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# LEADING INDICATORS FOR THE COUNTERCYCLICAL CAPITAL BUFFER IN LITHUANIA

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# LEADING INDICATORS FOR THE COUNTERCYCLICAL CAPITAL BUFFER IN LITHUANIA

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Statement of purpose
Occasional Papers describe research in progress by the author(s) and are published to stimulate discussion and critical comments.

## Contents



## Abbreviations

| | |
|---|---|
| AUROC | area under the receiver operator characteristic curve |
| BCBS | Basel Committee of Banking Supervision |
| CCB | countercyclical capital buffer |
| EA | euro area |
| ECB | European Central Bank |
| EU | European Union |
| ESRB | European Systemic Risk Board |
| GDP | gross domestic product |
| IMF | International Monetary Fund |
| p.p. | percentage points |
| ROC curve | receiver operator characteristic curve |

## SUMMARY

This paper presents the analysis of indicators that could signal the build-up of systemic risk in Lithuania during the periods of credit expansion. The resulting set of early warning indicators could be useful in operationalizing countercyclical macroprudential policy measures, especially the countercyclical capital buffer (CCB). It could serve as a starting point in considerations whether there is a need to increase banks' resilience in the upturn of financial cycle by accumulating additional capital buffers.

Taking into account the short Lithuanian data series which cover only one systemic banking crisis period, the analysis is extensively based on international research, particularly on findings of the European Systemic Risk Board (ESRB) Expert Group which provided analysis for the ESRB Recommendation on guidance on setting countercyclical buffer rates (ESRB 2014/1). Consistent with the existing research, we show that the deviation of the ratio of credit to gross domestic product (GDP) from its long-term trend (credit-to-GDP gap) is a suitable early warning indicator of financial crises in Lithuania. However, gap estimation faces uncertainty as the long-term trend is unobservable. To deal with the uncertainty, the estimation of the long-term trend was augmented with forecasts and most suitable alternative to the so called standardised ‚Basel gap' (suggested by the BCBS) is provided. In addition to this, complementary early warning indicators have been selected that could give concise yet comprehensive and robust view of the state of the Lithuanian economy. The performance of selected early warning indicators has also been evaluated for the three Baltic states (Lithuania, Latvia and Estonia).



***Keywords**: countercyclical capital buffer (CCB); early warning indicators; credit-to-GDP gap; signalling approach*

*JEL classification: C40, G01*



## SANTRAUKA

Straipsnyje nagrinėjami rodikliai, kurie galėtų iš anksto įspėti apie didėjančią sisteminę riziką Lietuvoje esant dideliam kredito augimui. Sudarytas ankstyvo įspėjimo rodiklių rinkinys galėtų būti naudingas taikant makroprudencinės politikos priemones, ypač anticiklinį kapitalo rezervą. Atrinkti rodikliai padėtų sudaryti pradines įžvalgas, ar bankai turėtų kaupti papildomą kapitalo rezervą ir taip didinti savo atsparumą finansinio ciklo plėtros fazėje.

Dėl trumpų Lietuvos duomenų eilučių, apimančių tik vieną sisteminės bankų krizės laikotarpį, tyrimas pirmiausia remiasi kitais tarptautiniais tyrimais, ypač – Europos sisteminės rizikos valdybos ekspertų grupės gautais rezultatais, kuriais buvo remtasi sudarant rekomendaciją dėl anticiklinio rezervo normų nustatymo rekomendacijų (ESRB 2014/1). Kaip nustatyta daugelyje tyrimų, straipsnyje parodoma, kad kredito ir BVP santykio nuokrypis nuo ilgo laikotarpio tendencijos (kredito ir BVP santykio atotrūkis) yra tinkamas ankstyvo įspėjimo apie finansų krizes rodiklis Lietuvoje. Tačiau atotrūkio įvertinimas susijęs su neapibrėžtumu, nes ilgo laikotarpio tendencija yra nestebimas dydis. Norint sumažinti neapibrėžtumą, ilgo laikotarpio tendencijos vertinimas buvo papildytas prognoze ir čia pateikiamas labiausiai tikęs metodas, kuris galėtų būti kaip alternatyva pasiūlytajam Bazelio bankų priežiūros komiteto. Be to, atrinkti papildomi ankstyvo įspėjimo rodikliai, kurie pateikia apibendrinančią informaciją iš kelių sričių, padedančių susidaryti nuomonę apie bendrą Lietuvos ekonomikos būklę. Išankstinio įspėjimo rodiklių naudingumas buvo įvertintas ir trims Baltijos šalims kartu (Lietuvai, Latvijai ir Estijai).



***Raktiniai žodžiai**: anticiklinis kapitalo rezervas; ankstyvo įspėjimo rodikliai; kredito ir BVP santykio atotrūkis; signalų metodas*

*JEL klasifikacija: C40, G01*

## INTRODUCTION

As IMF describes, ‘crises result from the collision of vulnerabilities of an economic or financial nature and specific trigger events’ (IMF (2010)). A crisis trigger could be almost any event – political shock, deterioration in external trade, worsening expectations, even contagion from other countries. The impact of shocks in a country is amplified if there are underlying imbalances, such as a credit or house price bubble, or balance sheet mismatch, and potentially leads to financial distress and great economic losses. Even though the prediction of crisis triggers is a tricky task, identifying the key vulnerabilities that are likely to emerge in the event of crisis is possible – this is where the analysis of financial cycles should shed some light. Financial cycle refers to fluctuations in the level of financial activities, similarly as the business cycle refers to fluctuations in the level of economic activities. More specifically, the financial cycle can be described as ‘self-inforcing interactions between perceptions of value and risk, attitudes towards risk and financing constraints, which translate into booms followed by busts’ (Borio (2012)).

Although financial cycle is less studied than the business cycle, its common stylized features are quite well known. Borio (2012) lists the main features that are also confirmed in other literature. Firstly, the main elements that describe the financial cycle are credit and property prices, analysed separately or in combination, however, there is no obvious measure of financial cycle readily available[1] (Stremmel (2015)). Secondly, the financial cycles are longer than the business cycles, between 16 and 20 years (Drehmann, Borio and Tsatsaronis (2012)), while business cycles are usually thought to last 1–8 years. Moreover, empirical observations show that systemic banking crises often occur close to the peaks of the financial cycle, and downturns that coincide with the contractions in the financial cycle are particularly harmful. Another often considered feature is the ability to measure the rising financial imbalances in real time. Deviations of credit and property price variables from their historical trends seem to be promising leading indicators of financial crises, while extensive flows of cross-border lending in relation to the domestic credit are also common before the busts. And lastly, policies influence the length and the amplitude of financial cycles: financial liberalization, overly accommodative monetary policy, real economy expansion due to globalization – all fuel the financial booms.

Countercyclical capital buffer (CCB) is a new macroprudential instrument that is linked to financial cycle[2]. It is an additional capital buffer which should enhance the resilience of banks to systemic crises by strengthening their capital base during periods of increasing financial imbalances and growing systemic risk. If the upswing of the cycle becomes too intense, the requirement for banks to raise the countercyclical capital buffer should be set to make them more resilient to the upcoming bust. If banks remained in a solid position after the bust, as a consequence, they would likely continue providing the necessary credit to the economy and would not hinder the recovery (or at least would not exacerbate the downturn). In this way, the amplitude of the financial cycle could be dampened. As raising capital can be costly, it is important to have some objective rules that would show the need to build up the capital buffer in order to avoid the ‚inaction bias‘. The recent European Systemic Risk Board’s (ESRB) Recommendation on guidance on setting countercyclical buffer rates (ESRB/2014/1) is designed to help European authorities tasked with setting the CCB to operationalize this macroprudential instrument.

The analysis underpinning the Recommendation was conducted by an expert group within the ESRB (Detken et al., 2014). As usual in the analysis of early warning systems it focused on a particular type of crisis and using multi-country data over an extended period of time to determine which indicators have been useful in indicating the possible crisis in advance. Specifically, the analysis focused on early warning models that would help to identify indicators that signal such crises which the CCB is designed to mitigate. This includes identifying leading indicators and associated thresholds that signal that the CCB might need to be built up as well as indicators and associated thresholds that suggest that the CCB should be reduced or fully released. Although early warning systems have been covered quite extensively in the literature (e.g., Goldstein et al. (2000), Borio et al. (2011), Drehmann and Juselius (2013)), this was the first comprehensive analysis covering all 28 Member States of the European Union.

This paper aims at providing analysis which can serve as a base for setting rules for the build-up phase of the CCB in Lithuania. In particular, the greatest emphasis is given to timely identification of the period when CCB has to be activated (i.e. CCB rate increased from 0). For this purpose, early warning indicators are analysed to determine those from which signals can be extracted in order to predict crises sufficiently early. The list of useful indicators for the system

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[1] Stremmel (2015) constucts synthetic measures of financial cycles for 11 developed European countries. He comes to the conclusion that bank credit-to-GDP ratio, bank credit annual growth and house price-to-income ratio (income is defined as nominal disposable income per capita) are the most relevant indicators in defining the financial cycle.

[2] Although countercyclical economic policy is not a new idea, see e.g. Elliott D. J., G. Feldberg, and A. Lehnert (2013): ‚The History of Cyclical Macroprudential Policy in the United States‘, Federal Reserve Board, Finance and Economics Discussion Series, Working Paper 2013/29.

suited for Lithuania is chosen from early warning literature – indicators that proved to be informative in other countries and during different financial crises. Based on the findings of the ESRB Expert Group (Detken et al. (2014)) and other research, this paper illustrates the performance of selected indicators, especially the credit-to-GDP gap, in Lithuania and provides a list of other early warning indicators that would give complementary information about the need to build up the capital buffer. Additional indicators are necessary because they help to avoid false signals and form a comprehensive and more robust picture of the state of the financial system. Tentative Lithuanian-specific thresholds of indicators are also estimated, based on Lithuanian data. The paper is organised as follows: in Section 1, we describe the evaluation approach by introducing the variables and the methods for estimation. The variables' part includes the motivation for choosing the particular variables and a discussion of credit-to-gap calculation. In Section 2, the results for estimation are provided, and, lastly, our conclusions are given in Section 3.

This paper does not analyse the release phase of CCB, as it would rely less on predetermined rules. The timeframe and the scale of releasing the buffer would depend on the nature of adjustment of financial imbalances and therefore different information to inform the decision could be used. Also, the paper does not touch the issue of mapping the indicators to the CCB rate as this problem needs a comprehensive study of the impact of CCB on credit and real economy, and therefore remains an open question for the future research. In the meantime, the method proposed by the Basel Committee of Banking Supervision (BCBS) can be used (BCBS (2010)) to map the credit-to-GDP gap to the indicative CCB rate. Discussion of the validity and effectiveness of CCB as a macroprudential instrument and its interactions with other instruments is also out of scope of this paper.

# 1. The evaluation approach

The early warning system for activation of CCB should warn about a future systemic banking crisis that is connected with excessive credit growth or excessive leverage in the country. The question what rate of credit growth or what level of credit is excessive in a particular country is not trivial, and cannot be determined simply from a set of indicators. However, a properly designed early warning system can be a useful starting point for the analysis.

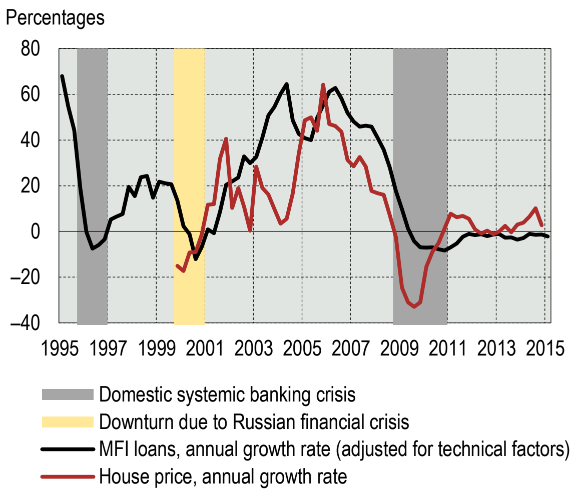
## 1.1. Variables

### 1.1.1. The 'crisis' variable

The 'crisis' variable is a variable against which the early warning capacity of other indicators is assessed. In line with objectives of the CCB, the same definition as in Detken et al. (2014) has been used to determine the binary crisis variable. I.e. a systemic banking crisis is considered to be a period of significant financial distress in the banking system, associated with a domestic credit cycle, 'as evidenced by bank runs in relevant institutions or losses in the banking system <...>, or significant public intervention in response to losses in the banking system or taken to prevent the realisation of such losses' (Detken et al. (2014)). Therefore, 'would be' crises are also included and they refer, for instance, to situations in which government's or actions of the parent institutions helped to avoid bank runs or permanent disruption of systemic banks' services. The inclusion of such 'would be' crises requires a judgement; this is the reason why the crisis database compiled by ESRB differs from other crisis databases. For example, according to the seminal database of systemic banking crises compiled by Leaven and Valencia (2008 and 2012), Lithuania experienced a systemic banking crisis only in 1995–1996.

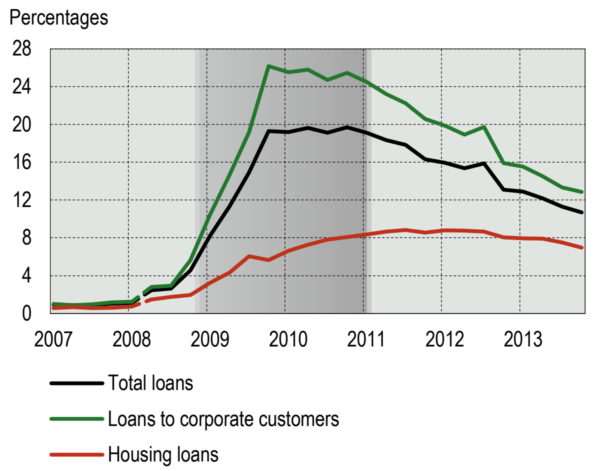
For the purposes of CCB, we assume that there have been two major episodes of banking distress which can be connected to unbalanced credit growth in Lithuania: in Q1 1995–Q4 1996 and Q4 2008–Q4 2010 (see Chart 1). The first crisis episode rose due to unsound bank management practices and inadequate risk monitoring. The poor loan quality of many Lithuanian banks eventually resulted in significant banking sector losses. Public confidence in the banking system was eroded and institutions experienced large deposit withdrawals. Because of low capital levels and liquidity problems, several major banks went bankrupt (see Enoch et al. (2002) for more details). Since credit rose rapidly before 1995 due to lax lending conditions and low initial credit base, this crisis episode can be classified as relevant for the CCB. The second episode of banking distress is linked to the past global financial crisis, when the level of economic activity in Lithuania fell sharply. This episode coincided with the bust in residential and commercial real estate market: average house price fell by more than 40% and commercial real estate price fell by approximately 30%, non-performing loans surged (see Chart 2), especially in construction and real estate activities. Banks operating in Lithuania experienced significant credit losses, and they were able to withstand the losses mostly because of the help from parent institutions. In line with the Europe-wide initiative, the government substantially increased deposit insurance guarantees (the insured amount of deposits in one credit institution was increased from EUR 22,000 to EUR 100,000) which may have also helped to avoid bank runs and maintain financial stability. Q4 2010 can be considered as a formal crisis ending period: the real GDP growth returned to a steady strong growth path, unemployment started declining, banks' non-performing loans began to shrink consistently.

***Chart 1. Credit and house price growth in Lithuania***




*Sources: Statistics Lithuania, State Enterprise 'Centre of Registers', and Bank of Lithuania calculations.*

***Chart 2. Non-performing loans of banking sector in Lithuania***




*Source: Bank of Lithuania.*
*Note: a break in the time series starting with mid-2008 occurred because of the changed non-performing loan definition; non-consolidated data.*

To estimate early warning abilities of the indicators, a pre-crisis period has to be set up as well. In the literature analysing the CCB, it is common to study pre-crisis period that starts 5 years before the beginning of crisis and ends 4 to 6 quarters before the beginning of the crisis (Detken et al. (2014), Drehmann and Juselius (2013)). This is because of the properties of the CCB: building up capital takes time and activation of the CCB should be announced one year in advance, therefore indicators should emit signals sufficiently early (at least 2–3 years prior to a crisis (BCBS (2010)). In addition to this, too early a signal is also undesirable, because premature activation of CCB could have overly limiting effect on credit supply from the banks to the real economy. The 'pre-crisis' variable is also a binary variable, which takes value 1 in the period 1–5 years before the crisis, and 0 elsewhere. 3 observations immediately before the crisis are eliminated, as well as the observations during the crisis.

Our analysis focuses on the second episode of distress (Q4 2008–Q4 2010). This analysis does not cover the first pre-crisis episode due to the lack of data – most of the Lithuanian time series start no earlier than 1995. The most recent data are excluded when indicator usefulness is assessed, since there is not enough information to attribute them to either a 'per-crisis' or calm period.

### 1.1.2. Credit-to-GDP gap as an early warning indicator

Financial crises are typically associated with rapid credit growth (BCBS (2010), IMF (2011), Schularick and Taylor (2012)). However, there are different views about which measure of credit growth would be the most suitable as an early warning indicator. In BCBS (2010) analysis of advanced economies, credit-to-GDP deviation from its long term trend (i.e. credit-to-GDP gap) is found to be the most precise early warning indicator of a future crisis among single indicators. In contrast, the IMF (2011) maintains that credit-to-GDP gap does not perform well as a signalling indicator for a broader set of countries since it misses too many crises. According to the IMF (2011), annual change in credit-to-GDP ratio could be promising, although it frequently issues false signals, and it should be combined with other variables such as asset price growth or house price growth to minimize the number of false signals.

Different definitions of credit can be used to construct the required early warning indicators. In general, the broad definition of credit is preferred over bank credit, because it captures the risks in the total economy and is less sensitive to moving financial intermediation into less regulated non-banking sector (Detken et al. (2014)). An internationally consistent definition of broad credit adopted by the BCBS includes total loans to private non-financial sector (non-financial corporations, households and non-profit institutions serving households) and debt securities issued by non-financial corporations, where lenders comprise both residents and non-residents (also non-banks)[3]. In some cases, different definitions of credit can lead to completely different conclusions: for example, in the US the growth of commercial bank credit did not emit crisis signals, while total credit (including consumer credit) would have signalled the crisis quite clearly (Arregui et al. (2013)). Also, total credit would be more suitable for the assessment of the impact of macroprudential policy measures: e.g., in Croatia, the effect of introducing credit growth caps in 2003 and 2007 on bank credit was more or less offset by other types of lending and direct lending from abroad (see Arregui et al. (2013)).

In the ESRB analysis of EU28 countries, deviation of credit-to-GDP from its long term trend has been found to be among the several best single early warning indicators (Detken et al. (2014)). This analysis considered plenty of various credit, real-economy, market-based, real estate variables or their transformations. When comparing single indicators, not only their overall performance in issuing early warning was taken into account, but also whether the indicator was relevant in the majority of countries and whether the signals were stable during the pre-crisis period. The general findings were that among single indicators, credit-to-GDP gaps performed better than other single indicators. Across countries, they rise slowly and reach high values already three to four years before the crisis (Drehmann and Juselius (2012)). Several variants of the gaps – bank credit-to-GDP gap, credit to households-to-GDP gap and total credit-to-GDP gap augmented with moving average forecast – performed better than the usual credit-to-GDP gap (further referenced as ‚Basel‘ gap), although the improvement was not statistically significant.

In general, a good early warning indicator is expected to possess a number of desirable properties (see e.g. Kauko (2012b), Detken et al. (2014)). A trigger indicator should be:

- valid for different countries and for many crisis episodes (crises have to be of the same type);
- reverting to some value – in order to be able to identify the thresholds;
- steady – the signal has to be consistent (it should not vary in opposite directions from one period to another);
- available in real-time (also – available with the least lag possible);
- simple – easy to calculate and understand;
- having sufficiently long time series.

Credit-to-GDP gap and its variations have most of these properties. They have been selected and recommended as a standard measure and initial point of analysis of systemic imbalances both by BCBS and ESRB. As is shown further, the standard Basel gap and its modification for Lithuanian data performed sufficiently well as an early warning indicator in the past pre-crisis period, even though the time series are rather short and gap estimates based solely on statistical filtering techniques may not be completely reliable.

### 1.1.3. Calculation of long-term trends and gaps

The BCBS and ESRB (BCBS (2010), ESRB/2014/1) suggest calculating the long-term trend of credit-to-GDP ratio by applying Hodrick-Prescott (HP) filter. Policy makers do not have access to the future information when they have to make a decision, so trend can be estimated only with the information which is available up to the moment of estimation. Such procedure can be called a real-time[4] procedure or a one-sided filter. To help guide the activation and release of the countercyclical capital buffer, the BCBS has suggested that the buffer should be raised when a country's credit-to-GDP ratio exceeds its long-term trend by two percentage points and should reach the maximum if the gap exceeds ten percentage points (BCBS, 2010). It is highly plausible that this BCBS guide will become an international benchmark for setting the CCB.

The Hodrick-Prescott (Hodrick and Prescott (1981)), or HP, filter is a widely used statistical method to estimate a long-term trend of a data series. It is simple to apply and is implemented in most statistical packages. HP filter is a detrending method that separates a series $y_t$ into a trend component $\mu_t$ and a cyclical component $c_t$; that is, $y_t = \mu_t + c_t$. The filter optimally extracts a smooth stochastic trend that is uncorrelated with the residual cyclical component. Specifically, the trend is derived from the optimization problem:

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[3] Lithuanian data series of 'broad' credit is calculated from Lithuanian financial accounts statistics. Data for Q4 2003–Q1 2014 are official quarterly data, while quarterly data for Q4 1993–Q3 2003 have been extrapolated from annual financial accounts statistics, taking into consideration the developments in MFI loans in that period. Data compiled according to ESA 2010 methodology have been used for analysis in this paper.

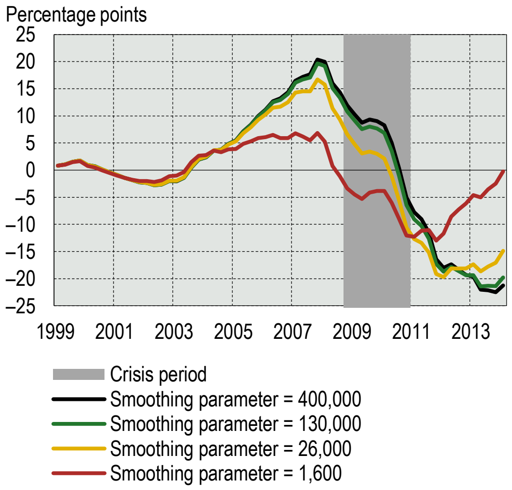
[4] Following this approach, we apply one-sided filter when calculating trends. In fact, the procedure we apply in this paper is pseudo-real time, because we analyse only the latest vintage of data, i.e. the data after all the revisions that occurred since the first publication of the data until Q2 2014. However, the revisions in statistics should be relatively insignificant, e.g., Orphanides and Van Norden (2002) show that influence of statistical revisions to output gap estimates is negligible, in fact, main revisions occur due to the HP trend revisions when new data are published. Giese et al. (2014) show that in the UK the data revisions for the credit-to-GDP gap were even smaller than in the credit-to-GDP ratio: due to autocorrelation of the revisions they are captured in the trend estimate.

$$\min_{\{\mu_t\}_{t=0}^{T}} \underbrace{\sum_{t=0}^{T} (y_t - \mu_t)^2}_{\substack{\text{deviation of data} \\ \text{from the trend}}} + \lambda \underbrace{\sum_{t=1}^{T-1} \big((\mu_{t+1} - \mu_t) - (\mu_t - \mu_{t-1})\big)^2}_{\substack{\text{variation in the growth rate} \\ \text{of the trend}}},$$

where the value of the parameter λ is the weight put on the variation in the growth rate of the trend and determines the smoothness of the trend. When output is the variable being filtered, λ is typically set at 1,600 which implies a business cycle duration of around 7.5 years. As $\lambda \to \infty$, the process for $\{\mu_t\}_{t=0}^{T}$ approaches a linear trend.

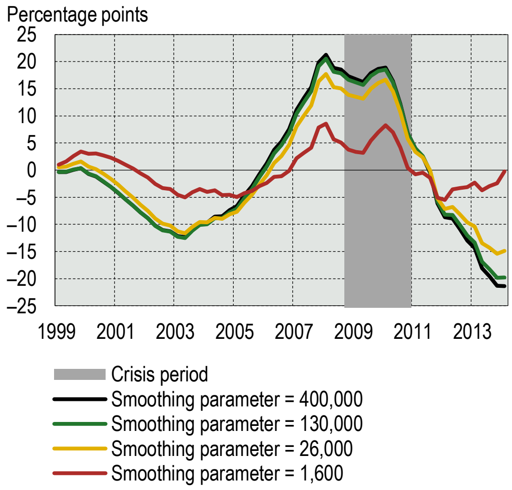
The BCBS and ESRB recommend to use the smoothing parameter λ = 400,000 when filtering the credit-to-GDP series. As financial cycle lasts longer than the business cycle (Borio (2012)), larger values of the smoothing parameter λ are used for financial variables. Smoothing parameter value of 400,000 in the BCBS proposal is based on the empirical fact that financial cycles are on average 4 times as long as real business cycles. However, in some cases this might give very persistent estimates of the gap. General recommendation for EU countries is to use the most suitable method for the gap estimation in the particular country[5]. For this purpose, several trends were constructed using different smoothing parameters: i.e. λ equal to 400,000, 130,000, 26,000, which correspond to a financial cycle that is 4, 3, 2 times the length of the real business cycle, and λ = 1,600, matching a financial cycle that coincides with the real business cycle (as in Detken et al. (2014)) in case of quarterly data. Gaps were then calculated as the percentage-point differences between actual series and the estimated trend. Trends for Lithuanian data are calculated from Q1 1997 (starting point has been chosen after the systemic banking crisis of 1995–1996, when the banks' loan growth recovered), but we discard the first several years of observations in the gap series as HP filter produces less reliable estimates in the beginning and the end of series. As can be seen in Charts 3 and 4, credit-to-GDP gaps perform similarly in the pre-crisis period, with the exception of the smallest lambda (1,600). Gaps with larger values of lambda increase gradually in the pre-crisis period and reach their peak values at 4 quarters before the beginning of the crisis. With regard to signalling properties, there is some empirical evidence that the signalling properties of the gap actually improve with the larger values of the smoothing parameter (e.g., Detken et al. (2014), Giese et al. (2014)).

***Chart 3. Credit-to-GDP gap using different values of the smoothing parameter: one-sided HP filter***




*Sources: Statistics Lithuania and Bank of Lithuania calculations.*

***Chart 4. Credit-to-GDP gap using different values of the smoothing parameter: two-sided HP filter***



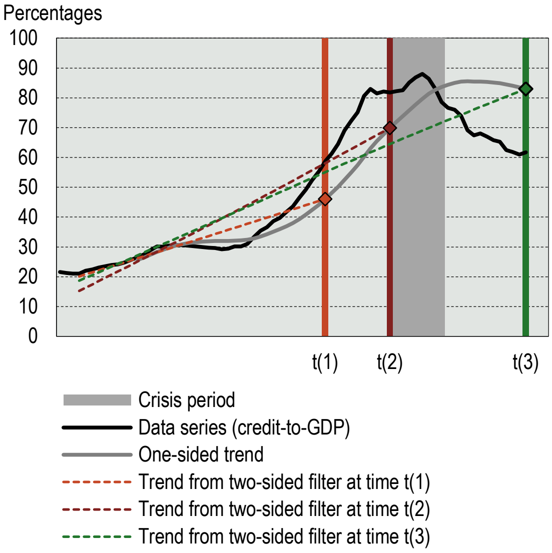

*Sources: Statistics Lithuania and Bank of Lithuania calculations.*

One of the properties of the standard (two-sided) HP filter is that it uses both past and future information around the period for which the trend is estimated. The problem with that is that it cannot be applied in real time and the estimates of the gap might change significantly when new information becomes available. For the real-time procedure, the so-called one-sided version of the HP filter can be applied, as suggested by the BCBS. In this case trend series is constructed by applying a two-sided filter recursively to the latest data vintage and then combining the resulting endpoint

[5] See Recommendation ESRB/2014/1 of the European Systemic Risk Board of 18 June 2014 on guidance for setting countercyclical buffer rates, Recommendation C — Guidance on variables that indicate the build-up of system-wide risk associated with periods of excessive credit growth.

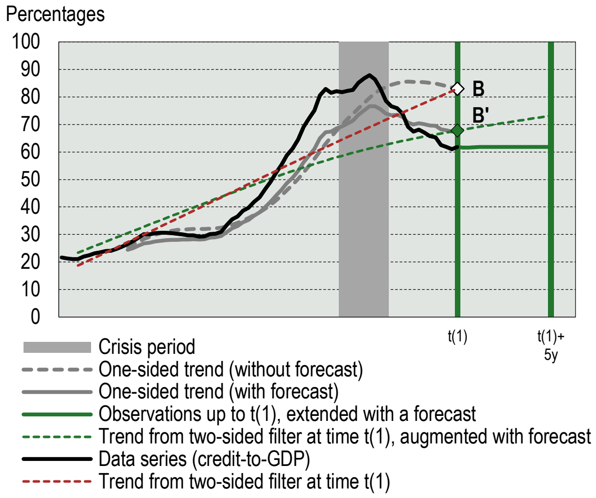
estimates to obtain the trend curve. Such estimate of the gap in any period only uses data up to that point in time and the procedure can be used for economic policy purposes, when future information is unknown (see Chart 5).

***Chart 5. Illustration of one-sided HP filter: credit-to-GDP ratio and its long-term trends (lambda = 400,000)***




*Source: Bank of Lithuania calculations.*

***Chart 6. Illustration of one-sided HP filter extended with simple projections: credit-to-GDP ratio and its long-term trends***




*Source: Bank of Lithuania calculations.*
*Notes: 1) forecast is weighted average of the last 4 quarterly observations for next 5 years; 2) B is the end-point of long term trend as calculated with one-sided HP filter (Basel method); B' is the end-point of long-term trend if extending time series with projections.*

Standard HP filter is often criticized as trend estimates towards the end of time series have large uncertainty (Edge and Meisenzahl (2011), Orphanides and Van Norden (2001)). One-sided procedure does not take the future information into account (as it is unavailable for policy maker at the point of decision) and the end-point problem is even more pronounced. Despite this, there is evidence that the uncertainty of the long-term trend estimate does not worsen the properties of credit-to-GDP gap as an early warning indicator (Drehmann and Tsatsaronis (2014)). On the contrary, gap calculated in the one-sided procedure emitted earlier signals and fewer of them were false than in the standard two-sided gaps. Borgy et al. (2009) and Giese et al. (2014) also maintain that the one-sided filter leads the two-sided filter and signals rapid credit growth earlier. This is also confirmed by Lithuanian data: the correlations between one-sided credit-to-GDP gaps (‘Basel gap' and gaps calculated using simple projections) with respective ex post gaps are significant. Largest correlations – around 0.9 – are reached when the ex post gap is lagged by 7 quarters (see column 7 in Table 1).

Nevertheless, the desired property of an indicator to be available in real time also implicates that a robust signal is expected, i.e. the conclusions from a real-time indicator should not change entirely when new information becomes available or when its construction method is slightly changed. Norges bank‘s and ESRB calculations suggest that augmenting historical data series with simple forecasts of the indicator make trend estimation at the end of the series more robust (Gerdrup et al. (2013)) and improve the signalling quality (Gerdrup et al. (2013), Detken et al. (2014)). Norges bank applies one-sided HP filter augmented with simple projections (average value of last 4 quarters of actual observations) alongside the simple one-sided HP filter to indicators of financial imbalances (see e.g. Norges Bank (2014)).

Charts 5 and 6 illustrate the simple and augmented one-sided HP filter procedure for Lithuanian credit-to-GDP ratio. The augmented one-sided HP filter procedure means that the one-sided filter has been applied to data series where actual data have been extrapolated with simple projections. The long-term one-sided trends (grey lines) more or less coincide during the expansion phase of the credit cycle (point A), and start to differ around the peak of the cycle. At the end of the data series the difference between the two trends is significant (points B and B‘) resulting in different values of the gaps, i.e. deviations of data series from its long-term trend, albeit still negative for the given data series. In general, gaps from simple HP filter without forecasts are very persistent, while gaps from augmented HP filter are less volatile and are more sensitive to the turning points of the cycle. As shown in Gerdrup et al. (2013) and Detken et al. (2014), projection-augmented one-sided credit-to-GDP gaps have slightly better signalling qualities in Norway and EU28 than simple one-sided gaps.

To check whether augmenting the one-sided HP filter procedure with projections would enhance the robustness of gap estimates in Lithuania, different recursive forecasts have been applied to Lithuanian data:

- last value;
- average value of the last 4 quarters;
- average value of the last 8 quarters;
- 4-quarter moving average[6];
- 8-quarter moving average;
- weighted average of the last 4 quarters[7];
- linear forecast[8].

In retrospect, the ex post two-sided gap can be regarded as the final and 'true' gap estimate somewhere in the middle of the series, because it has the advantage of using information from the whole sample. With the benefit of hindsight, it could reflect the size of the gap and therefore the severity of the crisis more accurately than using only the one-sided gap. This may be important from the policy-makers' point of view when deciding on the intensiveness of intervention, if one is needed. E.g., Ahn (2011) provides some evidence that gaps (in particular – house price gap) from the one-sided procedure do not necessarily correctly reflect the severity of past Norwegian crises. Although the final decision of intervention should be taken at policy makers' discretion, policy would only benefit from stable indicators and robust quantitative rules. We compare the properties of different gap estimates with respect to the final gap estimates (estimated at Q4 2014 using the same forecasting method or no forecast) in Table 1.

***Table 1. Summary statistics of various estimates of Lithuanian credit-to-GDP gap***
*(using gap estimates for the period Q1 2000–Q3 2014, $\lambda = 400{,}000$)*

| | Mean | Standard deviation | Min. value | Max. value | Correlation with final two-sided gap | Correlation with 7-quarter lagged final two-sided gap | Mean absolute final revision[1)] | Mean absolute final revision[1)] (2011–2014) | Variability of gap estimates[2)] | Variability of gap estimates[2)] (2011–2014) |
|---|---|---|---|---|---|---|---|---|---|---|
| | p.p. | p.p. | p.p. | p.p. | | | p.p. | p.p. | p.p. | p.p. |
| 'Basel gap' (no forecast) | -1.40 | 12.33 | -23.07 | 18.47 | 0.72 | 0.92 | 8.32 | 9.78 | 3.49 | 3.40 |
| Forecast: weighted average of last 4 quarters | 4.23 | 6.96 | -8.33 | 17.31 | 0.66 | 0.88 | 9.19 | 5.99 | 3.27 | 2.00 |
| Forecast: last value | 3.97 | 6.30 | -7.59 | 15.21 | 0.69 | 0.87 | 9.11 | 5.86 | 3.20 | 1.95 |
| Forecast: average of 4 last quarters | 4.36 | 7.32 | -8.60 | 18.29 | 0.64 | 0.88 | 9.27 | 6.15 | 3.31 | 2.07 |
| Forecast: average of 8 last quarters | 4.96 | 8.90 | -9.19 | 22.05 | 0.61 | 0.88 | 9.66 | 7.31 | 3.46 | 2.49 |
| Forecast: moving average of 4 last quarters | 4.23 | 6.98 | -8.34 | 17.35 | 0.65 | 0.88 | 9.20 | 5.99 | 3.27 | 2.01 |
| Forecast: moving average of 8 last quarters | 4.64 | 8.04 | -8.81 | 20.04 | 0.62 | 0.88 | 9.66 | 7.31 | 3.37 | 2.28 |
| Forecast: linear | -0.80 | 6.11 | -12.23 | 8.75 | 0.53 | 0.82 | 10.01 | 8.59 | 3.79 | 2.88 |

*Source: authors' calculations.*
*Note: 1) Mean final revision shows the average error of the initial quasi real-time estimate of the gap which comprises the one-sided gap series. It is mean difference of quasi real-time gap from the ex post two-sided gap, when final two-sided gap is estimated at Q4 2014 using the same method as one-sided gaps (see Gerdrup et al. (2013) for more detailed explanation); 2) Variability of gap estimates is measured as average standard deviation of each quarters' all gap estimates at every point in time.*

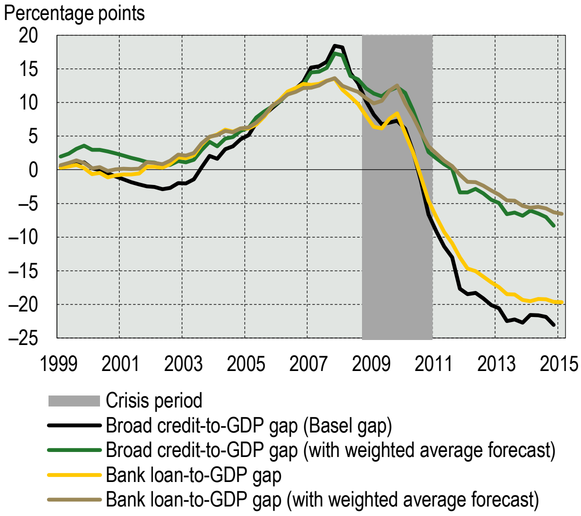
The results in Table 1 show that extending time series with a forecast using the last value, moving average of 4 last quarters or weighted average of the last 4 quarters gives the most robust results for Lithuanian credit-to-GDP series among the applied forecasts. As in Gerdrup et al. (2013), we use mean final revision (i.e. the mean difference between one-sided gap and the ex post two-sided gap) and the variability of gap estimates (i.e. average of standard deviations of all gap estimates) as the main criteria for comparison. Mean final revisions are quite large for all the methods, however they decrease towards the end of the sample in case of any forecasting method, while revisions for the 'Basel gap' increase. Small variability is another desired property: the less the gap estimate at each point in time varies as more observations become available, the more consistent are the rules based on it. Gaps using forecasts are less variable than the 'Basel gap', and the improvement is even more pronounced for the recent period (i.e. 2011–2014). In general, gaps using forecasts have smaller amplitude and standard deviation than 'Basel' gap (where no forecast is used), and

[6] I.e. a projection at time point *N+p* is calculated as $X_{N+p} = 0.25\sum_{t=N+p-4}^{N+p-1} X_t$, where *N* is the number of actual observations available at real-time, and *p* is the index of the quarter for which the projection is being made, $p = 1, \dots, 20$. In such manner, the weights for the last 4 actual observations $X_N, X_{N-1}, X_{N-2}$ and $X_{N-3}$ converge respectively to 0.4, 0.3, 0.2 and 0.1, while weights in a simple average of last 4 observations would be all equal to 0.25.
[7] Weighted average of the last 4 quarters is calculated by applying weights equal to 0.4, 0.3, 0.2 and 0.1 for the last 4 observations in the series (largest weight is applied to the latest observation).
[8] Pseudo-real time ordinary least squares estimate from the data (starting point is Q1 1997).

depend less on the starting point of the time series from which HP filter was applied[9]. To make the procedure less dependent on a single observation, we chose to use 4-quarter weighted average forecasts[10].

Different measures of credit-to-GDP gap move quite similarly in the credit boom phase, all indicating excessive credit growth (when the gap exceeds 2 percentage points) in the pre-crisis period (Chart 7). The 'Basel gap' shows a later signal and increases less gradually than the other estimates. After the crisis, however, the differences of the gaps become quite substantial: negative gaps are much smaller if the 4-quarter weighted average forecasts are used. The method with forecasts also seems to capture the turning points of the cycle better (see Charts 5 and 6).

***Chart 7. Broad and narrow definitions of credit: credit-to-GDP gap and bank loan-to-GDP gap***




*Sources: Statistics Lithuania and authors' calculations.*

All in all, the robustness of the 'Basel gap' seems to be quite similar to the chosen forecasting method for the past data. However, the 4-quarter weighted average forecast leads to smaller revisions and less variable gap estimates as more information becomes available in the recent period, makes estimates less dependent on the starting point of trend estimation and seems to manage the turning points better. It should be mentioned, that simple recursive forecasts have been used only in order to simulate the historical performance of various detrending methods. For the future calculations of the gap, however, more precise economic forecasts of credit-to-GDP ratio would give more robust results. Nevertheless, having in mind the sluggish credit developments in Lithuania in the recent years, the weighted average forecast of credit-to-GDP series should be adequate for the near future.

### 1.1.4. Other potential early warning indicators

Given the complexity and constant evolution of financial systems and the lack of experience in conducting macroprudential policies, it would be unwise to rely on a single indicator of financial imbalances. While credit-to-GDP gaps are among the best early warning indicators for the purposes of CCB, other indicators provide complementary information and diminish the degree of uncertainty. ESRB Expert Group (Detken et al. (2014)) provides analysis of many credit-, property-related, macroeconomic and market-based variables and their performance across the EU countries. Kalatie et al. (2015) extended their work on the panel of EU countries further by suggesting the most suitable transformations (i.e. ratios, growth rates, deviations from trend, deviations from mean etc.) of those additional variables. Most of the variables that were found to be the most reliable in this study have been chosen as potential complementary indicators for Lithuania. The early warning properties of those variables have been determined based on their performance during the past financial crisis in Lithuania.

In addition to credit-to-GDP gaps and their variations, credit growth variables (including lending to different sectors) and asset price variables were also checked as potential early warning indicators. Credit booms often coincide

[9] Results regarding the choice of starting point are not provided here for brevity, but are available on request.
[10] They have similar performance as 4-quarter moving average forecasts. However the latter method results in small oscillations of the credit-to-GDP series in the beginning of the forecasting period which is difficult to reason from economics point of view, although it should not have great influence on HP filtering. By using weighted average forecast, the oscillations are eliminated while the weights for the last 4 actual observations are the same as their final weights in moving average forecast. See footnotes 5 and 6 for calculation of the weights.

with real estate booms: cheap financing and overly optimistic expectations can push up the demand for real estate and its prices above the balanced level, increased collateral value can further stimulate the expansion of credit. Large property price increases that are not explained by fundamentals can be indicators of future price corrections and thus predictors of banking crises (Detken et al. (2014)).

In the recent literature (Drehmann and Juselius (2012, 2013), Alessi and Detken (2014)), debt service ratio (DSR) is found to be a good measure of financial imbalances. It is defined as debt repayments plus interest payments divided by income and it captures the debt burden while taking into account its variability due to changing maturities and interest rates. When the private sector is highly indebted relative to its income, the negative shocks to income and interest rate rises are substantially amplified. Output volatility is increased as borrowers are prevented from smoothing consumption and investing into profitable projects. DSRs are found to be reliable leading indicators of systemic crises – across countries most of the peaks are associated with a financial distress. Drehmann and Juselius (2012) advocate it as a useful early warning indicator of systemic banking crisis. Rapid rise in private sector‘s DSR above 6 percentage points relative to its long-term (15-year) average could signal the risk of a systemic banking crisis (Drehmann and Juselius (2012)). However, the signal is released only 1–2 year before the crisis, so it is not an ideal indicator for the build-up phase of CCB. Nevertheless, it can be useful as a complementary indicator to ensure the robustness of signals from credit-to-GDP gap and other indicators.

The means of funding credit are also important (Giese et al. (2014), Kauko (2012a)). Highly leveraged financial system is more vulnerable if financial stress occurs, and high leverage is often achieved through foreign debt. Accumulation of country’s foreign debt shows up in large and persistent current account deficits, which is also a useful complementary indicator (Reinhart and Reinhart (2008), Detken et al. (2014)). In fact, Kauko (2012a) finds that credit growth becomes problematic only if the country is running a current account deficit. Also, foreign borrowing by financial institutions, as a source of funds, tends to be less stable than domestic funding such as retail deposits. Hahm et al. (2012) show that stability of funds is important: non-core liabilities (i.e. non-deposits) appear to be a useful early warning indicator of rising risk premiums and financial system vulnerability, complementing the information from credit-to-GDP ratio. Drehmann and Juselius (2013) find that non-core liability ratio has somewhat less predicting power than credit-to-GDP gap and the DSR, however it is among a few variables that tend to emit stable signals during the pre-crisis period. Loan-to-deposit ratio is a traditional indicator that contains information about non-core liabilities. In a study by Laina et al. (2015) loan-to-deposit ratio and its growth rate are found to be one of the best leading indicators of systemic banking crises.

To sum up, the list of potential indicators is taken from the literature documenting various cross-country early warning systems. However, these studies often consider groups of countries that are rather different in their institutional set-up and financial structures (Giese et al. (2014)). Moreover, data definitions are often not consistent or some indicators are not used at all because of the lack of the data across panel. Following the approach by some other countries (see Giese et al. (2014), Ahn (2011), Gerdrup et al. (2011)) we take the robust findings from the panel data studies and cross-check them in a single-country – Lithuanian – setting which should help understand how these indicators would behave before a systemic banking crisis in Lithuania. In addition to this, we check the performance of indicators across the three Baltic states – Lithuania, Latvia, and Estonia – in cases where available time series are reasonably consistent and sufficiently long.

## 1.2. Evaluation methods

In this paper we employ two methods to evaluate the early warning properties of variables or their combinations, namely, the *signalling approach* and *discrete choice models*. The signalling approach is the simplest statistical approach, most suitable to analyse single country’s data. It can be used to check the signalling properties of any variable – a single indicator, or a composite indicator, derived as a combination of single indicators. This paper focuses on results from the univariate signalling approach. Discrete choice models, such as *logit* or *probit* models, link combinations of variables to crisis variables, producing an estimate of crisis probability. As these models should be estimated from large samples covering many crisis periods, here we use several most relevant models from the literature and apply the estimated coefficients to obtain the time series of estimated crisis probabilities for Lithuania.

### 1.2.1. Signalling approach

The signalling approach is a non-parametric approach, which can be used to rank indicators by their ability to provide good signals of forthcoming crises and to avoid false alarms. The main criterion we choose is the so-called 'area under the receiver operator characteristic curve' (AUROC), but other summary statistics are also provided as robustness checks. These rankings should be treated with caution given the single episode of a banking system distress in the sample.

The observations for each indicator are categorized as in Giese et al. (2014) (see Chart 8):

- A: If an indicator breaches the threshold value at any time during the pre-crisis period (the chosen pre-crisis period is the same as in Detken et al. (2014), i.e. between 20 quarters and 4 quarters before the start of crisis), the observation is categorised as a *good signal*. As a result, there are 17 potential good signals for the banking crisis, rather than just one for the single crisis.
- B: If an indicator does not breach the threshold value during the pre-crisis period, the observation is categorised as a *missed signal* (Type 1 error).
- C: If an indicator breaches the threshold value and a crisis does not occur at any time between 4 and 20 quarters afterwards, the observation is categorised as a *false alarm* (Type 2 error).
- D: If an indicator does not breach the threshold value and a crisis does not occur at any time between 4 and 20 quarters afterwards, the observation is categorised as a *good silence*.

***Chart 8. Categories of signals of crisis and relative indicators***

| | Crisis | No crisis |
|---|---|---|
| **Signal** | A | C |
| **No signal** | B | D |

Signal ratio (true positive rate): $SR = \frac{a}{a+b}$;

Noise ratio (false positive rate; Type 2 error rate): $NR = T_2 = \frac{c}{c+d}$;

Noise-to-signal ratio: $= \frac{NR}{SR} = \frac{c/(c+d)}{a/(a+b)}$.

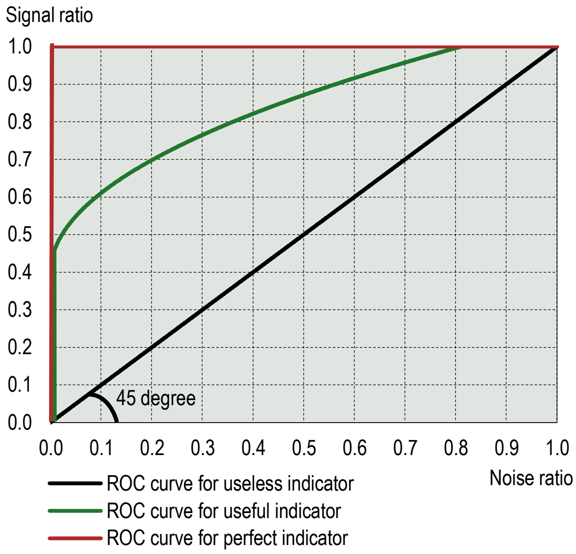
Type 1 error rate (i.e. 1 – signal ratio): $T_1 = \frac{b}{a+b}$;

Policy-makers' loss function: $L(\theta) = \theta \cdot \frac{b}{a+b} + (1-\theta) \cdot \frac{c}{c+d}, 0 \le \theta \le 1.$

Usefulness measure: $U(\theta) = min(\theta; 1-\theta) - L(\theta)$

*Note: small letters a, b, c and d indicate the number of observations in their respective category A, B, C and D.*

***Chart 9. ROC curve for useful and useless indicators***




*Source: based on Giese et al. (2014).*

As the chosen threshold changes, the number of observations prescribed to each category will change. For clarity, further we assume that high values of the early warning indicators show increasing systemic risk (as opposed to low values). Most of the analysed variables behave this way, and the ones that have opposite patterns – such as current account balance or capital adequacy ratio – are taken with the reverse sign. So a higher threshold is associated with higher values *b* and *d* (missed signals and good silences), and lower values *a* and *c* (good signals and false alarms).

The numbers of prescribed observations to each category can be used to calculate the signal ratio $SR = \frac{a}{a+b}$, also called the true positive rate, and the noise ratio $NR = \frac{c}{c+d}$, also called the false positive rate. For any given threshold, the policy-maker would prefer an indicator with a high signal ratio and a low noise ratio, but there is a trade-off between these two properties. If a low threshold is chosen, the indicator emits signals most of the time, consequently both the signal ratio and the noise ratio are high. For high thresholds, both the signal ratio and the noise ratio are likely to be low.

The optimal threshold can be found by comparing costs incurred from policy reaction to false signals with benefits gained if a crisis is foreseen in advance and averted. That means, for each variable the optimal threshold would be the threshold that minimizes the policy-makers' loss function $L(\theta) = \theta \cdot T_1 + (1-\theta) \cdot T_2 = \theta \cdot \frac{b}{a+b} + (1-\theta) \cdot \frac{c}{c+d}$, where $0 \leq \theta \leq 1$ is the policy-makers' preference parameter. A measure that summarises the usefulness of an indicator with the given preference parameter is $U(\theta) = min(\theta; 1-\theta) - L(\theta)$, which shows the extent to which relying on an indicator is better than just guessing.

In practice, policy-makers should be concerned about missed signals at least as much as about false alarms, since systemic crisis are costly and often have long-term effects. This means that the preference parameter should be no less than 0.5. If costs of macroprudential interventions are low and benefits high (i.e. $\theta$ is close to 1), policy-makers may prefer a low threshold value to avoid Type 1 errors rather than Type 2 errors.

The receiver operating characteristic (ROC) curve summarizes the trade-off between using low and high threshold values and the area under the ROC curve (AUROC) serves as a ranking criterion for indicators' usefulness. The ROC plots the noise ratio against the signal ratio. As the threshold value falls, both the noise and the signal ratio rise, so the ROC curve slopes upwards. The ROC curve associated with a useless indicator would be a 45 degree line, as shown in the Chart 9, while a useful indicator would have ROC above the 45 degree line. Respectively, AUROC of a useless indicator would be less or equal to 0.5, and that of a useful indicator – between 0.5 and 1. A perfect indicator emits no signals above a high threshold, only signals below a low threshold and neither Type 1 nor Type 2 errors in between (i.e. a signal ratio equal to one and noise ratio equal to zero) and its AUROC is equal to 1. AUROC summarises the degree to which the signal ratio exceeds the noise ratio for all thresholds and the higher an indicator's AUROC is, the more useful it will be for a policy-maker.

### 1.2.2. Discrete choice approach

Discrete choice models, such as *logit* or *probit* models, link combinations of variables to a joint continuous estimate of the probability of an event. In this case the event is a systemic bank crisis. Composite indicators obtained from discrete choice models are more complicated than single indicators and depend on the model's specification. However these models may enhance the signalling properties of a single indicator by reducing the number of false alarms. E.g., combining the credit-to-GDP gap with indicators that capture accelerating asset price growth (such as the property price and equity price gaps) can provide better early warning indicators (Borio and Drehmann (2009), Detken et al. (2014)).

The binary response model is:

$$y^* = \boldsymbol{X\beta} + \varepsilon, \; y = \boldsymbol{I}[y^* > 0],$$

where $y^*$ is the unobserved variable, $\boldsymbol{I}[y^* > 0]$ is the indicator function that denotes the binary outcome: 1 if $y^* > 0$ and 0 if $y^* \leq 0$, with $y$ as the observed binary variable (in our case – 1 if ‚crisis' and 0 if ‚non-crisis'), $\boldsymbol{\beta}$ is the vector of coefficients including intercept, $\boldsymbol{x}$ is the matrix of independent variables, $\varepsilon$ is the vector of residuals independent of $\boldsymbol{x}$ and in the case of *logit* model has the standard logistic distribution (and standard normal distribution in case of *probit* model). A non-linear logistic function is used to make sure that the probabilities are between 0 and 1:

$$P(y=1|\boldsymbol{X}) = P(y^* > 0|\boldsymbol{X}) = \frac{\exp(\boldsymbol{X\beta})}{1+\exp(\boldsymbol{X\beta})} = \frac{1}{1+\exp(-\boldsymbol{X\beta})}$$

where $y$ is the binary responce variable (in our case – ‚crisis' or ‚non-crisis'). If $\boldsymbol{X\beta} = 0$, then $P(y=1|X) = 0.5$. If $\boldsymbol{X\beta} \to +\infty$, then $P(y=1|\boldsymbol{X}) \to 1$. The theoretical properties of binary response models are covered in most econometric textbooks, e.g. Woolridge (2002).

However, the models can be subject to specification errors. For robustness, it is recommended to use cross-country datasets covering many countries and crisis periods. Therefore it is generally not advisable to build discrete choice models on a small panel of countries. Several models from panel studies (Detken et al. (2014), Arregui et al. (2013)) were applied to Lithuanian data to calculate the crisis probability. These models are summarized in Table 2, whereas the results for Lithuanian case are illustrated in Chart 10.

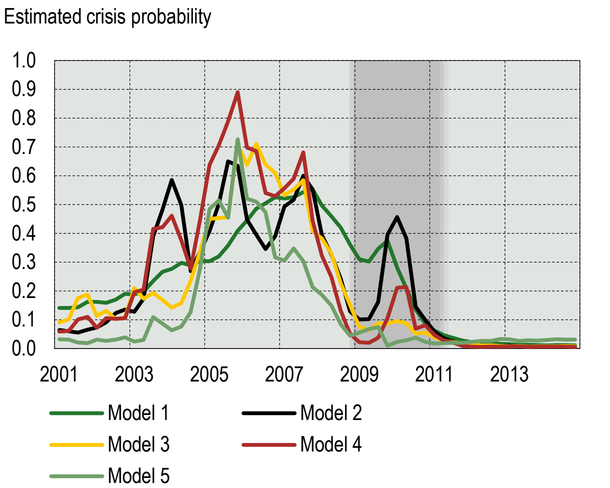
***Table 2. Selected estimations of multivariate logit models from cross-country studies***

| Variables | Model 1[1)] | Model 2[1)] | Model 3[1)] | Model 4[1)] | Model 5[2)] |
|---|---|---|---|---|---|
| Bank credit-to-GDP gap (without forecasts) | 0.142***<br>(0.018) | 0.153***<br>(0.016) | 0.133***<br>(0.017) | 0.140***<br>(0.015) | |

| | | | | | |
|---|---|---|---|---|---|
| Equity price, annual growth rate | | 0.016***<br>(0.003) | | 0.016***<br>(0.003) | |
| Debt service ratio | | 2.384***<br>(0.275) | 2.394***<br>(0.251) | 2.575***<br>(0.275) | |
| House price-to-income ratio, annual change | | | 0.050***<br>(0.010) | 0.050***<br>(0.010) | |
| Broad credit-to-GDP ratio, annual change | | | | | 0.059**<br>(0.029) |
| Real house prices, annual growth rate | | | | | –0.018<br>(0.030) |
| Real house prices, annual growth rate *<br>DUM[Broad credit-to-GDP ratio, annual change>3] | | | | | 0.073*<br>(0.010) |
| Constant | –1.709***<br>(0.104) | –2.479***<br>(0.106) | –2.340***<br>(0.101) | –2.653***<br>(0.128) | –3.221***<br>(0.269) |

*Sources: authors' calculations.*
*Notes: 1) Detken et al. (2014) Table F1, dependent variable is pre-crisis dummy (equal to 1 in a period 4-20 quarters before the crisis), estimated with quarterly data; 2) Arregui et al. (2013), dependent variable is a 2-year lead of a crisis dummy (equal to 1 during periods of crises), estimated with annual data; 3) *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.*

***Chart 10. Estimates of crisis probabilities from selected panel models***




*Sources: Detken et al. (2014), Arregui et al. (2013), Statistics Lithuania, Bank of Lithuania calculations, and authors' calculations.*
*Note: estimates given here are only approximate measures, they do not take into account the possibly significant fixed country effect from the models.*

## 2. Comparison of early warning indicators for the build-up of CCB in Lithuania

First, the signalling method was applied to the Lithuanian time series. All data were seasonally adjusted, where appropriate. Quarterly data until Q4 2014 have been used, and only those data series or their transformations that start at least from 1999 (or can be reliably extrapolated to that point in time) were included in the analysis. That gives almost 15-year long data series. However, the time series for the signalling method are even shorter – only the period until the financial crisis of 2008–2010 (to be precise – until Q4 2007) can be used. The crisis period and 3 quarters before the onset of crisis are eliminated, as we are interested in early warning indicators that would issue a signal at least 1 year before a crisis. The observations after the last crisis are also eliminated because they cannot be linked to any of the signal categories (i.e. good signals, missed signals, false alarms or good silences) yet. The final selection of transformations for variables was based on the findings of Kalatie et al. (2015). Their study gave the most comprehensive analysis of various transformations of the variables from different variable categories, which have been listed in the ESRB's recommendation and which countries have to monitor. Where consistent data for Latvia and Estonia were available, the signalling approach was also applied in a three-country setting.

The main results are listed in Table 2 (see Annex 1 for detailed results). Firstly, AUROCs have been calculated to check whether the indicator performed well across all the thresholds in the analysed period. In the case of Lithuania many variables show up as 'perfect' early warning indicators (i.e. AUROC=1). This should be treated with caution, because of the small data sample. Table 2 also suggests optimal threshold values for the indicators. The threshold values depend on the unknown policy-makers' preference parameter $\theta$ (unless the indicator is near perfect – in that case, there is a single optimal threshold for a large set of preference parameters). Data analysis suggests that in the estimation setting similar to ours, the value of the policy-makers' preference parameter is likely to be in the range between 0.5 and 0.7. Value of 0.5, as mentioned earlier, is associated with situation when both identification of crisis and avoiding false signals are equally important. Value of 0.7 puts more weight on obtaining 'good signals' and is associated with lower thresholds. Detken et al. (2014) show that with $\theta = 0.7$, the thresholds become too low to be useful in many cases[11]: although signal ratio (or true positive ratio) improves as $\theta$ increases, noise ratio also increases.

***Table 2. Summary of results for the best performing indicators***

*(with balanced preferences, i.e.* $\theta = 0.5$*)*

| | | Lithuania | | | | | Baltic states | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | | **AUROC** | **Optimal threshold** | **Signal ratio (SR) at optimal threshold** | **Noise ratio (NR) at optimal threshold** | **Usefulness** | **AUROC** | **Optimal threshold** | **Signal ratio (SR) at optimal threshold** | **Noise ratio (NR) at optimal threshold** | **Usefulness** |
| **Main credit-to-GDP gaps**[1] | | | | | | | | | | | |
| Broad credit-to-GDP gap (stand. Basel gap) | p.p. | 1.00 | 1.7 | 1.00 | 0.00 | 0.50 | 0.90 | 3.2 | 0.82 | 0.02 | 0.40 |
| Broad credit-to-GDP gap (with forecast)[2] | p.p. | 1.00 | 3.6 | 1.00 | 0.00 | 0.50 | 0.85 | 3.6 | 0.94 | 0.35 | 0.29 |
| **Other credit variables** | | | | | | | | | | | |
| Bank loan-to-GDP gap (stand.) | p.p. | 1.00 | 4.9 | 1.00 | 0.00 | 0.50 | 1.00 | 1.9 | 0.98 | 0.04 | 0.47 |
| Bank loan-to-GDP gap (with forecast) | p.p | 1.00 | 4.9 | 1.00 | 0.00 | 0.50 | 0.98 | 3.9 | 0.94 | 0.07 | 0.43 |
| Household credit-to-GDP gap (stand.) | p.p. | 1.00 | 1.6 | 1.00 | 0.00 | 0.50 | 1.00 | 1.6 | 1.00 | 0.02 | 0.49 |
| Household credit-to-GDP gap (with forecast) | p.p | 1.00 | 1.7 | 1.00 | 0.00 | 0.50 | 0.99 | 2.8 | 0.96 | 0.04 | 0.46 |
| Household credit-to-GDP, 2-year difference | p.p | 1.00 | 3.1 | 1.00 | 0.00 | 0.50 | 0.99 | 5.2 | 0.96 | 0.02 | 0.47 |
| **Private sector debt burden** | | | | | | | | | | | |
| Household debt service-to-income, 2-year difference | p.p. | 1.00 | 0.5 | 1.00 | 0.00 | 0.50 | 0.94 | 0.8 | 0.82 | 0.04 | 0.39 |
| **Potential overvaluation of property prices** | | | | | | | | | | | |
| House price-to-income | - | 0.94 | 87.9 | 0.82 | 0.00 | 0.41 | 0.98 | 87.9 | 0.94 | 0.09 | 0.42 |
| House price-to-income gap (with forecast) | p.p | 0.90 | 8.8 | 0.82 | 0.11 | 0.36 | 0.90 | 11.0 | 0.90 | 0.20 | 0.35 |
| **External imbalances** | | | | | | | | | | | |
| Current account deficit-to-GDP | % | 0.76 | 6.5 | 1.00 | 0.37 | 0.32 | 0.88 | 7.6 | 0.90 | 0.31 | 0.29 |
| **Potential mispricing of risk** | | | | | | | | | | | |
| Stock market index, 2-year growth rate | % | 0.97 | 12.5 | 1.00 | 0.11 | 0.45 | 0.95 | 37.4 | 0.92 | 0.11 | 0.41 |
| **Strength of bank balance sheets** | | | | | | | | | | | |
| Bank loan-to-deposit ratio | % | 1.00 | 98.9 | 1.00 | 0.00 | 0.50 | 0.93 | 108.8 | 0.88 | 0.15 | 0.37 |
| **Estimate of crisis probabilities from *logit* models** | | | | | | | | | | | |
| Model No. 1[4] Variables: bank credit-to-GDP gap | | 1.00 | 0.25 | 1.00 | 0.00 | 0.50 | | | | | |
| Model No. 2[4] Variables: bank credit-to-GDP gap, yoy growth rate of real equity prices, and debt service ratio | | 0.98 | 0.22 | 1.00 | 0.08 | 0.46 | | | | | |
| Model No. 3[4] Variables: bank credit-to-GDP gap, yoy change in house price-to-income ratio, and debt service ratio | | 0.93 | 0.22 | 0.82 | 0.00 | 0.41 | | | | | |
| Model No. 4[4] Variables: bank credit-to-GDP gap, yoy growth rate of real equity prices, yoy change in house price-to-income ratio, and debt service ratio | | 0.99 | 0.24 | 1.00 | 0.08 | 0.46 | | | | | |
| Model No. 5[5] Variables: broad credit-to-GDP yoy change, yoy growth rate in real house prices | | 0.98 | 0.06 | 1.00 | 0.06 | 0.41 | | | | | |

*Source: authors' calculations.*
*Notes: [1] – gaps are calculated using one-sided HP filter with smoothing parameter 400,000; [2] – forecast is a 4-quarter weighted average for 5 years ahead; [3] – bank credit-to-GDP gap (in the Lithuanian case, bank loan-to-GDP gap is almost equivalent to bank credit-to-GDP gap); [4] – based on Detken et al. (2014); [5] – based on Arregui et al. (2013).*

From several transformations, the indicators with the highest AUROCs, usefulness measures, and reasonable thresholds have been selected as the most informative in the case of Lithuania and the Baltics. The thresholds obtained for both Lithuanian data and the data for the three countries are optimal in a narrow sense that they minimise the loss

[11] E.g., some credit-to-GDP gap variations and house price-to-income gaps suggest negative optimal threshold, annual growth of real bank credit would emit signal at -0.25%, debt service ratio of households – at meagre 1%. Such small threshold values have no motivation from the practical point of view.

function of the policy-maker. In practice, they could serve as tentative lower thresholds, breaching of which would emit a signal of possible financial imbalances. The lower threshold for the standardised Basel gap is 1.7 p.p. in Lithuania, which is somewhat lower than the BCBS proposed value of 2.0 p.p. (BCBS (2010)) and the corresponding threshold 2.7 p.p. estimated in Detken et al. (2014). The credit-to-GDP gap from the estimation with forecasts, would emit a signal after exceeding 3.6 p.p. in Lithuania, while a common threshold estimated in the ESRB study 4.65 p.p. The thresholds for Lithuania are somewhat lower than estimates provided in the literature, however they are still quite close to the lower threshold (2 p.p.) suggested by BCBS and ESRB. However, these estimates should be regarded with caution in a forward-looking exercise. Lithuanian economy experienced an intense expansion in 2003–2007 and the same thresholds that applied previously might not be entirely valid in the future.

Resulting AUROC values from various credit-to-GDP gap calculations are provided in Annex 1 Table A2. In cases of higher smoothing parameter, all gaps perform similarly, while the results using parameter value 1,600 are slightly worse. According to our calculations, signalling properties of the gap indicator do not change significantly (if compared to the standardised 'Basel' gap) when the HP filter is augmented with simple projections. These findings are consistent with the findings from Detken et al. (2014), where 'Basel' gap ('broad' credit-to-GDP gap without forecast), bank credit-to-GDP gap, 'broad' credit-to-GDP gap with a moving average forecast are among the best gap indicators and their performance does not differ significantly. Therefore, these three gap series are most likely to be used as early warning indicators for the activation of the CCB. Series including 'broad' credit could be chosen as the main indicators for benchmark buffer rate calculation, while narrow bank loan-to-GDP gap could be useful as a complementary early warning indicator, because it can be calculated quite timely[12]. Household credit-to-GDP gaps also perform well, although in the study by Detken et al. (2014) the difference was not statistically significant[13].

Based on the conclusions from the EU-wide analysis by Detken et al. (2014), Kalatie et al. (2015) and calculations for available Lithuanian data (Table 2), important early warning indicators from other data categories are household debt service ratios, house price-to-income ratios or gaps, bank loan-to-deposit ratio. Though the current account-to-GDP ratio performs relatively poorly as a single indicator, Detken et al. (2014) and Kauko (2012a) show that it is useful in a multivariate setting and reduces the incidence of false signals. The reason why current account variables appear to be less informative might be that current account itself may depend not only on the financial cycle, but also other measures which are less cyclical (Comunale and Hessel (2014)) or have an opposite cycle. This problem could be solved by using an indicator of current account misalignment, however it is a more complicated measure and is not readily available, especially for a panel of countries. Debt service ratios tend to emit signal shortly before the crisis, therefore their use as single early warning indicators is not entirely consistent with the purpose of CCB. Also, the use of multivariate models for crisis prediction can be a promising solution to combine information from many indicators, but these models still need to be enhanced to suit better to particular groups of countries, like the transitional economies.

## 3. Conclusions

The analysis presented in this paper shows that most of the early warning indicators of financial crises as documented in various cross-country studies of systemic banking crises can also be applied in the case of Lithuania. Among these variables we can find: credit-to-GDP gaps, house-price-to-income gaps, loan-to-deposit ratios, current account balance data. Both in a single-country (Lithuania) and a three-country (Lithuania, Latvia, Estonia) setting, they gave a robust signal 1–5 years before a financial stress period.

The method proposed by the Basel Committee of Banking Supervision (BCBS) to calculate the credit-to-GDP gap (i.e. one-sided HP filter with smoothing parameter 400,000) is applicable to Lithuanian data, although the uncertainty in the long-term trend estimation is high. Therefore, we propose to calculate a complementary alternative gap measure, which is estimated using simple projections (i.e. one-sided HP filter with smoothing parameter 400,000, where data series are extrapolated with weighted average of the last 4 quarterly observations). The alternative method seems to give more credible estimates of the long-term trend not only for the credit-to-GDP ratio, but also for MFI loans-to-GDP ratio and house-price-to-income variables. The lower and higher thresholds of credit-to-GDP gap would indicate the need to build-up the countercyclical capital buffer and were proposed by the BCBS (i.e. 2 and 10 percentage points). These thresholds also apply well to Lithuanian data, therefore the use of the standard threshold values is justifiable.

The list of indicators that would indicate the need to activate the CCB should provide timely general information

[12] MFI loan data are available around 30 days after the end of quarter, while ‚broad credit data are available around 100 days after the end of quarter.
[13] I.e. the confidence intervals of AUROC measure are overlapping. Confidence intervals are expressed in terms of two standard deviations above and below AUROC measures, where standard deviations are calculated from cross-country data.

about the possible build-up of financial imbalances in the economy. For example, a set of indicators that would provide a rather broad picture of the economy, relevant for the systemic risk assessment could include the broad credit-to-GDP gap (standardised Basel gap as well as the gap calculated using simple projections), MFI loan-to-GDP gap, house price-to-income ratio or its gap from long-term trend, loan-to-deposit ratio, current account balance-to-GDP ratio. Some key time series (credit, house prices) are published with a lag exceeding one quarter, therefore complementary indicators that are published with shorter lag or more frequently (e.g. MFI balance sheet statistics) would be essential for regular monitoring of financial imbalances.

In addition to the selected key indicators, a broad list of data should be monitored closely when making decisions on increasing the CCB rate. The broad list should comprise key sectoral indicators, other indicators that have short history in Lithuania but proved to be useful in other countries[14], as well as indicators from multivariate models. The list of indicators should be regularly reviewed as new research and recommendations for operationalizing the countercyclical capital buffer emerge. Since the experience in setting CCB rates and its impact is limited, the final decision on increasing the CCB rate should be based on expert judgement, taking into account the available quantitative and qualitative information, inferences from a thorough analysis, and the use of other policy measures.

[14] Such as commercial real estate prices, indicators of lending conditions, bank leverage ratio etc.

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## ANNEX 1. Results for the signalling approach

***Table A1. Results for credit-to-GDP gaps***

**Lithuania**

| Sector | Variable[1), 2), 3)] | | AUROC[4),5)] | Optimal thresholds (percentage points) | | | Signal ratio (SR)[6)] | | | Noise ratio (NR)[6)] | | | Noise-to-signal ratio (NSR)[6)] | | | Usefullnes[4),7)] | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | *Thetas: 0.5* | *0.6* | *0.7* | *0.5* | *0.6* | *0.7* | *0.5* | *0.6* | *0.7* | *0.5* | *0.6* | *0.7* | *0.5* | *0.6* | *0.7* |
| Private non-financial sector | Broad credit-to-GDP gap | without forecast | 1.00 | 1.7 | 1.7 | 1.7 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | | with forecast | 1.00 | 3.6 | 3.6 | 3.6 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | Broad credit-to-GDP gap (excl. Latvia) | without forecast | | | | | | | | | | | | | | | | |
| | | with forecast | | | | | | | | | | | | | | | | |
| | Bank loan-to-GDP gap | without forecast | 1.00 | 4.9 | 4.9 | 4.9 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | | with forecast | 1.00 | 4.9 | 4.9 | 4.9 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | Bank credit-to-GDP gap | without forecast | 1.00 | 4.5 | 4.5 | 4.5 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | | with forecast | 1.00 | 4.4 | 4.4 | 4.4 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | All financial liabilities-to-GDP gap | without forecast | 1.00 | 7.1 | 7.1 | 7.1 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | | with forecast | 1.00 | 9.5 | 9.5 | 9.5 | 1.00 | 1.00 | 1.00 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.47 | 0.38 | 0.28 |
| Households | Broad credit-to-GDP gap | without forecast | 1.00 | 1.6 | 1.6 | 1.6 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | | with forecast | 1.00 | 1.7 | 1.7 | 1.7 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | Bank loan-to-GDP gap | without forecast | 1.00 | 1.8 | 1.8 | 1.8 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | | with forecast | 1.00 | 1.7 | 1.7 | 1.7 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | All financial liabilities-to-GDP gap | without forecast | 1.00 | 4.1 | 4.1 | 4.1 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | | with forecast | 1.00 | 3.7 | 3.7 | 3.7 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| Non-financial corporations | Broad credit-to-GDP gap | without forecast | 0.93 | 1.4 | 0.2 | -0.8 | 0.71 | 0.94 | 1.00 | 0.00 | 0.26 | 0.37 | 0.00 | 0.28 | 0.37 | 0.35 | 0.26 | 0.19 |
| | | with forecast | 0.87 | 4.0 | 1.9 | 1.9 | 0.65 | 0.94 | 0.94 | 0.00 | 0.42 | 0.42 | 0.00 | 0.45 | 0.45 | 0.32 | 0.20 | 0.13 |
| | Broad credit-to-GDP gap (excl. Latvia) | without forecast | | | | | | | | | | | | | | | | |
| | | with forecast | | | | | | | | | | | | | | | | |
| | Bank loan-to-GDP gap | without forecast | 1.00 | 2.9 | 2.9 | 2.9 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | | with forecast | 1.00 | 3.1 | 3.1 | 3.1 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | Bank credit-to-GDP gap | without forecast | 0.98 | 2.1 | 2.1 | 2.1 | 1.00 | 1.00 | 1.00 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.47 | 0.38 | 0.28 |
| | | with forecast | 0.99 | 2.2 | 2.2 | 2.2 | 1.00 | 1.00 | 1.00 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.47 | 0.38 | 0.28 |
| | All financial liabilities-to-GDP gap | without forecast | 1.00 | 2.8 | 2.8 | 2.8 | 1.00 | 1.00 | 1.00 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.47 | 0.38 | 0.28 |
| | | with forecast | 1.00 | 5.7 | 5.7 | 5.7 | 1.00 | 1.00 | 1.00 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.47 | 0.38 | 0.28 |
| | Money M3-to-GDP gap | without forecast | 0.77 | 1.4 | 1.4 | 0.7 | 0.59 | 0.59 | 0.88 | 0.00 | 0.00 | 0.53 | 0.00 | 0.00 | 0.60 | 0.29 | 0.15 | 0.06 |
| | | with forecast | 0.98 | 4.1 | 4.1 | 3.7 | 0.94 | 0.94 | 1.00 | 0.11 | 0.11 | 0.21 | 0.11 | 0.11 | 0.21 | 0.42 | 0.32 | 0.24 |

**Baltic countries**

| Sector | Variable[1), 2), 3)] | | AUROC[4),5)] | Optimal thresholds (percentage points) | | | Signal ratio (SR)[6)] | | | Noise ratio (NR)[6)] | | | Noise-to-signal ratio (NSR)[6)] | | | Usefullnes[4),7)] | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | *0.5* | *0.6* | *0.7* | *0.5* | *0.6* | *0.7* | *0.5* | *0.6* | *0.7* | *0.5* | *0.6* | *0.7* | *0.5* | *0.6* | *0.7* |
| Private non-financial sector | Broad credit-to-GDP gap | without forecast | 0.90 | 3.2 | 3.2 | 1.7 | 0.82 | 0.82 | 0.88 | 0.02 | 0.02 | 0.13 | 0.02 | 0.02 | 0.15 | 0.40 | 0.29 | 0.18 |
| | | with forecast | 0.85 | 3.6 | 3.6 | 3.6 | 0.94 | 0.94 | 0.94 | 0.35 | 0.35 | 0.35 | 0.37 | 0.37 | 0.37 | 0.29 | 0.22 | 0.15 |
| | Broad credit-to-GDP gap (excl. Latvia) | without forecast | 0.99 | 3.2 | 1.7 | 1.7 | 0.94 | 1.00 | 1.00 | 0.03 | 0.11 | 0.11 | 0.03 | 0.11 | 0.11 | 0.46 | 0.35 | 0.27 |
| | | with forecast | 0.96 | 3.6 | 3.6 | 3.6 | 0.91 | 0.91 | 0.91 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.46 | 0.35 | 0.24 |
| | Bank loan-to-GDP gap | without forecast | 1.00 | 1.9 | 1.9 | 1.9 | 0.98 | 0.98 | 0.98 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.47 | 0.37 | 0.28 |
| | | with forecast | 0.98 | 3.9 | 3.9 | 3.9 | 0.94 | 0.94 | 0.94 | 0.07 | 0.07 | 0.07 | 0.08 | 0.08 | 0.08 | 0.43 | 0.34 | 0.24 |
| | Bank credit-to-GDP gap | without forecast | 1.00 | 2.2 | 2.2 | 2.2 | 0.98 | 0.98 | 0.98 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.47 | 0.37 | 0.28 |
| | | with forecast | 0.97 | 4.5 | 4.5 | 4.4 | 0.90 | 0.90 | 0.92 | 0.07 | 0.07 | 0.11 | 0.08 | 0.08 | 0.12 | 0.41 | 0.31 | 0.21 |
| | All financial liabilities-to-GDP gap | without forecast | 0.85 | 6.2 | 6.2 | 4.5 | 0.82 | 0.82 | 0.84 | 0.02 | 0.02 | 0.06 | 0.02 | 0.02 | 0.07 | 0.40 | 0.29 | 0.17 |
| | | with forecast | 0.80 | 5.8 | 5.8 | 4.4 | 0.92 | 0.92 | 0.94 | 0.39 | 0.39 | 0.43 | 0.42 | 0.42 | 0.45 | 0.27 | 0.20 | 0.13 |
| Households | Broad credit-to-GDP gap | without forecast | 1.00 | 1.8 | 1.8 | 1.6 | 0.98 | 0.98 | 1.00 | 0.00 | 0.00 | 0.04 | 0.00 | 0.00 | 0.04 | 0.49 | 0.39 | 0.29 |
| | | with forecast | 0.99 | 2.8 | 2.8 | 2.8 | 0.96 | 0.96 | 0.96 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.46 | 0.36 | 0.26 |
| | Bank loan-to-GDP gap | without forecast | 1.00 | 1.4 | 1.4 | 1.2 | 0.98 | 0.98 | 1.00 | 0.00 | 0.00 | 0.04 | 0.00 | 0.00 | 0.04 | 0.49 | 0.39 | 0.29 |
| | | with forecast | 0.99 | 2.3 | 1.7 | 1.7 | 0.94 | 1.00 | 1.00 | 0.06 | 0.13 | 0.13 | 0.06 | 0.13 | 0.13 | 0.44 | 0.35 | 0.26 |
| | All financial liabilities-to-GDP gap | without forecast | 1.00 | 2.0 | 2.0 | 2.0 | 1.00 | 1.00 | 1.00 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.47 | 0.38 | 0.28 |
| | | with forecast | 1.00 | 3.3 | 3.3 | 3.3 | 1.00 | 1.00 | 1.00 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.48 | 0.39 | 0.29 |
| Non-financial corporations | Broad credit-to-GDP gap | without forecast | 0.79 | 1.4 | 1.4 | -0.8 | 0.69 | 0.69 | 0.84 | 0.11 | 0.11 | 0.43 | 0.16 | 0.16 | 0.51 | 0.29 | 0.17 | 0.06 |
| | | with forecast | 0.66 | 0.8 | 0.8 | -2.4 | 0.90 | 0.90 | 1.00 | 0.57 | 0.57 | 0.76 | 0.64 | 0.64 | 0.76 | 0.16 | 0.11 | 0.07 |
| | Broad credit-to-GDP gap (excl. Latvia) | without forecast | 0.96 | 2.9 | 2.9 | -0.8 | 0.82 | 0.82 | 1.00 | 0.00 | 0.00 | 0.34 | 0.00 | 0.00 | 0.34 | 0.41 | 0.29 | 0.20 |
| | | with forecast | 0.84 | 1.9 | 1.1 | -2.4 | 0.76 | 0.85 | 1.00 | 0.23 | 0.34 | 0.63 | 0.30 | 0.40 | 0.63 | 0.27 | 0.17 | 0.11 |
| | Bank loan-to-GDP gap | without forecast | 0.98 | 1.5 | 1.5 | 0.7 | 0.90 | 0.90 | 0.98 | 0.02 | 0.02 | 0.19 | 0.02 | 0.02 | 0.19 | 0.44 | 0.33 | 0.23 |
| | | with forecast | 0.93 | 3.1 | 3.1 | 2.5 | 0.82 | 0.82 | 0.86 | 0.00 | 0.00 | 0.07 | 0.00 | 0.00 | 0.09 | 0.41 | 0.29 | 0.18 |
| | Bank credit-to-GDP gap | without forecast | 0.98 | 1.6 | 1.6 | 0.7 | 0.90 | 0.90 | 0.96 | 0.02 | 0.02 | 0.13 | 0.02 | 0.02 | 0.13 | 0.44 | 0.33 | 0.23 |
| | | with forecast | 0.91 | 2.8 | 2.8 | 2.2 | 0.80 | 0.80 | 0.86 | 0.07 | 0.07 | 0.17 | 0.09 | 0.09 | 0.19 | 0.36 | 0.25 | 0.15 |
| | All financial liabilities-to-GDP gap | without forecast | 0.82 | 3.8 | 3.8 | 3.8 | 0.78 | 0.78 | 0.78 | 0.04 | 0.04 | 0.04 | 0.05 | 0.05 | 0.05 | 0.37 | 0.26 | 0.14 |
| | | with forecast | 0.66 | 4.0 | 4.0 | -3.6 | 0.80 | 0.80 | 1.00 | 0.41 | 0.41 | 0.78 | 0.51 | 0.51 | 0.78 | 0.20 | 0.12 | 0.07 |
| | Money M3-to-GDP gap | without forecast | 0.67 | 1.4 | 1.4 | -3.1 | 0.63 | 0.63 | 1.00 | 0.15 | 0.15 | 1.00 | 0.24 | 0.24 | 1.00 | 0.24 | 0.12 | 0.00 |
| | | with forecast | 0.87 | 4.2 | 3.4 | 3.0 | 0.65 | 0.82 | 0.88 | 0.04 | 0.26 | 0.39 | 0.06 | 0.31 | 0.44 | 0.31 | 0.19 | 0.10 |

*Source: authors' calculations.*
*Notes:*
*1) gaps are calculated using HP filter with parameter 400,000 (pseudo-real time procedure);*
*2) forecast is a 4-quarter weighted average for 5 years ahead as described in Section 1.1.2.;*
*3) Broad credit – loans and debt securities held by all creditors; bank credit – loans and debt securities held by MFIs (credit institutions); bank loans – loans held by MFIs (credit institutions); all financial liabilities – loans, debt securities and trade credits and other accounts payable, held by all creditors;*
*4) AUROC (area under the receiver operating curve) is a measure of the indicator's usefulness across all thresholds and all preferences, while 'Usefulness' is a measure of indicator's usefulness at the optimal threshold with a given preference parameter;*
*5) highlighted brown cells indicate high values of the AUROC parameter: the darker the colour, the higher AUROC.*
*6) highlighted red cells indicate low signal ratios as well as high noise and noise-to-signal ratios: the darker the colour, the more the value differs from the corresponding value of the best indicators in the table;*
*7) highlighted green cells indicate high values of the 'Usefulness' parameter: the darker the colour, the more the indicator is useful at the estimated optimal threshold with the given preference parameter.*

### *Table A2. Results for credit[1)]-to-GDP gaps in Lithuania with different values of smoothing parameter*

**One-sided filter**

| | Method[2),3)] | AUROC[4),5)] | Optimal thresholds (percentage points) Thetas: 0.5 | 0.6 | 0.7 | Signal ratio (SR)[6)] 0.5 | 0.6 | 0.7 | Noise ratio (NR)[6)] 0.5 | 0.6 | 0.7 | Noise-to-signal ratio (NSR)[6)] 0.5 | 0.6 | 0.7 | Usefulnes[4),7)] 0.5 | 0.6 | 0.7 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Lambda | No forecast | 1.00 | 1.7 | 1.7 | 1.7 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| 400,000 | Forecast: 4-quarter moving average | 1.00 | 3.6 | 3.6 | 3.6 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | Forecast: 8-quarter moving average | 1.00 | 4.5 | 4.5 | 4.5 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | Forecast: last value | 1.00 | 3.0 | 3.0 | 3.0 | 1.00 | 1.00 | 1.00 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.47 | 0.38 | 0.28 |
| | Forecast: average of last 4 quarters | 1.00 | 4.0 | 4.0 | 4.0 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | Forecast: average of last 8 quarters | 1.00 | 5.1 | 5.1 | 5.1 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | Forecast: weighted average of last 4 quarters | 1.00 | 3.6 | 3.6 | 3.6 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | Forecast: linear | 1.00 | 0.8 | 0.8 | 0.8 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| Lambda | No forecast | 1.00 | 1.7 | 1.7 | 1.7 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| 130,000 | Forecast: 4-quarter moving average | 1.00 | 3.6 | 3.6 | 3.6 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | Forecast: 8-quarter moving average | 1.00 | 4.4 | 4.4 | 4.4 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | Forecast: last value | 0.99 | 2.9 | 2.9 | 2.9 | 1.00 | 1.00 | 1.00 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.47 | 0.38 | 0.28 |
| | Forecast: average of last 4 quarters | 1.00 | 4.0 | 4.0 | 4.0 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | Forecast: average of last 8 quarters | 1.00 | 5.0 | 5.0 | 5.0 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | Forecast: weighted average of last 4 quarters | 1.00 | 3.5 | 3.5 | 3.5 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | Forecast: linear | 1.00 | 0.8 | 0.8 | 0.8 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| Lambda | No forecast | 1.00 | 1.8 | 1.8 | 1.8 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| 26,000 | Forecast: 4-quarter moving average | 1.00 | 3.2 | 3.2 | 3.2 | 1.00 | 1.00 | 1.00 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.47 | 0.38 | 0.28 |
| | Forecast: 8-quarter moving average | 1.00 | 4.1 | 4.1 | 4.1 | 1.00 | 1.00 | 1.00 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.47 | 0.38 | 0.28 |
| | Forecast: last value | 0.98 | 3.5 | 2.6 | 2.6 | 0.88 | 1.00 | 1.00 | 0.00 | 0.16 | 0.16 | 0.00 | 0.16 | 0.16 | 0.44 | 0.34 | 0.25 |
| | Forecast: average of last 4 quarters | 1.00 | 3.6 | 3.6 | 3.6 | 1.00 | 1.00 | 1.00 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.47 | 0.38 | 0.28 |
| | Forecast: average of last 8 quarters | 1.00 | 4.6 | 4.6 | 4.6 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| | Forecast: weighted average of last 4 quarters | 1.00 | 3.2 | 3.2 | 3.2 | 1.00 | 1.00 | 1.00 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.47 | 0.38 | 0.28 |
| | Forecast: linear | 1.00 | 0.9 | 0.9 | 0.9 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| Lambda | No forecast | 1.00 | 2.2 | 2.2 | 2.2 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |
| 1,600 | Forecast: 4-quarter moving average | 0.99 | 2.9 | 2.9 | 2.5 | 0.94 | 0.94 | 1.00 | 0.00 | 0.00 | 0.11 | 0.00 | 0.00 | 0.11 | 0.47 | 0.36 | 0.27 |
| | Forecast: 8-quarter moving average | 1.00 | 3.4 | 3.4 | 3.4 | 1.00 | 1.00 | 1.00 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.47 | 0.38 | 0.28 |
| | Forecast: last value | 0.99 | 1.9 | 1.9 | 1.9 | 1.00 | 1.00 | 1.00 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 | 0.45 | 0.36 | 0.27 |
| | Forecast: average of last 4 quarters | 0.99 | 3.3 | 3.3 | 2.9 | 0.94 | 0.94 | 1.00 | 0.00 | 0.00 | 0.11 | 0.00 | 0.00 | 0.11 | 0.47 | 0.36 | 0.27 |
| | Forecast: average of last 8 quarters | 0.99 | 3.8 | 3.8 | 3.8 | 1.00 | 1.00 | 1.00 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.47 | 0.38 | 0.28 |
| | Forecast: weighted average of last 4 quarters | 0.99 | 2.9 | 2.9 | 2.5 | 0.94 | 0.94 | 1.00 | 0.00 | 0.00 | 0.11 | 0.00 | 0.00 | 0.11 | 0.47 | 0.36 | 0.27 |
| | Forecast: linear | 1.00 | 1.1 | 1.1 | 1.1 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 |

**Two-sided filter**

| | Method[2),3)] | AUROC[4),5)] | Optimal thresholds (percentage points) 0.5 | 0.6 | 0.7 | Signal ratio (SR)[6)] 0.5 | 0.6 | 0.7 | Noise ratio (NR)[6)] 0.5 | 0.6 | 0.7 | Noise-to-signal ratio (NSR)[6)] 0.5 | 0.6 | 0.7 | Usefulnes[4),7)] 0.5 | 0.6 | 0.7 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Lambda | No forecast | 0.73 | 2.0 | -9.6 | -9.6 | 0.47 | 1.00 | 1.00 | 0.00 | 0.74 | 0.74 | 0.00 | 0.74 | 0.74 | 0.24 | 0.11 | 0.08 |
| 400,000 | Forecast: 4-quarter moving average | 0.81 | -2.7 | -2.7 | -10.0 | 0.65 | 0.65 | 1.00 | 0.00 | 0.00 | 0.63 | 0.00 | 0.00 | 0.63 | 0.32 | 0.19 | 0.11 |
| | Forecast: 8-quarter moving average | 0.81 | -2.7 | -2.7 | -10.0 | 0.65 | 0.65 | 1.00 | 0.00 | 0.00 | 0.63 | 0.00 | 0.00 | 0.63 | 0.32 | 0.19 | 0.11 |
| | Forecast: last value | 0.81 | -2.6 | -2.6 | -10.0 | 0.65 | 0.65 | 1.00 | 0.00 | 0.00 | 0.63 | 0.00 | 0.00 | 0.63 | 0.32 | 0.19 | 0.11 |
| | Forecast: average of last 4 quarters | 0.81 | -2.7 | -2.7 | -10.0 | 0.65 | 0.65 | 1.00 | 0.00 | 0.00 | 0.63 | 0.00 | 0.00 | 0.63 | 0.32 | 0.19 | 0.11 |
| | Forecast: average of last 8 quarters | 0.81 | -2.7 | -2.7 | -10.0 | 0.65 | 0.65 | 1.00 | 0.00 | 0.00 | 0.63 | 0.00 | 0.00 | 0.63 | 0.32 | 0.19 | 0.11 |
| | Forecast: weighted average of last 4 quarters | 0.81 | -2.7 | -2.7 | -10.0 | 0.65 | 0.65 | 1.00 | 0.00 | 0.00 | 0.63 | 0.00 | 0.00 | 0.63 | 0.32 | 0.19 | 0.11 |
| | Forecast: linear | 0.79 | -0.8 | -0.8 | -9.7 | 0.59 | 0.59 | 1.00 | 0.00 | 0.00 | 0.68 | 0.00 | 0.00 | 0.68 | 0.29 | 0.15 | 0.09 |
| Lambda | No forecast | 0.69 | 0.9 | -10.2 | -10.2 | 0.47 | 1.00 | 1.00 | 0.00 | 0.74 | 0.74 | 0.00 | 0.74 | 0.74 | 0.24 | 0.11 | 0.08 |
| 130,000 | Forecast: 4-quarter moving average | 0.72 | 0.9 | -11.1 | -11.1 | 0.47 | 1.00 | 1.00 | 0.00 | 0.74 | 0.74 | 0.00 | 0.74 | 0.74 | 0.24 | 0.11 | 0.08 |
| | Forecast: 8-quarter moving average | 0.72 | 0.9 | -11.1 | -11.1 | 0.47 | 1.00 | 1.00 | 0.00 | 0.74 | 0.74 | 0.00 | 0.74 | 0.74 | 0.24 | 0.11 | 0.08 |
| | Forecast: last value | 0.72 | 0.9 | -11.2 | -11.2 | 0.47 | 1.00 | 1.00 | 0.00 | 0.74 | 0.74 | 0.00 | 0.74 | 0.74 | 0.24 | 0.11 | 0.08 |
| | Forecast: average of last 4 quarters | 0.72 | 0.9 | -11.1 | -11.1 | 0.47 | 1.00 | 1.00 | 0.00 | 0.74 | 0.74 | 0.00 | 0.74 | 0.74 | 0.24 | 0.11 | 0.08 |
| | Forecast: average of last 8 quarters | 0.72 | 0.9 | -11.1 | -11.1 | 0.47 | 1.00 | 1.00 | 0.00 | 0.74 | 0.74 | 0.00 | 0.74 | 0.74 | 0.24 | 0.11 | 0.08 |
| | Forecast: weighted average of last 4 quarters | 0.72 | 0.9 | -11.1 | -11.1 | 0.47 | 1.00 | 1.00 | 0.00 | 0.74 | 0.74 | 0.00 | 0.74 | 0.74 | 0.24 | 0.11 | 0.08 |
| | Forecast: linear | 0.72 | 1.1 | -10.6 | -10.6 | 0.47 | 1.00 | 1.00 | 0.00 | 0.74 | 0.74 | 0.00 | 0.74 | 0.74 | 0.24 | 0.11 | 0.08 |
| Lambda | No forecast | 0.41 | -3.4 | 15.8 | 15.8 | 0.53 | 1.00 | 1.00 | 0.47 | 1.00 | 1.00 | 0.89 | 1.00 | 1.00 | 0.03 | 0.00 | 0.00 |
| 26,000 | Forecast: 4-quarter moving average | 0.41 | -3.9 | 15.6 | 15.6 | 0.53 | 1.00 | 1.00 | 0.47 | 1.00 | 1.00 | 0.89 | 1.00 | 1.00 | 0.03 | 0.00 | 0.00 |
| | Forecast: 8-quarter moving average | 0.41 | -3.8 | 15.6 | 15.6 | 0.53 | 1.00 | 1.00 | 0.47 | 1.00 | 1.00 | 0.89 | 1.00 | 1.00 | 0.03 | 0.00 | 0.00 |
| | Forecast: last value | 0.41 | -3.9 | 15.6 | 15.6 | 0.53 | 1.00 | 1.00 | 0.47 | 1.00 | 1.00 | 0.89 | 1.00 | 1.00 | 0.03 | 0.00 | 0.00 |
| | Forecast: average of last 4 quarters | 0.41 | -3.8 | 15.6 | 15.6 | 0.53 | 1.00 | 1.00 | 0.47 | 1.00 | 1.00 | 0.89 | 1.00 | 1.00 | 0.03 | 0.00 | 0.00 |
| | Forecast: average of last 8 quarters | 0.41 | -3.8 | 15.7 | 15.7 | 0.53 | 1.00 | 1.00 | 0.47 | 1.00 | 1.00 | 0.89 | 1.00 | 1.00 | 0.03 | 0.00 | 0.00 |
| | Forecast: weighted average of last 4 quarters | 0.41 | -3.9 | 15.6 | 15.6 | 0.53 | 1.00 | 1.00 | 0.47 | 1.00 | 1.00 | 0.89 | 1.00 | 1.00 | 0.03 | 0.00 | 0.00 |
| | Forecast: linear | 0.59 | 2.3 | -10.6 | -10.6 | 0.35 | 1.00 | 1.00 | 0.05 | 0.84 | 0.84 | 0.15 | 0.84 | 0.84 | 0.15 | 0.06 | 0.05 |
| Lambda | No forecast | 0.64 | -0.3 | -0.3 | -0.3 | 0.76 | 0.76 | 0.76 | 0.42 | 0.42 | 0.42 | 0.55 | 0.55 | 0.55 | 0.17 | 0.09 | 0.01 |
| 1,600 | Forecast: 4-quarter moving average | 0.64 | -0.3 | -0.3 | -0.3 | 0.76 | 0.76 | 0.76 | 0.42 | 0.42 | 0.42 | 0.55 | 0.55 | 0.55 | 0.17 | 0.09 | 0.01 |
| | Forecast: 8-quarter moving average | 0.64 | -0.2 | -0.2 | -0.2 | 0.76 | 0.76 | 0.76 | 0.42 | 0.42 | 0.42 | 0.55 | 0.55 | 0.55 | 0.17 | 0.09 | 0.01 |
| | Forecast: last value | 0.64 | -0.3 | -0.3 | -0.3 | 0.76 | 0.76 | 0.76 | 0.42 | 0.42 | 0.42 | 0.55 | 0.55 | 0.55 | 0.17 | 0.09 | 0.01 |
| | Forecast: average of last 4 quarters | 0.64 | -0.3 | -0.3 | -0.3 | 0.76 | 0.76 | 0.76 | 0.42 | 0.42 | 0.42 | 0.55 | 0.55 | 0.55 | 0.17 | 0.09 | 0.01 |
| | Forecast: average of last 8 quarters | 0.64 | -0.2 | -0.2 | -0.2 | 0.76 | 0.76 | 0.76 | 0.42 | 0.42 | 0.42 | 0.55 | 0.55 | 0.55 | 0.17 | 0.09 | 0.01 |
| | Forecast: weighted average of last 4 quarters | 0.64 | -0.3 | -0.3 | -0.3 | 0.76 | 0.76 | 0.76 | 0.42 | 0.42 | 0.42 | 0.55 | 0.55 | 0.55 | 0.17 | 0.09 | 0.01 |
| | Forecast: linear | 0.64 | -0.2 | -0.2 | -0.2 | 0.76 | 0.76 | 0.76 | 0.42 | 0.42 | 0.42 | 0.55 | 0.55 | 0.55 | 0.17 | 0.09 | 0.01 |

*Source: authors' calculations.*

*Notes:*

*1) broad credit – loans to non-financial corporations and households from all creditors, and debt securities issued by non-financial corporations, held by all creditors;*

*2) gaps are calculated using HP filter with parameter 400,000 (pseudo-real time procedure);*

*3) forecast is a 4-quarter weighted average for 5 years ahead as described in Section 1.1.2.;*

*4) AUROC (area under the receiver operating curve) is a measure of the indicator's usefulness across all thresholds and all preferences, while 'Usefulness' is a measure of indicator's usefulness at the optimal threshold with a given preference parameter;*

*5) highlighted brown cells indicate high values of the AUROC parameter: the darker the colour, the higher AUROC.*

*6) highlighted red cells indicate low signal ratios as well as high noise and noise-to-signal ratios: the darker the colour, the more the value differs from the corresponding value of the best indicators in the table;*

*7) highlighted green cells indicate high values of the 'Usefulness' parameter: the darker the colour, the more the indicator is useful at the estimated optimal threshold with the given preference parameter.*

***Table B. Results for the best early warning indicators by categories of variables in accordance with ESRB Recommendation (ESRB/2014/1)***

| | | | Lithuania | | | | | | | | | | | | | | | | Baltic countries | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Variable[1] | Transformations[2,3] | AUROC[4,5] | Optimal thresholds (percentage points) | | | Signal ratio (SR)[6] | | | Noise ratio (NR)[6] | | | Noise-to-signal ratio (NSR)[6] | | | Usefullnes[4,7] | | | AUROC[4,5] | Optimal thresholds (percentage points) | | | Signal ratio (SR)[6] | | | Noise ratio (NR)[6] | | | Noise-to-signal ratio (NSR)[6] | | | Usefullnes[4,7] | | |
| | | | | Thetas: 0.5 | 0.6 | 0.7 | 0.5 | 0.6 | 0.7 | 0.5 | 0.6 | 0.7 | 0.5 | 0.6 | 0.7 | 0.5 | 0.6 | 0.7 | | 0.5 | 0.6 | 0.7 | 0.5 | 0.6 | 0.7 | 0.5 | 0.6 | 0.7 | 0.5 | 0.6 | 0.7 | 0.5 | 0.6 | 0.7 |
| **Credit variables** | Broad credit-to-GDP | trend gap | 1.00 | 1.7 | 1.7 | 1.7 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 | 0.90 | 3.2 | 3.2 | 1.7 | 0.82 | 0.82 | 0.88 | 0.02 | 0.02 | 0.13 | 0.02 | 0.02 | 0.15 | 0.40 | 0.29 | 0.18 |
| | | trend gap, with forecast | 1.00 | 3.6 | 3.6 | 3.6 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 | 0.85 | 3.6 | 3.6 | 3.6 | 0.94 | 0.94 | 0.94 | 0.35 | 0.35 | 0.35 | 0.37 | 0.37 | 0.37 | 0.29 | 0.22 | 0.15 |
| | Bank credit-to-GDP | trend gap | 1.00 | 4.9 | 4.9 | 4.9 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 | 1.00 | 1.9 | 1.9 | 1.9 | 0.98 | 0.98 | 0.98 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.47 | 0.37 | 0.28 |
| | | trend gap, with forecast | 1.00 | 4.9 | 4.9 | 4.9 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 | 0.98 | 3.9 | 3.9 | 3.9 | 0.94 | 0.94 | 0.94 | 0.07 | 0.07 | 0.07 | 0.08 | 0.08 | 0.08 | 0.43 | 0.34 | 0.24 |
| | | 2-year difference | 1.00 | 8.3 | 8.3 | 8.3 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 | 0.97 | 9.1 | 8.3 | 8.3 | 0.88 | 0.92 | 0.92 | 0.02 | 0.07 | 0.07 | 0.02 | 0.08 | 0.08 | 0.43 | 0.32 | 0.22 |
| | Household credit-to-GDP | trend gap | 1.00 | 1.6 | 1.6 | 1.6 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 | 1.00 | 1.6 | 1.6 | 1.6 | 1.00 | 1.00 | 1.00 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.49 | 0.39 | 0.29 |
| | | trend gap, with forecast | 1.00 | 1.7 | 1.7 | 1.7 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 | 0.99 | 2.8 | 2.8 | 2.8 | 0.96 | 0.96 | 0.96 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.46 | 0.36 | 0.26 |
| | | 2-year difference | 1.00 | 3.1 | 3.1 | 3.1 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 | 0.99 | 5.2 | 5.2 | 4.3 | 0.96 | 0.96 | 0.98 | 0.02 | 0.02 | 0.06 | 0.02 | 0.02 | 0.06 | 0.47 | 0.37 | 0.27 |
| **Private sector debt burden** | Debt service-to-income | 2-year difference | 0.81 | 0.6 | -0.4 | -0.4 | 0.82 | 1.00 | 1.00 | 0.32 | 0.58 | 0.58 | 0.38 | 0.58 | 0.58 | 0.25 | 0.17 | 0.13 | 0.72 | 0.8 | -0.9 | -0.9 | 0.63 | 0.92 | 0.92 | 0.28 | 0.67 | 0.67 | 0.44 | 0.72 | 0.72 | 0.17 | 0.09 | 0.05 |
| | | 1-year difference | 0.84 | 0.1 | 0.1 | 0.1 | 1.00 | 1.00 | 1.00 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.32 | 0.25 | 0.19 | 0.81 | 0.2 | 0.0 | 0.0 | 0.84 | 0.88 | 0.88 | 0.28 | 0.33 | 0.33 | 0.33 | 0.38 | 0.38 | 0.28 | 0.20 | 0.12 |
| | Household debt service-to-income | 2-year difference | 1.00 | 0.5 | 0.5 | 0.5 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 | 0.94 | 0.8 | 0.8 | 0.6 | 0.82 | 0.82 | 0.88 | 0.04 | 0.04 | 0.13 | 0.04 | 0.04 | 0.15 | 0.39 | 0.28 | 0.18 |
| **Potential overvaluation of property prices** | House price-to-income | trend gap | 0.74 | 10.0 | 10.0 | 4.9 | 0.65 | 0.65 | 0.71 | 0.11 | 0.11 | 0.21 | 0.16 | 0.16 | 0.30 | 0.27 | 0.15 | 0.03 | 0.53 | 11.8 | 0.9 | -25.4 | 0.27 | 0.65 | 1.00 | 0.04 | 0.44 | 1.00 | 0.13 | 0.69 | 1.00 | 0.12 | 0.01 | 0.00 |
| | | trend gap, with forecast | 0.90 | 8.8 | 8.8 | 8.8 | 0.82 | 0.82 | 0.82 | 0.11 | 0.11 | 0.11 | 0.13 | 0.13 | 0.13 | 0.36 | 0.25 | 0.14 | 0.90 | 11.0 | 8.3 | 8.3 | 0.90 | 0.94 | 0.94 | 0.20 | 0.26 | 0.26 | 0.23 | 0.28 | 0.28 | 0.35 | 0.26 | 0.18 |
| | | - | 0.94 | 87.9 | 87.9 | 78.6 | 0.82 | 0.82 | 1.00 | 0.00 | 0.00 | 0.37 | 0.00 | 0.00 | 0.37 | 0.41 | 0.29 | 0.19 | 0.98 | 87.9 | 87.9 | 87.9 | 0.94 | 0.94 | 0.94 | 0.09 | 0.09 | 0.09 | 0.10 | 0.10 | 0.10 | 0.42 | 0.33 | 0.23 |
| | | 2-year difference | 0.80 | 18.2 | 6.3 | 1.3 | 0.65 | 0.88 | 0.94 | 0.11 | 0.42 | 0.53 | 0.16 | 0.48 | 0.56 | 0.27 | 0.16 | 0.10 | 0.86 | 6.3 | 6.3 | 1.3 | 0.96 | 0.96 | 0.98 | 0.31 | 0.31 | 0.35 | 0.33 | 0.33 | 0.36 | 0.32 | 0.25 | 0.18 |
| **External imbalances** | Current account deficit-to-GDP | - | 0.76 | 6.5 | 6.5 | 6.5 | 1.00 | 1.00 | 1.00 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.32 | 0.25 | 0.19 | 0.88 | 7.6 | 7.6 | 7.6 | 0.90 | 0.90 | 0.90 | 0.31 | 0.31 | 0.31 | 0.35 | 0.35 | 0.35 | 0.29 | 0.22 | 0.14 |
| | | 2-year growth rate | 0.90 | 4.4 | 4.4 | 4.4 | 1.00 | 1.00 | 1.00 | 0.32 | 0.32 | 0.32 | 0.32 | 0.32 | 0.32 | 0.34 | 0.27 | 0.21 | 0.73 | -10.5 | -10.5 | -32.4 | 0.90 | 0.90 | 1.00 | 0.50 | 0.50 | 0.67 | 0.55 | 0.55 | 0.67 | 0.20 | 0.14 | 0.10 |
| | | 1-year growth rate | 0.85 | 23.9 | 23.9 | -21.6 | 0.71 | 0.71 | 1.00 | 0.00 | 0.00 | 0.68 | 0.00 | 0.00 | 0.68 | 0.35 | 0.22 | 0.09 | 0.68 | -5.4 | -27.2 | -27.2 | 0.82 | 0.98 | 0.98 | 0.48 | 0.70 | 0.70 | 0.58 | 0.72 | 0.72 | 0.17 | 0.11 | 0.08 |
| **Potential mispricing of risk** | Stock market index | 2-year growth rate | 0.97 | 12.5 | 12.5 | 12.5 | 1.00 | 1.00 | 1.00 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 | 0.45 | 0.36 | 0.27 | 0.95 | 37.4 | 37.4 | 37.4 | 0.92 | 0.92 | 0.92 | 0.11 | 0.11 | 0.11 | 0.12 | 0.12 | 0.12 | 0.41 | 0.31 | 0.21 |
| **Strength of bank balance sheets** | Bank loan-to-deposit ratio | - | 1.00 | 98.9 | 98.9 | 98.9 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.50 | 0.40 | 0.30 | 0.93 | 108.8 | 108.8 | 108.8 | 0.88 | 0.88 | 0.88 | 0.15 | 0.15 | 0.15 | 0.17 | 0.17 | 0.17 | 0.37 | 0.27 | 0.17 |
| | | 2-year growth rate | 0.84 | 2.9 | 2.9 | 2.9 | 1.00 | 1.00 | 1.00 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.32 | 0.25 | 0.19 | 0.85 | 10.2 | 4.0 | 4.0 | 0.82 | 0.98 | 0.98 | 0.19 | 0.41 | 0.41 | 0.22 | 0.42 | 0.42 | 0.32 | 0.23 | 0.16 |
| | | 2-year difference | 0.90 | 8.3 | 3.2 | 3.2 | 0.88 | 1.00 | 1.00 | 0.21 | 0.37 | 0.37 | 0.24 | 0.37 | 0.37 | 0.34 | 0.25 | 0.19 | 0.91 | 10.7 | 8.2 | 6.2 | 0.86 | 0.92 | 0.94 | 0.17 | 0.24 | 0.28 | 0.19 | 0.26 | 0.30 | 0.35 | 0.26 | 0.18 |

*Source: authors' calculations.*
*Notes:*
*1) variables and their transformations were taken from Kalatie et al. (2015), since it is the most comprehensive analysis and extensive description of most valuable transformations, to keep as many observations as possible, 2-year changes and differences were calculated for Lithuania and the Baltics, instead of 3-year changes;*
*2) gaps are calculated using HP filter with parameter 400,000 (pseudo-real time procedure);*
*3) forecast is a 4-quarter weighted average for 5 years ahead as described in Section 1.1.2.;*
*4) AUROC (area under the receiver operating curve) is a measure of the indicator's usefulness across all thresholds and all preferences, while 'Usefulness' is a measure of indicator's usefulness at the optimal threshold with a given preference parameter;*
*5) highlighted brown cells indicate high values of the AUROC parameter: the darker the colour, the higher AUROC.*
*6) highlighted red cells indicate low signal ratios as well as high noise and noise-to-signal ratios: the darker the colour, the more the value differs from the corresponding value of the best indicators in the table;*
*7) highlighted green cells indicate high values of the 'Usefulness' parameter: the darker the colour, the more the indicator is useful at the estimated optimal threshold with the given preference parameter.*

## ANNEX 2. Data description and sources

***Table A. Data description and sources: Lithuania***

| | Variable | Definition, calculation | Source | Start date | End date | Notes |
|---|---|---|---|---|---|---|
| Credit variables | ‘Broad’ credit | Loans to non-financial private sector (non-financial corporations, households and non-profit institutions serving household) and debt securities issued by non-financial corporations. Creditors are resident MFIs, other institutional sectors, as well as non-residents. ESA 2010 methodology.<br><br>Separate series of credit to households and non-financial corporations are available. | Statistics Lithuania, National accounts | 1995 | 2012 | |
| | | | Bank of Lithuania; Lithuanian quarterly financial accounts | Q4 1995 (official quarterly data: from Q4 2003) | Q4 2014 | Quarterly data for Q4 1995–Q3 2003 are interpolated according to development of MFI loans to households and non-financial corporations separately. Series is then calculated as the sum of credit to households and credit to non-financial corporations. |
| | | | Bank of Lithuania | Q1 1993 | Q3 1995 | Quarterly series extended for Q1 1993–Q3 1995 with respect to development of MFI loans to households and non-financial corporations. Series is then calculated as the sum of credit to households and credit to non-financial corporations. |
| | MFI loans | Loans to non-financial private sector (non-financial corporations, households and non-profit institutions serving household). Creditors are resident MFIs (banks and credit unions). | Bank of Lithuania; MFI balance sheet statistics | M12 1993 | continued | Series have been adjusted for reclassifications and other technical factors. For details see Annex 2 in Lithuanian Economic Review, December 2014. |
| | Bank credit | Loans to non-financial private sector (non-financial corporations, households and non-profit institutions serving household) and debt securities issued by non-financial corporations. Creditors are resident MFIs. ESA 2010 methodology.<br><br>Separate series of bank credit to households and non-financial corporations are available. | Bank of Lithuania; Lithuanian quarterly financial accounts | Q1 1993 (official quarterly data: from Q4 2003) | Q4 2014 | Quarterly series extended for Q1 1993–Q3 2003 with respect to development of MFI loans to households and non-financial corporations separately. Series is then calculated as the sum of credit to households and credit to non-financial corporations. |
| | Financial liabilities | Loans to non-financial private sector (non-financial corporations, households and non-profit institutions serving household) and debt securities issued by non-financial corporations, as well as other debt financial instruments: amounts payable and trade credits. Creditors are resident MFIs, other institutional sectors, as well as non-residents. ESA 2010 methodology.<br><br>Separate series of credit to households and non-financial corporations are available. | Statistics Lithuania, National accounts | 1995 | 2012 | |
| | | | Bank of Lithuania; Lithuanian quarterly financial accounts | Q4 1995 (official quarterly data: from Q4 2003) | Q4 2014 | Quarterly data for Q4 1995–Q3 2003 are interpolated according to development of MFI loans to households and non-financial corporations separately. Series is then calculated as the sum of financial liabilities of households and non-financial corporations. |
| | Real credit variables | Real credit/ bank credit/ loans/ financial liabilities of private non-financial sector, households and non-financial corporations | Bank of Lithuania, Statistics Lithuania | Differently | continued | Deflated by HICP (harmonized index of consumer prices) – the results |
| | Credit-to-GDP ratio | Ratio between ‘broad’ credit and 4-quarter sum of nominal GDP, multiplied by 100%. (same calculation for other types of credit as well) | Bank of Lithuania, Statistics Lithuania | Q4 1995 | continued | GDP is not seasonally adjusted to reduce the revisions in the ratio when new data are released. |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Debt service ratios (DSR) | Time series are calculated from the formula: $DSR_t = \frac{DSR_t}{Y_t} = \frac{i_t D_t}{(1-(1+i_t)^{-s_t})Y_t}$<br>where<br>$D_t$ – 'Broad' credit<br>$i_t$ – average interest rate per quarter on the stock<br>$s_t$ – average remaining maturity in quarters of the credit stock rate per quarter on the stock<br>$Y_t$ – quarterly aggregate income<br>Appropriate time series are used to calculate the DSRs of the whole private non-financial sector, or just the non-financial corporations or households. Income for the private sector is nominal GDP, non-financial corporations – mixed surplus (GDP by income approach), households – wages and salaries (GDP by income approach)<br>Average remaining maturity of the loans is calculated from MFI balance sheet statistics by duration of the loan, an alternative measure includes a more precise measure of remaining maturity from the Credit risk database of the Bank of Lithuania. | Bank of Lithuania, Statistics Lithuania | Q1 1999 | continued | The same approach as in Drehmann and Juselius (2012). |
| Credit cycle indicators | Credit-to-GDP gaps (without forecast) | Difference between credit-to-GDP ratio and its long-term trend in p.p. The trend is estimated with one-sided HP filter, with smoothing parameter equal to 400,000.<br>Q1 1997 is the starting point, but the first observations until Q1 1999are discarded: gap estimates are less reliable at the very beginning of the series when the trend has not settled down yet. (Same calculation applied to all types of credit.) | Bank of Lithuania, Statistics Lithuania | Q1 1999 | continued | Broad credit-to-GDP gap is also called the 'Basel' gap, because this method to calculate the gap was proposed by the Basel Committee of Banking Supervision. |
| | Credit-to-GDP gaps (with forecast/ with simple forecasts) | Procedure is the same as above, only recursive forecasts of 4-quarter weighted average are used to extend the credit-to-GDP ratio 5 years ahead at each point in time. This procedure helps to reduce the amplitude of the deviations, to reduce the uncertainty of the trend estimate at the end of the series and timely captures the turning points of the cycle. (Same calculation applied to all types of credit.) | Bank of Lithuania, Statistics Lithuania | Q1 1999 | continued | |
| Bank funding | MFI loan-to-deposit ratio | Ratio between MFI loans to non-financial sector (excluding general government) and deposits of non-financial sector (excluding general government, seasonally adjusted) | Bank of Lithuania | M12 1993 | continued | |
| Property prices | House price index | House price index in Lithuania (total territory), 2010 = 100 | State Enterprise Centre of Registers | Q4 1998 | Q4 2005 | Quarterly data of the house price index for Q4 1998–Q4 2005 are extrapolated according to growth rate in the house price data from the Centre of Registers (available from Q4 1998) |
| | | House price index, 2010 = 100 | Statistics Lithuania | Q1 2006 | Q4 2014 | |
| | House price-to-income ratio | Ratio between HPI (4-quarter moving average) and wages and salaries (4-quarter moving sum). Ratio is expressed as an index with base year 2010. | Statistics Lithuania, | Q1 1999 | continued | |
| | Equity prices | NASDAQ OMX Vilnius index | Bloomberg | Q1 1999 | continued | |
| Macro variables | GDP | Gross domestic product. ESA 2010 methodology. | Statistics Lithuania | Q1 1995 | continued | |
| | Income | Wages and salaries of the employed (GDP by income approach) | Statistics Lithuania | Q1 1995 | continued | |
| | Current account deficit-to-GDP | Ratio between 4-quarter moving sum of the current account deficit, and 4-quarter moving sum of nominal GDP. Not seasonally adjusted. | Statistics Lithuania, Bank of Lithuania calculations | Q4 1995 | continued | |

*Source: compiled by the authors.*

***Table B. Data sources: Latvia, Estonia***

Crisis period for Latvia: Q4 2008–Q3 2010 (Detken et al.(2014)).

Crisis period for Estonia: Q1 2008–Q3 2010 (set by the authors) in accordance with developments in real GDP, unemployment rate, credit growth and non-performing loans in the banking sector. The situation in the Estonian financial sector was better during the bust period if compared to the other Baltic states and the recovery was quicker. Estonian banks did not experience as much losses as in the other Baltic states and no bank failed, therefore in international sources the 2008–2009 recession in Estonia is not classified as a systemic banking crisis. However, in retrospect, Estonia experienced a boom and bust in the credit and real estate markets, and we classify the crisis in Estonia as relevant 'would be' crisis for the CCB in this paper. The European wide initiative to increase the insured amount of deposits to EUR 100,000 was introduced in Estonian 2008, and the foreign parent banks helped local banks to absorb the losses.

| | Latvia | | | | Estonia | | | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **Source** | **Start date** | **End date** | **Notes** | **Source** | **Start date** | **End date** | **Notes** |
| 'Broad' credit | Latvian Financial and capital market commission[1], Latvijas Banka | Q4 1995 | Q4 2014 | ESA 2010 | Eesti Pank | Q4 2003 | Q4 2014 | ESA 2010 |
| | | | | | Eesti Pank, authors' calculations | Q1 1997 | Q3 2003 | Extrapolated with respect to MFI loans, eliminating structural changes as in Dembiermont et al. (2010)[2] |
| MFI loans | Latvijas Banka | M07 2003 | M03 2015 | | Eesti Pank | M01 1997 | M03 2015 | |
| | Latvijas Banka, authors' calculations | Q4 1995 | Q2 2003 | Extrapolated with respect to bank credit, eliminating structural changes as in Dembiermont et al. (2010)[2] | | | | |
| Bank credit ('narrow credit') | Latvian Financial and capital market commission[1], Latvijas Banka | Q4 1995 | Q4 2014 | | Eesti Pank | M01 1997 | M03 2015 | |
| Financial liabilities | Latvijas Banka | Q1 2004 | Q4 2014 | ESA 2010 | Eesti Pank | Q4 2003 | Q4 2014 | ESA 2010 |
| | Latvijas Banka, authors' calculations | Q4 1995 | Q4 2003 | Extrapolated with respect to broad credit, eliminating structural changes as in Dembiermont et al. (2010)[2] | Eesti Pank, authors' calculations | Q1 1997 | Q3 2003 | Extrapolated with respect to MFI loans, eliminating structural changes as in Dembiermont et al. (2010)[2] |
| Debt service ratios (DSR) | Latvijas Banka, authors' calculations | Q1 1999 | Q4 2014 | The same approach as in Drehmann and Juselius (2012). | Eesti Pank, authors' calculations | Q1 1999 | Q4 2014 | The same approach as in Drehmann and Juselius (2012). |
| MFI loan-to-deposit ratio | Latvijas Banka, authors' calculations | Q4 1995 | Q1 2015 | | Eesti Pank, authors' calculations | Q1 1997 | Q1 2015 | |
| House price index | Real estate agencies, Bank of Lithuania calculations. | Q2 2000 | Q4 2005 | Extrapolated | Real estate agencies, Bank of Lithuania calculations | Q2 2000 | Q4 2004 | Extrapolated |
| | Eurostat | Q1 2006 | Q4 2014 | | Eurostat | Q1 2005 | Q4 2014 | |
| House price-to-income ratio | Real estate agencies, Bank of Lithuania calculations | Q2 2000 | Q4 2014 | | Real estate agencies, Bank of Lithuania calculations | Q3 2003 | Q4 2014 | |
| Equity prices | Bloomberg | Q4 1999 | Q1 2015 | NASDAQ OMX Riga | Bloomberg | Q2 1996 | Q1 2015 | NASDAQ OMX Tallinn |
| GDP | Central Statistical Bureau of Latvia | Q1 1995 | Q4 2014 | ESA 2010 | Statistics Estonia | Q1 1995 | continued | ESA 2010 |
| Income | Central Statistical Bureau of Latvia | Q1 1995 | Q4 2014 | ESA 2010 | Statistics Estonia | Q1 1995 | continued | ESA 2010 |
| Current account balance | Latvijas banka | Q1 1995 | Q4 2014 | | Eesti pank | Q1 1995 | Q4 2014 | |

*Source: compiled by the authors.*

*Notes:*

*1) http://www.fktk.lv/en/publications/macroprudential-supervision/countercyclical-capital-buffer.html*

*2) Dembiermont C., M. Drehmann, and S. Muksakunratana (2013): 'How much does the private sector really borrow? A new database for total credit to the private nonfinancial sector', BIS Quarterly Review, March 2013.*