Reinhart (1999) mark the beginning of a banking crisis by two types of events: (1) bank runs lead to closure, merging or nationalization of one or more financial institutions; (2) there are no bank runs, but there are closure, merging, takeover, or large-scale government assistance of an important financial institution (or group of institutions), that mark the beginning of a series of similar events for other institutions. The authors also rely on the information from previous studies on banking crisis and on financial press, to better determine the beginning, peak and end of the crises experienced by various countries included in their study. Later authors (such as Lo Duca and Peltronen, (2011)), make also use of information from various financial stress indices to determine the start, peak and ending point of banking crises or systemic events. *Second*, one must agree on a list of variables that are potential leading indicators and which will then be tested against past episodes of systemic crises. *Third*, for every indicator considered in the analysis, it should be decided upon criteria (that means a critical value or threshold value) that helps to classify the behavior of the indicator as either a signal of a potential crisis or normal (no signal). *Last*, if an indicator is giving a signal, it should be determined if a crisis happens (or not) within a reasonable period of time or if the signal was a false alarm. Therefore, it should be defined what is considered to be the lead horizon within which a signal is considered correct.

Technically, every indicator is transformed into a binary variable (It) which takes the value of "1" (indicator issues a signal) if its values at time t (V^i_t) exceeds a threshold value V_{th}; and takes the value "0"(indicator does not issue a signal), when the threshold is not exceeded:

$$\mathrm{It} = \begin{cases} 1 \text{ if } V_t^i > Vth \\ 0 \text{ if } V_t^i t < Vth \end{cases}$$

Whenever the indicator exceeds (or not) the threshold value, therefore issuing (not issuing) the "signal" of a potential crisis, the observations can be categorized as in the following matrix (see Table 2) known as the "contingency matrix":

Table2. Contingency matrix of signal analysis categorization and performance measures.

	Crisis occurs within the horizon 'h'	Crisis does not occur within the horizon 'h'	*Type I errors (%)*	*Type II errors (%)*	*Predicted crises (%)*	*Noise-to-signal*
Indicator issues a signal $V_t^{\,i} > V_{th} \rightarrow I_t = 1$	**A** (good signals)	**B** (false alarms)	*C/(A+C)*	*B/(B+D)*	*A/(A+C)*	$\frac{B/(B+D)}{A/(A+C)}$
Indicator does not issue a signal $V_t < V_{th} \rightarrow I_t = 0$	**C** (missed signals)	**D** (good silence)				

A: If an indicator is above a threshold value, so the indicator issues a "signal" (V_t^i> Vth) and a crisis occurs at any time within a predefined time horizon (usually 1 to 4 years afterwards). In this case the observation is categorized as a "good signal" or "a predicted crisis".

B-the indicator issues a "signal", but no crisis occur within the time horizon. In this case, the observation is considered as a "false signal" or a "false alarm";

C-the indicator value is below the threshold, so it does not issue any signal, but the crisis occurs at any time within the time horizon. In this case, the observation is categorized as a "missed signal" or "a missed crisis";

D- the indicator is below the threshold, so it does not issue any signals and the crisis does not happen. It this case, the observation is considered as "a correct or a good silence".

The rate of missing signals to total crises is known a "Type I error", while the rate of "false alarm" to the total of "good silences" is called as known as "Type II error".

An optimal indicator would issue only good signals and/or correct silences, and no false signal or missed crisis, which means that all the observations would fall only on A and D in the confusion matrix, and there would be no observation under C and B. Considering the complexity of a crisis, such an indicator is very hard to find in reality. Therefore, a good indicator would predict the majority of crises causing

the minimum of false alarms, or “noises”, which means that this indicator should have a low noise to signal rate. The noise-to-signal ratio is calculated as follows:

$$\text{min (noise –to-signal)} = \min\left(\frac{B/(B+D)}{A/(A+C)}\right) = \min\left(\frac{\text{Type II errors (\%)}}{1-\ \text{Type I erros (\%)}}\right)$$

When this ratio is minimized, the share of correct signals (or the % of correctly predicted crises) is at maximum relative to the share of false signals. Therefore, the threshold where the noise-to-signal ratio is minimized is chosen. As the chosen threshold changes, the values for A to D will also change, since a higher threshold will be associated with higher values for B and D, missed signals and good silences, and lower values for A and C, good signals and false alarms.

Kaminsky and Reinhart (1999), test different threshold values for each of the selected indicators, in several time windows, in order to find the best combination of them. Various thresholds of the indicator will generate different results. Accordingly, a high threshold would allow the indicator to issue only few signals (which will mostly be correct), while most part of the observations will fall under the categories of C and D, (missing crisis and correct silence). This increases the risk of "Type I errors", so raises the probability that crisis are not predicted. On the other hand, choosing a low threshold value will cause the indicator to issue more signals. In this case, most of the observations will fall under the category of A and B (predicted crises and false alarms). This means that most of the crisis will be correctly predicted by the indicator, but there will also be many false alarms, therefore increasing significantly the probability of "Type II error".

An important point in this approach is also the selection of a *reasonable time horizon*, to judge over the accuracy of the signals issued by the indicator. This is the time span between the moment a signal is issued and the moment the impending crisis materializes. A good indicator should signal ahead in time, enough to for the policymakers to take preventive measures to avoid or mitigate the outcomes of a potential crisis. In literature, the time horizon usually varies from 1 to 4 years, which means that a signal that points to a crisis is judged to be correct if the crisis occurs any time within the predefined horizon. Signals issued very close to the occurrence of the crisis are considered to be useless, since they do not

provide sufficient time for policy makers to react, while the extent of the time window generally improves the indicator's performance.

3.2- Loss function minimization - the policymaker choice

This approach defines a loss function for the policy makers, in this case the central bankers, to analyze the usefulness of each indicator. The loss function is defined as:

$$\mathcal{L} = \theta \frac{C}{(A+C)} + (1 - \theta) \frac{B}{(B+D)}$$

θ is the parameter revealing the policy maker's relative risk aversion between type I and type II errors. The loss can be interpreted as the policymakers preference weighted sum of type I and type II errors. A θ lower than 0.5 reveals that the central banker is less averse towards missing a signal for an upcoming crisis than towards receiving a false alarm.

The usefulness of an indicator can then be defined as:

$$Min(\theta; 1 - \theta)$$

which means that the optimal indicator is the one that minimizes the loss function of the policymakers preferences.

4. Assessing leading indicators of systemic banking crisis in the case of Albania.

This section tries to assess the performance of a selection of possible leading indicators for the case of Albania. First, we try to determine the beginning and ending point of the episodes of systemic distress experienced by the Albanian banking sector, which we consider as "crisis episodes". Then, we test the predicting ability of a selection of variables against these episodes, using the *signal extraction approach* and *the loss function minimization approach*, through various time windows.

4.1. Episodes of "crisis" in the Albanian banking sector

Most studies on banking crisis rely on cross-country analyses to investigate on potential leading indicators of these crises. The range of literature during the '90-ies and early '00, focus mostly on early warning/leading indicators of

financial/banking crisis in emerging and developing countries (such as Latin American countries and Asian countries), due to the high frequency of crisis events that characterized these countries at that time and the common belief that the crises are a typical feature of emerging economies[6]. The global financial crisis of 2007-2008, which hit mostly the developed economies rather that the emerging ones, changed this belief and many authors included in their analysis developed countries such as euro area countries, previously not considered prone to banking crises.

The inclusion of several countries in the analysis creates the obvious advantage of having a large database of crisis episodes observations, comparing to a single country crises history, increasing the chances of a better understanding of the indicators that have tended to signal banking crisis in the past. On the other hand, the inclusion in the same panel analysis of different countries, which may have different institutional arrangements and financial structure, increases the risk of producing inaccurate results, often difficult to interpret. Moreover, the data definitions across countries often tend to be heterogeneous and the time series employed in the panel tend to be limited. In this regard, investigating the leading indicators for an individual country might be more accurate, but there is the risk of insufficient data or short time series. Also, the number of crises episodes experienced by a single country is usually small compared to a panel of countries, which makes it difficult to test the variables through the signal approach. For this reason the literature addressing this issue for individual countries is generally scarce. However, in the works by Giese et al (2011), Pasricha et al (2013), the authors rely on lessons from the cross-country literature but focus on individual countries (respectively UK and Canada) for their own analysis, being this way less limited by data availability and focusing closely on individual series which can provide greater context.

We try to follow this reasoning and focus on the case of Albania only. The Albanian banking sector has never experienced a systemic banking crisis according to the definitions usually found in the literature[7]. However, over the past 20 years, some

[6] Kaminsky and Reinhart (1999), Demirguç and Detriagiache (1998), Borio and Lowe (2002, 2004).

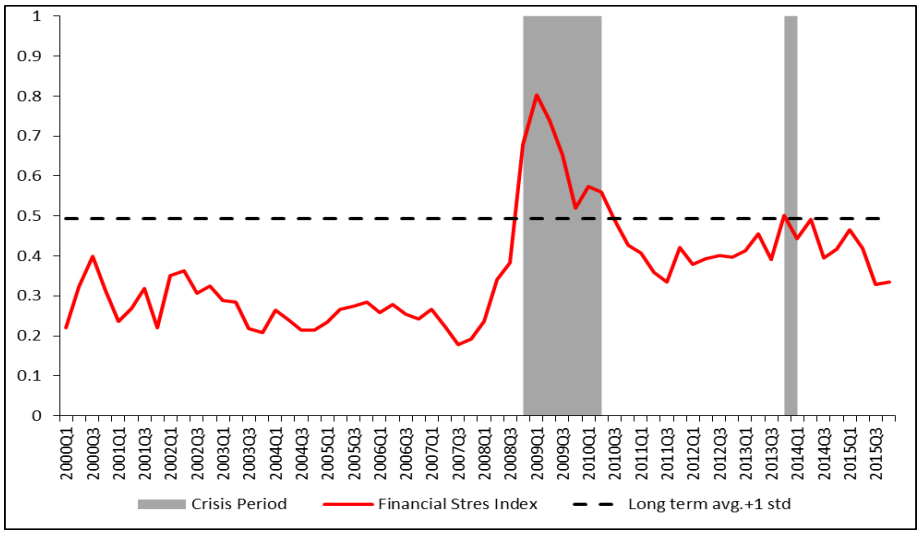
[7] Occurrence of simultaneous failures in the banking sector, which significantly impairs the capital of the banking system as a whole, and accordingly a crisis mostly results in large economic effects and government intervention (Laina et al, 2014).

episodes of severe financial distress have occurred, showing similar symptoms to crisis episodes. To define the beginning and ending dates of these episodes, we rely on the information provided by Financial Systemic Stress Index (FSSI) developed by Kota and Saqe (2013) as an instrument to diagnose the level of systemic stress in the financial system, as well as other useful sources of information (BoA reports and other financial literature addressing this issue). FSSI covers the period from January 2000 to June 2017 and aggregates in a single measure the information coming from the developments in three main parts of the financial system in Albania: a) the banking sector, b) money market and c) the exchange rate. The index takes values from 0 to 1, where 0 implies a tranquil situation without stress and 1 means a situation of maximal stress, which can materialize into a systemic crisis. To identify the time span of past "crisis episode", we choose to consider as such all the moments when the index values exceed the *index long-term average* with at least 1 standard deviation. Following this condition, two "crisis episodes" are identified:

The first crisis episode lies during 'Q3 2008 to Q2 2010'. This period can be divided in two parts; the first part covering Q3 2008 up to Q3 2009, relates to the period when the adverse effects of the global financial crisis started to affect the Albanian banking sector mainly in the form of declining solvency of banks clients, either households and firms, mostly due to deteriorating economic conditions in the country (drop in exports, drop in remittances). The second part covering the period from the end of 2009, up to the half of 2010, relates mainly to the adverse spillover effects of the Greek crisis in the Albanian banking sector. Increased level of stress during this period is mostly driven by a general decline in banks profitability as a result of a decrease in credit growth and increased level of liquidity stress in the Greek banks operating in Albania due to deposits runs. The whole period is characterized by a very high level of stress, which seems to peak in 2009, were the index marks the highest historical values.

The second crisis episode covers the period from the end of 2013 up to mid-2014 (Q4 2013 - Q2 2014). The increasing banking sector distress during this time is mostly due the foreign banks deleveraging process, as part of their management strategies related to the South Eastern Countries after the crisis and a rapid increase in the banks NPLs, from the low level of 6.6% in the end of 2008, up to 24.9% at the end of 2014. On the other hand, the high level of banks capitalization (sometimes above the required level of 12 %) and as well as the high level of deposits, have played a balancing role reducing the stress level during this period.

Chart 1. Financial Systemic Stress Index (FSSI) and the episodes of systemic banking stress.



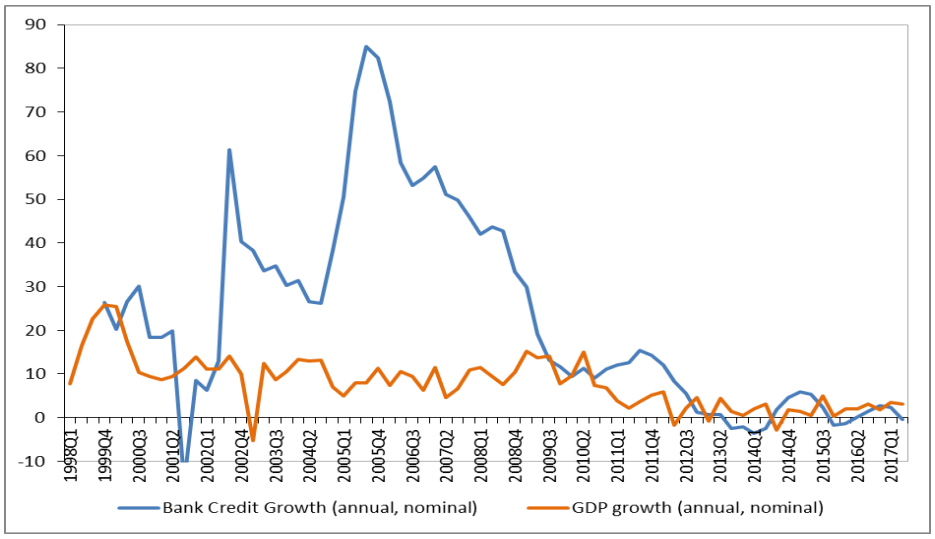
Sources: Kota and Saqe (2013), Bank of Albania, Author's calculation.

Note: The grey shaded area represents the identified periods of financial distress or "crisis".

4.2. The selection of leading indicators in the Albanian context.

Similar to many central and Eastern Europe countries, Albania lacked any financial development prior of 1990. Banking sector experienced a rapid credit growth after its full privatization in 2004. The rapid economic growth was the main driver of credit demand in an environment with initially low financial penetration, while on the supply side, the increasing presence of foreign banks played an important role in relaxing the credit standards.

Chart 2. Growth indicators of bank credit to private sector and GDP



Sources: Bank of Albania, INSTAT

Starting from a low level, credit growth peaked fast up to 85% in annual terms prior to the onset of financial crisis, which was much higher than the GDP growth, implying a credit overheating. On this context, the credit related indicators might show some useful early warning properties.

Drawing upon the existing literature on leading indicators and methods (discussed in Section 2) and taking into account the Albanian data availability, we choose to restrict the analysis on the following credit related indicators:

4.2.a - Credit- to- GDP gaps for Albania

Theoretically, this is an indicator of lending activity development related to countries GDP and is defined as the difference between the credit-to-GDP ratio and its long term trend[8]. When the values of credit-to-GDP ratio exceeds the indicators long-term trend, the lending to the private sector is growing faster than the GDP, meaning that the new lending does not contribute enough to the growth of GDP, but rather is channeled into consumption of imported goods and/or assets price increase, mainly real estate prices. The credit gap indicators have taken a special attention lately, since Basel III included such indicators it in the recommendations regarding the macroprudential policy instruments. To help guide the activation and release of the countercyclical capital buffer, the Basel Committee on Banking Supervision has suggested that it should be raised when a country's credit-to-GDP ratio exceeds its long-run trend by *two percentage points*. This BCBS guide will

[8] In the rest of the material, the indicator will be considered simply as "credit gap".

serve as a common international guideline for policymakers taking buffer decisions – alongside other indicators and judgement (see BCBS 2010).

In the Albanian context, we build the credit –to-GDP gaps for *banking credit to private sector,* which includes total credit to households and firms for both residents and nonresidents; and the respective gaps for the sectorial break down of banking credit (*banking credit to households* and *banking credit to firms*). For each of these credit components, the series of their rate to GDP is de-trended by its long term component. The construction of the indicators long-term trend series can be accomplished in several ways, the outcome of which could bring significant changes in the final series of indicators. Based on the approach followed by Laina et al. (2014), Giese et al. (2013), etc., as well as the Basel III recommendations, we calculate the credit indicator's long –term trend using one-sided Hodrick Prescott filter, employing various smoothing parameters λ (1600, 25.000, 100.000 and 400.000).

Box 1- The selection of the filter and the smoothing parameter λ

Hodrick-Prescott filter[9], known as "HP filter", is a mathematical tool commonly used in macroeconomics, especially in the business cycle theory. It is used to separate the cyclical component of the time series from the raw data, obtaining this way a smoothed representation of the original series, which is more sensitive to long-term rather than short-term fluctuations. The adjustment of the sensitivity of the trend is achieved by modifying the smoothing parameter λ which in the case of the business cycle generally takes the value of 1600.

As argued by Edge and Meinsenzahl (2011), the true underlying trend measured using the standard two-sided HP filter, may differ substantially from the real-time estimates of the trend. The standard HP filter is not purely backward looking since it uses observations at t + 1, i> 0 to construct the current time point t. This means that it is reestimated every time more data points are added, because previous estimates of the trend line will be updated to reflect the new data. This is not an accurate approach when constructing gap indicators for early warning purposes, since the behavior of the indicator round past crisis might change every time new information is added, thus being not useful for decision makers. To avoid this shortcoming, Edge

[9] This filter was firstly proposed by the English mathematician E.T.Whittaker in 1923, but was later popularized in the field of economics in the 1990s by economists Robert J. Hodrick and Nobel Memorial Prize winner Eduard C. Prescott.

and Meinsenzahl (2011), recommend using one-sided HP filter to detrend the ratios of credit variables to GDP. This means that each point of the trend line corresponds to the last point of the estimated trend line using data from the beginning up to this particular point. So, this filter uses only the information set available to the policymakers at each point in time while calculating the trend and the introduction of new data does not change the pervious trend estimations. In contrast to the standard filter (two –sided), the one –sided HP filter produces a trend line which is purely backward looking. In addition, the analysis in Borgy et al. (2009) suggests that for the same smoothing parameter λ, the one-sided HP filter leads the two-sided filter since it is influenced more by the latest observation and hence more pro-cyclical. But since the trend lags the actual observations, this implies that the credit gap crosses the one-sided trend earlier than the two-sided trend, making the credit gap based on the one-sided trend more useful as a leading indicator.

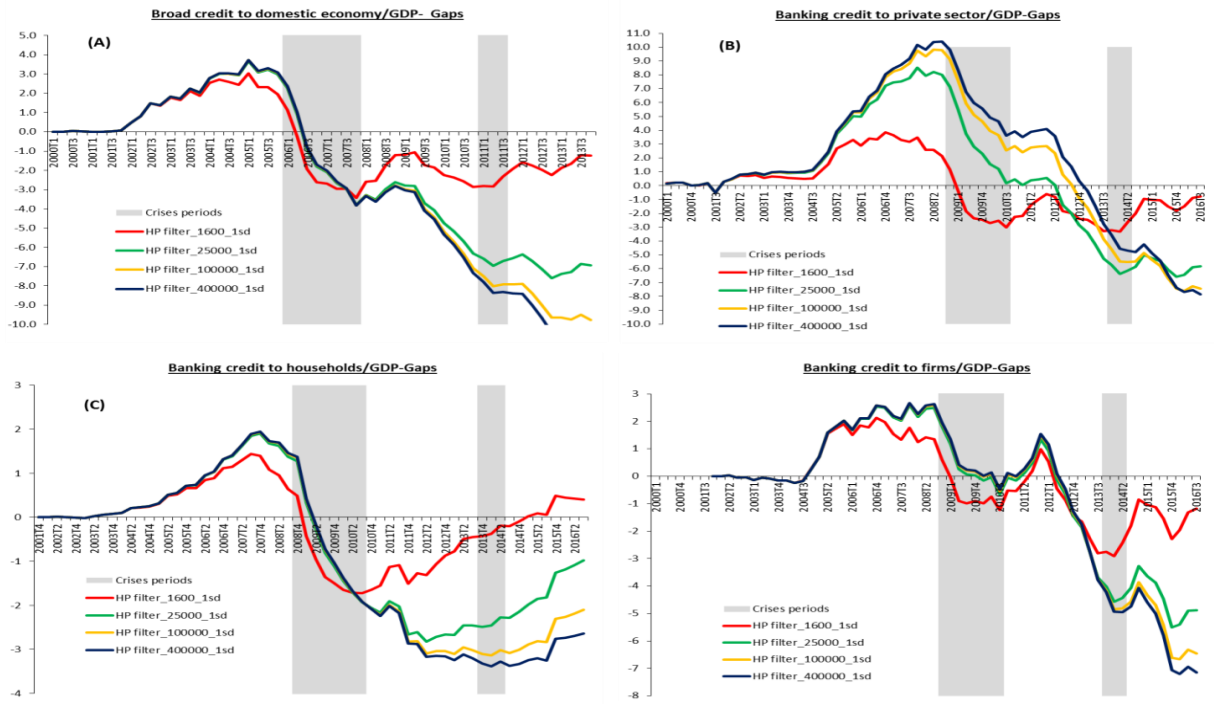
Regarding the choice of the smoothing parameter λ while calculating the long-term trend of the credit indicators to GDP, one should take into account the length of the credit cycle as well as its frequency in relation to the business cycle. A number of authors, as well as ESRB (2014), argue that the predictive abilities of credit gaps improve if using HP filter with a smoothing parameter higher than 1600, traditionally used in smoothing the business cycle. This because the credit cycle is considered a medium-term phenomenon (i.e. longer than 10 years) and estimated to be about 2 to 4 times longer than the business cycle. Depending on the country, that can range from 5 to 30 years (average 15 years)[10]. For the purpose of constructing credit –to-GDP gaps as leading indicators, ESRB (2014) recommends a smoothing parameter of 400 000, assuming that EU countries credit cycle is about 4 times longer than the business cycle. However, this assumption might not hold in the case of emerging and developing countries that usually are characterized by low level of financial liberalization and shorter credit cycle, comparing to developed countries. In such cases, smaller smoothing parameters (such as 25.000, 100.000) might be considered.

Picture 2 (A, B, C and D) below shows the behavior of gap indicators around the crisis periods identified from the FSSI (section 4.1). These graphs clearly illustrate

[10]According to Ravn and Uhlig (2002), the calculation of the smoothing parameter (the lambda) for the credit cycle in relation to the business cycle (with quarterly data), can be computed as follows:
λcredit cycle = λbusiness cycle * (frequency) 4 = 1.600 * (2) 4 = 25.000
λcredit cycle = λbusiness cycle * (frequency) 4 = 1.600 * (4) 4 = 400.000

the difference in the indicators' values depending on the computing technique of the long-term trend, highlighting the importance of the filter choice in the final results.

Chart 3. Credit –to-GDP gaps calculated with one-sided HP filter and different smoothing parameters



Source. Bank of Albania, Author's calculations.

Note: The grey shaded area represents the identified periods of financial distress or "crisis" according to the Financial Stress Index and the relevant literature.

4.2.b- Other credit related indicators.

The credit-to-GDP gap ratio may be insufficient to determine whether lending is creating imbalances in the economy, which can materialize in a future crisis, since it does not provide sufficient information to judge whether the current level of credit in the economy is high or whether its sectorial distribution is likely to pose a threat to the financial system. As stated by Giese et.al.(2013), the credit gap measure assumes that policy would be agnostic about the level of credit in the economy. However, some post crisis research has shown that the level also matter and that high level of indebtedness makes the economy more vulnerable to shocks while the adverse effect of subsequent deleveraging may be bigger (Reinhart and

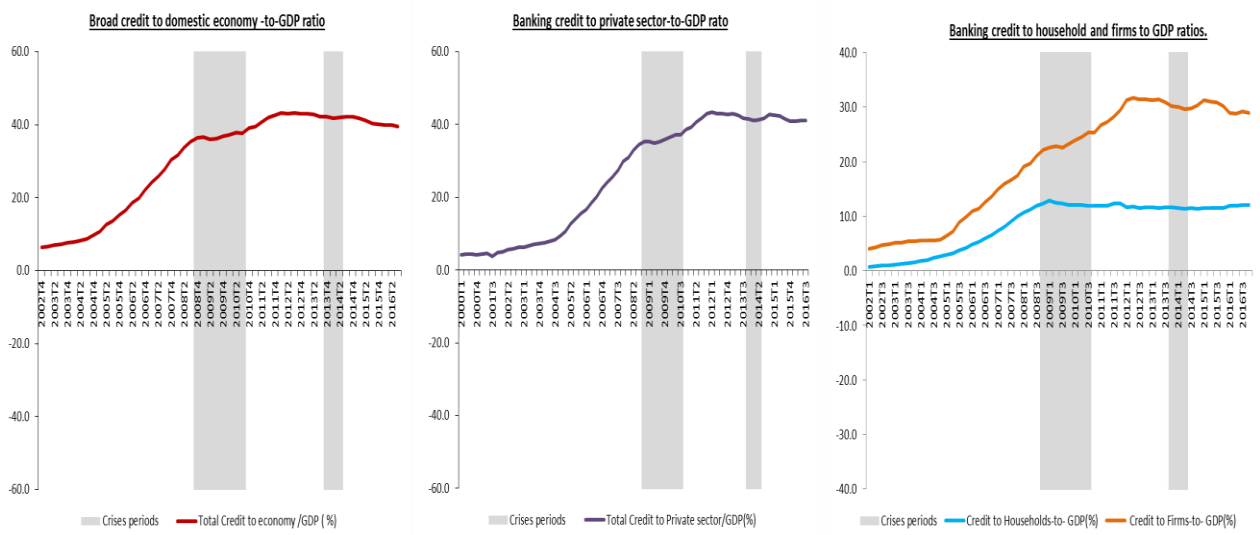
Rogoff, 2009). This suggests that the absolute level of the credit-to-GDP ratio could serve also as a possible leading indicator of financial or banking crisis.

The credit to GDP gap does not provide enough information on the pace of credit growth. But many works on banking crisis have found that these crises are generally preceded by a rapid credit growth to private sector, which makes it necessary to investigate the predicting power of such indicators, as well. On the other hand, credit –to-GDP gap does also not provide information on the sources of credit. However, the way lending is funded is important and if the banking sector funding is highly depend on deposits (like in Albania), a high and increasing loan-to-deposit ratio would signal accumulation of weakness in banks' balance sheet.

Referring to the abovementioned, we have included in the analysis on potential leading indicators for Albania, three other indicators related to the lending process: (1) absolute level of credit –to-GDP ratio; (2) annual credit growth ratio and (3) the loan-to-deposit ratio. To compute these indicators, we have taken into account the total stock of banks credit to private sector.

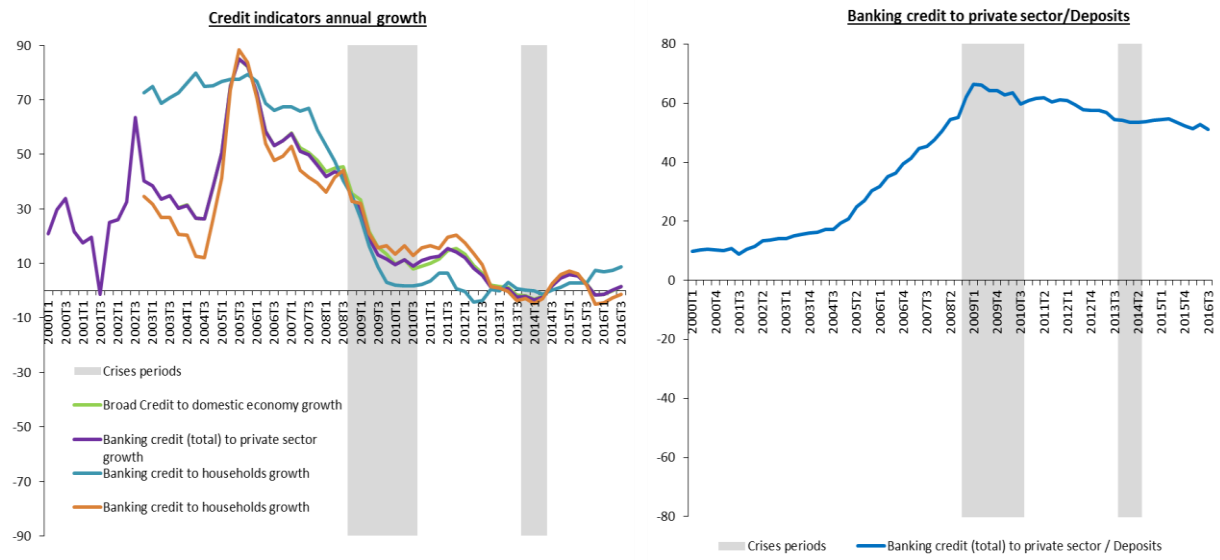
As seen from the graphs, all the selected indicators tend to increase rapidly in the periods before the crisis outbreak, but the speed and the magnitude of this reaction is rather different.

Chart 4. Credit indicators to GDP (in %)



Source. Bank of Albania, Author's calculations

Chart 5. Credit indicators growth rates (annual) and credit to private sector to deposits ratio.



Source: Bank of Albania, Authors calculations.

5 – Data

For the case of Albania, we have taken into analysis the following data series:

1- Credit to private sector (bank credit to residents and nonresidents)
2- Credit to firms (bank credit to firms-residents, nonresidents)
3- Credit to households (bank credit to households –residents, nonresidents)
4- Credit to deposits ratio (total bank credit to residents and nonresidents, total deposits).

The data for the above series are quarterly and in nominal values. Various transformations are computed for each of them, such as: ratio to GDP[11] annual growth rate and gaps of credit series ratio to GDP, from its long term trend. The long term trends are estimated using one sided HP filter, with 3 different smoothing parameters λ (25.000, 100.000 and 400.000).

Table 2 below, summarizes some key statistics on the investigated indicators data series. All the constructed indicators' data series are up to Q1 2007 (for the gap indicators) and up Q2 2017 for the growth indicators, while their starting date differs.

[11] Nominal GDP, annualized and seasonally adjusted.

Table 3. Descriptive statistics of indicators' series

	Indicator	Starting date	No. obs.	Min.	Max.	Mean	Median	St.Dev.
1-	Banking credit (total) to private sector-to- GDP ratio	Q4 1996	80	3.14	43.44	22.37	35.68	16.44
2-	Banking credit to households-to- GDP ratio	Q4 2001	60	0.71	12.86	8.56	11.47	4.39
3-	Banking credit to firms-to-GDP ratio	Q4 2001	60	4.04	31.67	19.98	22.70	10.18
4-	Broad credit to economy growth (annual)	Q4 2003	53	-3.09	84.96	24.99	13.39	24.82
5-	Banking credit (total) to private sector growth (annual)	Q4 1994	88	-3.5	84.9	26.42	21.11	22.30
6-	Banking credit to households growth(annual)	Q4 2002	56	-4.09	79.89	32.24	8.77	33.31
7-	Banking credit to firms growth(annual)	Q4 2002	56	-4.95	88.29	23.23	16.69	22.79
8-	Banking Credit(total)-to-Deposits Ratio	Q4 1998	72	8.67	66.31	43.38	52.67	18.81

Source: Bank of Albania, INSTAT, Authors' calculations.

6- Results of signal approach and loss minimization approach

All the series are turned into binary variables and compared to the crisis periods, as described in the 'signal approach'. The observations for each of them are categorized as "good signal", "missed signAll the final indicators are tested against various thresholds: whenever the indicator's values exceed these thresholds, it is considered to issue a signal of an impending crisis. In the case of credit gap indicators (such as broad credit to economy and bank credit), the thresholds starts from 1 percentage points (pp) up to 5 pp, while for the other indicators (credit growth indicators, credit to GDP indicators), we use two thresholds: the indicators' series long term average and 1 standard deviation from the average.

In each case, if the indicators' values stand above the threshold for several quarters, each of those quarters is considered as "one signal". The generated

signals are analyzed against the "crisis episodes" defined through the Financial Systemic Stress Index in a predefined lead horizon, as described in signal methodology.

Based on the work from Borio and Lowe (2002) and Borio and Drehmann (2009), the performance of each indicator is assessed on multiple and cumulative horizons, starting from 5 quarters ahead of the crises and increasing it gradually to 13 quarters ahead of the crisis. A signal issued during the same quarter of the crisis occurrence, is not considered valid, since it does not leave enough time for the policymakers to take preventive action. Consequently, the signal is considered to be 'correct' if the crisis occurs at least one quarter later.

Only those indicators predicting more than 50% of crisis episodes are considered valuable. An indicator predicting 50% of the crisis episodes is said to be the same as flipping a coin.

The optimal indicator (and the optimal thresholds) are chosen based on the minimization of Noise-to-Signal ratio (T2 error/(1-Type 1 error) and the minimization of Loss function (θ*Type 1 error+ (1-θ) Type2 error).

In the case of 'loss function', since we don't have enough information to calibrate the policymakers preferences, we assume 3 scenarios: (1) *a neutral scenario*, when the policymakers give the same weight to missed crisis and false alarm and in the case the coefficient *θ=0.5; (2) the crises adverse scenario,* where the policymaker gives a larger importance to missing crises rather that the costs of false alarms (*θ=0.7)* and (3) *cost adverse scenario*, where the policymaker gives a larger importance to costs of interventions in case of false alarm than the costs of missing crisis(*θ=0.3)*.

Tables 4/a/b/c and Table 5 below, summarize the best results of this exercise:

Table 4/a

			Total banking Credit to Private sector (total)_ HP _400.000				
	Thresholds		1	1.5	2	2.5	3
H= 7 q	Predicted Crisis (%)		61.9%	61.9%	61.9%	57.1%	52.4%
	Noise-to-Signal (%)		0.57	0.47	0.34	0.29	0.32
	Loss function scenarios	*Neutral*	0.37	0.34	0.29	0.30	0.32
		Crises Adverse	0.37	0.35	0.33	0.35	0.38
		Cost Adverse	0.36	0.32	0.26	0.25	0.26

			Total banking Credit to Private sector (total)_ HP _100.000				
	Thresholds		1	1.5	2	2.5	3
H= 7 q	Predicted Crisis (%)		61.9%	61.9%	57.1%	42.9%	42.9%
	Noise-to-Signal (%)		0.50	0.34	0.33	0.39	0.39
	Loss function scenarios	*Neutral*	0.35	0.29	0.31	0.37	0.37
		Crises Adverse	0.36	0.33	0.36	0.45	0.45
		Cost Adverse	0.33	0.26	0.26	0.29	0.29

Table 4/b

			Total banking Credit to Private sector (total)_ HP _400.000				
	Thresholds		1	1.5	2	2.5	3
H= 9 q	Predicted Crisis (%)		68.0%	68.0%	64.0%	56.0%	52.0%
	Noise-to-Signal (%)		0.43	0.33	0.25	0.24	0.26
	Loss function scenarios	*Neutral*	0.31	0.27	0.26	0.29	0.31
		Crises Adverse	0.31	0.29	0.30	0.35	0.38
		Cost Adverse	0.30	0.26	0.22	0.23	0.24

			Total banking Credit to Private sector (total)_ HP _100.000				
	Thresholds		1	1.5	2	2.5	3
H= 9 q	Predicted Crisis (%)		68.0%	64.0%	56.0%	52.0%	46.2%
	Noise-to-Signal (%)		0.37	0.25	0.28	0.26	0.30
	Loss function scenarios	*Neutral*	0.29	0.26	0.30	0.31	0.34
		Crises Adverse	0.30	0.30	0.36	0.38	0.42
		Cost Adverse	0.27	0.22	0.24	0.24	0.26

Table 4/c

			Total banking Credit to Private sector (total)_ HP _400.000				
	Thresholds		1	1.5	2	2.5	3
H= 13 q	Predicted Crisis (%)		75.8%	72.7%	60.6%	54.5%	51.5%
	Noise-to-Signal (%)		0.18	0.11	0.14	0.10	0.11
	Loss function scenarios	*Neutral*	0.19	0.18	0.24	0.26	0.27
		Crises Adverse	0.21	0.22	0.30	0.33	0.36
		Cost Adverse	0.17	0.14	0.18	0.18	0.18

			Total banking Credit to Private sector (total)_ HP _100.000				
	Thresholds		1	1.5	2	2.5	3
H= 13 q	Predicted Crisis (%)		70.0%	55.0%	50.0%	50.0%	50.0%
	Noise-to-Signal (%)		0.26	0.24	0.26	0.21	0.21
	Loss function scenarios	*Neutral*	0.24	0.29	0.32	0.30	0.30
		Crises Adverse	0.27	0.35	0.39	0.38	0.38
		Cost Adverse	0.22	0.23	0.24	0.22	0.22

Table 5. Credit to private sector/GDP – level

	Thresholds		25.03 (avg)	20.0	25	30	35	40
H= 7 q	Predicted Crisis (%)		100.0%	100.0%	100.0%	85.7%	71.4%	38.1%
	Noise-to-Signal (%)		0.40	0.46	0.40	0.46	0.55	0.88
	Loss function scenarios	*Neutral*	0.20	0.23	0.20	0.27	0.34	0.48
		Crises Adverse	0.12	0.14	0.12	0.22	0.32	0.53
		Cost Adverse	0.28	0.32	0.28	0.32	0.36	0.42

	Thresholds		25.03 (avg)	20.0	25	30	35	40
H= 9 q	Predicted Crisis (%)		92.0%	100.0%	92.0%	80.0%	68.0%	40.0%
	Noise-to-Signal (%)		0.42	0.41	0.42	0.48	0.57	0.80
	Loss function scenarios	*Neutral*	0.23	0.20	0.23	0.29	0.35	0.46
		Crises Adverse	0.17	0.12	0.17	0.26	0.34	0.52
		Cost Adverse	0.29	0.29	0.29	0.33	0.37	0.40

	Thresholds		25.03 (avg)	20.0	25	30	35	40
H=11 q	Predicted Crisis (%)		86.2%	96.6%	86.2%	75.9%	65.5%	41.4%
	Noise-to-Signal (%)		0.44	0.39	0.44	0.49	0.57	0.73
	Loss function scenarios	*Neutral*	0.26	0.20	0.26	0.31	0.36	0.44
		Crises Adverse	0.21	0.14	0.21	0.28	0.35	0.50
		Cost Adverse	0.30	0.27	0.30	0.33	0.37	0.39

	Thresholds		25.03 (avg)	20.0	25	30	35	40
H=13 q	Predicted Crisis (%)		86.2%	96.6%	86.2%	75.9%	65.5%	41.4%
	Noise-to-Signal (%)		0.44	0.39	0.44	0.49	0.57	0.73
	Loss function scenarios	*Neutral*	0.26	0.20	0.26	0.31	0.36	0.44
		Crises Adverse	0.21	0.14	0.21	0.28	0.35	0.50
		Cost Adverse	0.30	0.27	0.30	0.33	0.37	0.39

The analysis results show that among the tested indicators, the *'total credit to private sector –to-GDP gap'* shows better leading properties comparing to the other indicators. Its performance improves if the long term trend is computed using HP filter with a smoothing parameter higher than 25.000 (such as 100.000 and 400.000) and if the cumulative lead horizon is extended from 7 up to 13 quarters ahead of the crisis and between the threshold of 2pp and 3pp.

In the case of the sectorial break down of the credit series, so in the case of the indicators of *'bank credit to corporates –to-GDP gap'* and *'bank credit to households –to-GDP gap'*, the leading properties are much lower, since the indicators fail to predict more than 50% of the crisis periods, for each of the time horizons taken into account.

Also, the indicator of credit to GDP ratio seems to show some good leading properties in the thresholds between 25%-30%, predicting a high percentage of crises. Nevertheless, in terms of noise to signal ratio, the performance of this indicator is lower than the gap indicator.

The early warning properties of 'broad credit to economy gap' and 'annual credit growth' are also weak. Despite the fact that the performance of these indicators improves while extending the leading horizon, they still fail to predict more than 50% of the crises episodes, making them unsuitable as a leading indicators.

Conclusions

This paper aims to explore potential leading indicators of macro-financial imbalances that could become a source of crisis in the Albanian banking sector. Drawing on contemporary literature on this issue, we choose to focus only on a set of credit related indicators, widely accepted to have good predictive ability of future crises. Following *'the signal extraction approach'* by Kaminsky and Reinhart (1999), we test indicators of credit- to-GDP gap for total credit to private sector, credit to households, credit to firms, as well as indicators related to the speed, level and source of lending in the bank lending within the country. The analysis results show that the *credit gap indicators* perform better in detecting the accumulation of imbalances which could turn into a financial or banking crisis in the future, and this goes in line with most of the results found in the literature.

However, regarding the followed methodology, some caveats should be kept in mind. *First*, the signal approach requests a large dataset and a considerable number of past crises episodes. But crises episodes are rare events, especially when only a single country is considered. *Second*, the indicators might perform well in predicting past episodes of crisis, but this does not guarantee that they will be as effective in predicting such future episodes, which usually evolve in different economic conditions. Borio and Lowe (2002) state that "the past need to be a reliable guide for the future", so they recommend that selected indicators be tested in sample as well as out of sample. *Third*, the analysis includes much judgment regarding the definition of 'crisis episodes' and their exact timing, as well as the choice of the indicators' critical thresholds, which is also done arbitrary. For any given threshold, the policymaker would prefer an indicator that predicts a high percentage of crises episodes, generating a minimum of noise. However, there is a trade-off between these two desirable features. For low thresholds, both the generated signals and the noises are likely to be high as the indicator emits signals most of the time. The opposite scenario applies for high threshold values. To minimize this drawback, many authors make use of the receiver operating curve

(ROC curve) which summarize this trade off and helps in choosing the optimal threshold.

Despite the abovementioned drawbacks, in balance the results are encouraging. The information provided by the behaviour of the leading indicators should be considered as complementary information aside other macroprudential tools and analysis, while monitoring the accumulation of macro financial vulnerabilities.

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