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# Credit –to- GDP gap as an early warning indicator of banking stress in Albania

**Odeta Koçillari**
*Bank of Albania*

## Abstract

This paper investigates the performance of credit-to-GDP gap as a potential early warning indicator of systemic banking distress in the case of Albania. Following the "signal extraction approach" by Kaminsky and Reinhart (1999), we test the early warning abilities of indicators of credit-to-GDP gap for total credit to private sector, credit to households and credit to firms, computed using one sided HP filter with different smoothing parameters. These indicators are tested upon various thresholds and time horizons. We find that credit to GDP gap for total credit to private sector, computed using HP filter 25000 or 400000 work best as EWI in terms of our evaluation criteria and up to years ahead of a potential episode of distress or crisis.

**Keywords***:* early warning indicators, credit-to-GDP gap, banking stress, signal extraction approach.

## Introduction

The high economic costs associated with the late financial crisis (2007-2008) highlighted the need for a careful monitoring of systemic risks threatening financial system in general and banking sector in particular. Many central banks have already included in their tasks the monitoring and assessment of systemic risk on a regular basis, in order to prevent future crises. These assessments can provide early signals of vulnerabilities build-up, known as "macro - financial imbalances", thus helping in obtaining timely preventive measures to reduce such imbalances and maintain financial stability in the country. Despite the different methods and instruments developed by various institutions and researchers on this matter, the identification of a unified set of reliable indicators that can serve as "early warning indicators" has been quite challenging. This because the ability of such indicators to predict future crisis 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 a particular crisis in a particular country may not result as such if these conditions change. However, among various indicators investigated, most authors agree that the indicators related to credit, especially credit-to-GDP gaps, are the most efficient one and as history tend to repeat itself, they can be used to signal future episodes of banking sector distress as well.

Taking guidance on the existing literature addressing this issue, this paper aims to investigate the early warning properties of potential banking sector stress of the *credit –to-GDP gap*, in the case of Albanian banking sector. Various transformations of this indicator are tested over past moments of strong systemic stress experienced by the Albanian banking sector, which we agree to consider as "crisis episodes". The analysis is based on the "signal extraction approach" originally developed by Kaminsky and Reinhart (1999). 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 the indicator taken into analysis: if the indicator value is above this threshold value, it "issues a signal" of a possible future crises which might or might not happen during a fixed time window (usually from 1 to 3, 4 years after the signal is issued).

The paper is organized as follows: *Section 2* reviews the existing literature and the main finding on early warning indicators of systemic financial/banking crisis, focusing especially on the predicting properties of credit-to-GDP gap; *Section 3* explains the "signal extraction approach" by Kaminsky and Reinhart (1999) which is used to test the early warning properties of various transformations of credit-to-GDP gap in the case of the Albanian banking sector; *Section 4* reviews past episodes of systemic stress experienced by the Albanian banking sector, considered as "crisis episodes" and discusses the construction of different credit-to-GDP gaps and their behavior around these crises episodes; *Section 5* presents the main results of the analysis.

## Literature Review on early warning indicators (EWI)

The literature on early warning 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/or the exchange rate crisis in emerging economies. After the 2007-2008 global crisis, the issue of early warning 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 framework and the operationalization of macroprudential policies.

According to Borio and Lowe (2002 a,b), and later Borio and Drehmann (2009), the idea of early warning indicators for banking crisis is based on the view that such 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 economic agents (such as individuals and companies), which is driven by and 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 and Drehmann, 2009). 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 early warning indicator should: *firstly*, 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 many false alarms or "noise". Technically speaking, 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 criterion,* which means that the indicator should be consistent in issuing signals and not fluctuate from one period to another inducing uncertainty. The third criterion 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 early warning 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[1], 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.

## Credit-to-GDP gap as a EWI

This is an indicator of lending activity developments related to the country's GDP and is defined as the difference between the credit-to-GDP ratio and its long term trend. When the value of credit-to-GDP ratio exceeds the indicator's long-term trend, the lending to the private sector is growing faster than the country's GDP. This means that the new lending does not contribute enough to GDP growth, but rather is channeled into consumption of imported goods and/or assets price increase, mainly real estate prices. In the first case, credit growth would contribute in the expansion of the current account, while in the second case it would contribute mostly to the price increase of the existing housing stock.

[1] 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.

The indicator of private credit-to-GDP gap has taken a special attention during the recent years, since Basel Committee included it in the recommendations regarding the macroprudential policy instruments. The Basel III framework has proposed the activation of countercyclical capital buffer as one of the tools to enhance the resilience of the banking system. To help guide the activation and release of this tool, the Basel Committee on Banking Supervision has recommended credit-to- GDP gap to be used as a reference guide indicator (alongside judgment) in detecting the emergence of vulnerabilities and therefore activating the countercyclical level when it exceeds a certain level. This BCBS guide will serve as a common international guideline for policymakers taking buffer decisions – alongside other indicators and judgement (see BCBS 2010).

There are many pros and cons regarding the use of credit –to-GDP gap as an early warning indicator. Among the criticism, some authors state that 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. Also, 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 a high and increasing loan-to-deposit ratio would signal accumulation of weakness in banks' balance sheet.

However, this paper will focus on the indicator of credit gap only as a starting point in exploring early warning indicators for systemic stress in banking sector in Albania. Additional complimentary indicators might also be considered for the future.

## The "signal extraction" approach

This is a non-parametric approach firstly developed by Kamminsky and Reinhart (1999) and subsequently used in different versions by many other authors who have addressed the issue of banking crises[2]. It 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

[2] 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.

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. The authors 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 as potential early warning 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 the 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 period (no signal). *Last*, it should be defined what is considered to be the lead horizon within which a signal is considered as correct (or not).

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:

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":

**A**- the indicator issues a "signal" ($V^i_t V^i_t$> Vth) and a crisis occurs within the predefined time horizon. 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 signal 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 under A and D in the confusion matrix, and there would be no observation under C and B.

**Table 1. Contingency matrix of signals 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 (predicted crisis)** | **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 crises)** | **D (correct silence)** | | | | |

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 a low noise to signal ratio, calculated as follows:

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

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. 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 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 macroprudential measures to avoid a potential crisis, which is minimal one year. Signals issued very close or very far to the occurrence of the crisis are considered to be useless. In the first case they do not provide sufficient time for policy makers to react, while in the second case the signal might be confusing since many conditions might change in a long time span. In literature, the time horizon usually varies from 1 to 3-4 years.

## Credit –to- GDP gap for Albania and its early warning properties

This section aims to investigate the early warning properties of credit-to-GDP gap for the case of Albania. First, we try to determine the beginning and ending point of systemic stress episodes experienced by the Albanian banking sector, which we would call "crisis episodes". Then, we construct indicators of credit-to-GDP and test them against these episodes, using the *signal extraction approach* through various time windows.

### *Stress episodes in the Albanian banking sector*

The Albanian banking sector has never experienced a systemic banking crisis according to the definitions usually found in the literature[3]. However, over the past 20 years, some 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 well as other useful sources of information® addressing this issue. Most of these sources identify two stressful episodes experienced by the banking sector, which we agree to call "crisis episodes": The index as well as the relevant information, usually identify two "crises episodes":
*The first episode* lies during 'Q3 2008 to Q2 2010' and it 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 as a result of deposits runs from Greek banks operating in Albania, as well as the general decline in profitability of banks as a result of a decrease in credit growth. The whole period is characterized by a very high level of stress, which seems to peak in 2009.
*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 to a rapid increase in the banks NPLs. 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.

[3] 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).

## *Construction of Credit - to- GDP gap for Albania*

In the case of Albania, we build the credit-to-GDP gap for three credit related variables: *a) total credit to private sector*; *b) total credit to households*, and *c) total 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 parameter $\lambda$.

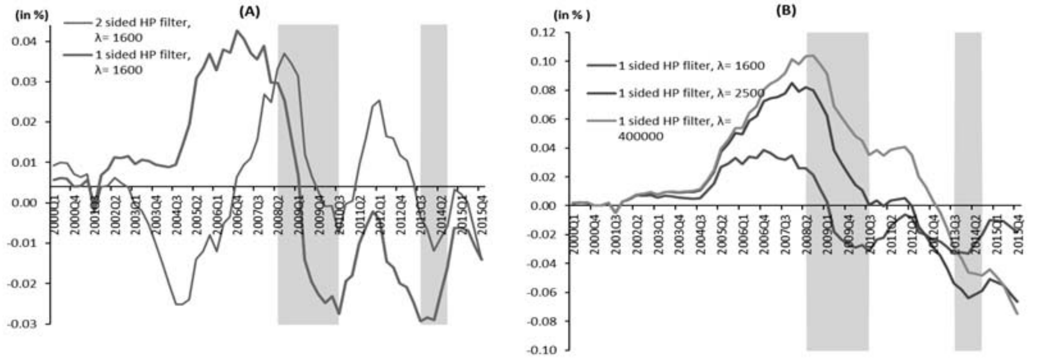
Regarding *the choice of the smoothing parameter* $\lambda$ while calculating the long-term trend of the credit indicators to GDP, one should take into account the length of the credit cycle as well as its frequency in relation to the business cycle. A number of authors, as well as ESRB (2014), argue 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). 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.

## *Data*

The data used in this paper are quarterly. The series of "total credit to private sector –to-GDP gap" span the period of Q4 1996 to Q4 2015, while the gap series of "credit to households" and "credit to firms" are much shorter (Q4 2001- 2015Q4) (Table A1 in Anex 1 summarizes some key statistics on the investigated indicators). Graphs 1, 2 (A, B) below, show the behavior of the investigated gaps around the identified crisis period. Graph 1(A) shows the *total credit to private sector –to-GDP gap*, computed using standard HP filter (two-sided) and one-sided, with 1600 smoothing parameter, while graph 1 (B) shows the *total credit –to-GDP gap* computed using the one-sided HP filter with three different smoothing parameters. Graph 2 (A, B) shows the sectorial breakdown of credit-to-GDP gap for *households* and *firms*, also computed using one-sided HP filter, with three different smoothing parameters. These figures clearly illustrate 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. As seen from the graphs, all the computed gaps tend to increase rapidly in the period before the crisis outbreak, but the speed and the magnitude of the reaction might differ.

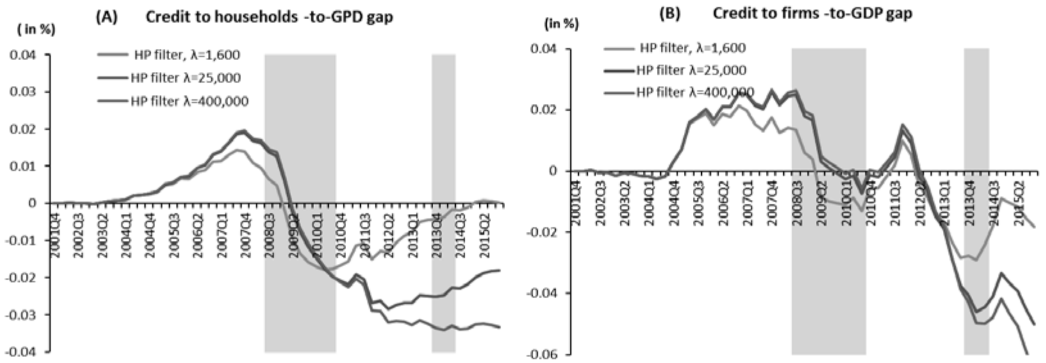
**Graph 1. Total credit (to private sector)–to-GDP gap, with different HP filters.**

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




*Source: Bank of Albania, Author's calculations.*

**Graph 2. Credit –to-GDP gap for households and firms (one-sided HP filter, with three smoothing parameters).**




*Source: Bank of Albania, Author's calculations.*

## Conclusions

The early warning performance of the above credit-to-GDP gaps are investigated through the "signal extraction approach", considering different thresholds and upon multiple, cumulative horizons, ranging from 1 to 3 years after the 'signal' is issued. Based on the work from Borio and Lowe (2002) and Borio and Drehmann (2009), a signal issued during the same quarter of the crisis occurrence, is considered "not valid", since it does not leave enough time for policymakers to take preventive action and is considered "correct" if the crisis occurs at least one quarter later. The observations for each indicator are classified as "good signals or correctly predicted crisis", "missed signals or missed crises", "false alarms" and "good silence" and the Noise-to-Signal ratios (NSR) are calculated. An optimal leading indicator should minimize the NSR but also predict most of the crises. If less than 50% of the crises episodes are predicted, the indicator would be as informative as flipping a coin. Most authors consider an indicator to have good predicting power if it can predict at least 2/3 (or 66%) of crisis episodes. Since we have a low number of crises, we set the condition of > 50% of crisis predicted while choosing the best performing indicator.

**Table 2. Core results on the performance of credit gap indicators*.**

| | H= 1 year | | | | H= 1,2 years | | | | H= 1,2, 3 years | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Threshholds | Credit to Private sector/GDP_GAP (λ= 25.000) | | Credit to Private sector/GDP_GAP (λ= 400.000) | | Credit to Private sector/GDP_GAP (λ= 25.000) | | Credit to Private sector/GDP_GAP (λ= 400.000) | | Credit to Private sector/GDP_GAP (λ= 25.000) | | Credit to Private sector/GDP_GAP (λ= 400.000) | |
| | Predicted crisis(%) | *Noise-to-Signal* | Predicted crisis(%) | *Noise-to-Signal* | Predicted crisis(%) | *Noise-to-Signal* | Predicted crisis(%) | *Noise-to-Signal* | Predicted crisis(%) | *Noise-to-Signal* | Predicted crisis(%) | *Noise-to-Signal* |
| 1 | 63.2% | 0.40 | 68.4% | 0.65 | 59.3% | 0.35 | 77.8% | 0.43 | 57.1% | 0.23 | 82.9% | 0.19 |
| 2 | 52.6% | 0.40 | 63.2% | 0.61 | 51.9% | 0.30 | 74.1% | 0.35 | 51.4% | 0.13 | 80.0% | 0.08 |
| 3 | - | - | 63.2% | 0.54 | - | - | 70.4% | 0.33 | | | 77.1% | 0.04 |
| 4 | - | - | 63.2% | 0.30 | - | - | 63.0% | 0.16 | | | 60.0% | 0.00 |
| 5 | - | - | 52.6% | 0.28 | - | - | 51.9% | 0.15 | | | 51.4% | 0.00 |

The testing results show that *total credit to private sector-to-GDP gap,* performs fairly well as an early warning indicator of systemic banking stress and its predicting powers improve while the gap is calculated with lambda higher than the traditional 1600. The performance of this indicator also improves when the leading horizon is extended from 1 year to 2, 3 years. In terms of threshold, 2 and 3 seem to be suitable for gaps calculated using HP filter the smoothing parameter 25000 or 400000. In this case, it might be recommended to monitor two thresholds rather than one- a lower one (credit gap = 2) signalling "increased risk" and a higher one (credit gap = 3) signalling "high risk", with different consequences for macroprudential policy.
The gap indicators calculated using the traditional lambda 1600 fail to predict more that 50% of stress episodes and produce too much noise, therefore the results for these indicators do not display in the table of results. The performance of the sectorial break down of credit gap, so *households* and *firms* credit to-GDP- gap, is also weak. These indicators generate low noise rates but fails in predicting most part the stress episodes, making it useless for macroprudential policy purposes.

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Anex 1. One-sided Hodrick Prescott filter

Hodrick-Prescott filter, known as "HP filter", is a mathematical tool commonly used in macroeconomics, especially in the business cycle theory. HP filter 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 $\lambda$ which in the case of the business cycle generally takes the value of 1600. Lately, many authors (such as Edge and Meinsenzahl , 2011), have argued that the standard two-sided HP filter is not suitable when calculated the credit –to GDP gap for macroprudential purposes, since the true underlying trend measured 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 and Meinsenzahl (2011), recommend using one-sided HP filter to de-trend 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 $\lambda$, 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.

**Anex 2.**

Table A1. Descriptive statistics-credit gap indicators

| **HP filter_ one sided, λ** | **Credit (total) to private sector-to-GDP gap** | | | **Credit to Households-to-GDP gap** | | | **Credit to firms-to-GDP gap** | | |
|---|---|---|---|---|---|---|---|---|---|
| | *1600* | *25000* | *400000* | *1600* | *25000* | *400000* | *16000* | *25000* | *400000* |
| Mean | -0.07 | 0.61 | 1.67 | -0.14 | -0.66 | -0.95 | -0.17 | -0.38 | -0.51 |
| Median | 0.00 | 0.22 | 0.83 | 0.01 | -0.02 | -0.02 | -0.15 | -0.06 | 0.00 |
| Std.Dev | 1.91 | 3.95 | 4.40 | 0.87 | 1.51 | 1.86 | 1.34 | 2.27 | 2.67 |
| Min | -3.30 | -6.63 | -7.72 | -1.78 | -2.85 | -3.39 | -2.90 | -5.01 | -6.76 |
| Max | 3.86 | 8.51 | 10.41 | 1.44 | 1.90 | 1.95 | 2.14 | 2.59 | 2.67 |
| *No.Observ.* | *79* | *79* | *79* | *59* | *59* | *59* | *59* | *59* | *59* |