VILNIUS UNIVERSITY
FACULTY OF MATHEMATICS AND INFORMATICS
MODELLING AND DATA ANALYSIS MASTER'S STUDY PROGRAMME

Master's thesis

An early warning indicators for cyclical systemic risk cross country analysis

Ciklinės sisteminės rizikos ankstyvojo įspėjimo rodiklių analizė tarp šalių

Arūnė Zaborskė

Supervisor Dr. Dmitrij Celov

Vilnius, 2021

An early warning indicators for cyclical systemic risk cross country analysis

Abstract

Consistent with the research of the Bank of Lithuania (N. Valinskytė and G. Rupeika, 2015), this master's thesis presents application of one-sided Hodrick-Prescott filter augmented with 5-year ahead random walk forecasts method and analysis of quarterly the Credit-to-GDP ratio gap as main indicator that could signal of systemic risk in countries during the periods of credit expansion.

Research reveals, all twenty countries are homogenous and one-sided Hodrick-Prescott filter augmented with random walk forecast identifies periods of increased cyclical systemic risk, event for countries with small observations but comparisons of results for countries have to be interpreted carefully because of the small number of crisis events per country (1 or 2) and because of the different macroeconomic vulnerabilities.

The results of signalling in all nineteen euro area countries and Sweden could be useful for further studies of early warning indicators for the identification of cyclical systemic risks. It could serve as a starting point in considerations whether here is a possibility to have a better early warning indicator.

Key words: early warning indicators, financial cycle, Credit-to-GDP ratio gap, Hodrick-Prescott filter, signaling approach.

Ciklinės sisteminės rizikos ankstyvojo įspėjimo rodiklių analizė tarp šalių

Santrauka

Atsižvelgiant į Lietuvos banko tyrimą (N. Valinskytė ir G. Rupeika, 2015), šiame magistro darbe pateikiamas vienpusio Hodricko–Prescotto filtro, papildyto paprastu 5 metų į priekį atsitiktinio klaidžiojimo prognozės metodu, taikymas bei ketvirtinių kredito ir bendrojo vidaus produkto santykio atotrūkio analizė, kaip pagrindinio rodiklio galinčio signalizuoti apie sisteminę riziką šalyje kredito augimo laikotarpiu.

Tyrimas atskleidžia, kad šalys yra homogeniškos, o vienpusis Hodricko–Prescotto filtras, papildytas atsitiktinio klaidžiojimo prognoze, nustato padidėjusios ciklinės sisteminės rizikos laikotarpius net šalims su trumpomis laiko eilutėmis. Tačiau reikia atsargiai interpretuoti šalių rezultatus dėl mažo krizių skaičiaus kiekvienoje šalyje (1 arba 2) ir dėl skirtingų makroekonominių pažeidžiamumų.

Darbe pateikti signalizacijos rezultatai visoms devyniolikai euro zonos šalių bei Švedijai galėtų būti naudingi tolimesniems ankstyvojo įspėjimo rodiklių tyrimams nustatyti ciklinei sisteminei rizikai. Tai galėtų būti atspirties taškas svarstant, ar yra galimybė turėti geresnį išankstinio įspėjimo rodiklį.

Raktiniai žodžiai: ankstyvojo įspėjimo rodikliai, finansų ciklas, kredito ir BVP santykio atotrūkis, Hodricko–Prescotto filtras, signalų metodas.

CONTENTS

ABBREVIATIONS

AUROC	area under the receiver operating characteristic
BIS	Bank for International Settlements
ECB	European Central Bank
EU IFIs	European Union Independent Fiscal Institutions
EWI	early warning indicator
FN	false negatives
FP	false positives
GDP	gross domestic product
HP	Hodrick–Prescott
TN	true negatives
TP	true positives

1. INTRODUCTION

In 2007/2009 global financial crisis was an unprecedented event. As an ex-post response to the weak monitoring capabilities of existing macroprudential tools, researchers and institutions developed plenty of methods for the identification of cyclical systemic risks. From 2015 the Bank of Lithuania uses one-sided Hodrick-Prescott (HP) filter augmented with random walk forecast method, which was proposed by Nijolė Valinskytė and Giedrius Rupeika[1]. Method was tested on Lithuania, Latvia and Estonia data. All three Baltic countries are small open economies therefore how this method fits for other countries remained an open question.

The objective of this master's thesis is to test the Bank of Lithuania method on all nineteen euro area countries and Sweden's data, provide an overview of the strengths and weaknesses of one-sided HP filter augmented with forecasts method along quantitative and qualitative features. In addition to descriptive statistics such as the observations, the mean and median value, and the standard deviation of the risk measure, the following key quantitative criteria considered at the pooled and country level are:

- early warning performance,
- length of resulting cycles.

In addition to quantitative criteria, method is also assessed based on a set of qualitative criteria, primarily aimed at gauging the suitability of method to be used for the identification of cyclical systemic risk and to potentially calibrate macroprudential instruments in the future. The qualitative features considered encompass aspects such as:

- whether results are easy to communicate,
- whether the measure of excess credit is derived from economic theory/economic principles,
- whether a methodology is robust to real-time estimation,
- whether it allows to account for country-specificities,
- whether it is easy to implement for all countries.

It is assumed that systemic crises has higher value of indicator and this master's thesis checks hypothesis if one-sided HP filter augmented with random walk forecast method:

H_0: identifies periods of increased cyclical systemic risk, i.e. if area under the receiver operating characteristic (AUROC) is higher than 0.8, it means that countries included to this research are homogenous.

H_1: suitable only for the Baltic countries because countries are similar, small open economies and here is a difference between Baltic and other countries.

The thesis is organized in the following three parts. In the 2nd section the theoretical framework of evaluation approach: systemic risk and its measurement methods. The empirical research results and key messages are presented in the 3rd section. The following part of the thesis introduces assessing the likelihood of financial crises, financial cycle length, distribution around systemic crises and signalling about systemic risk. The final part concludes.

[1] N. Valinskytė, G. Rupeika. Leading indicators for the countercyclical capital buffer in Lithuania, 2015.

2. THE EVALUATION APPROACH

This part of the thesis provides a description of methodological approach that has been previously explored by N. Valinskytė, G. Rupeika (2015) and now used in this research. The design of the research starts with identification of systemic and macroprudentially-relevant crises start date in twenty countries: Austria, Belgium, Cyprus, Germany, Estonia, Spain, Finland, France, Greece, Ireland, Italy, Lithuania, Luxembourg, Latvia, Malta, Netherlands, Portugal, Sweden, Slovenia, Slovakia. In second section focusing on the Credit-to-GDP ratio gap as main indicator and its estimation with simple 5-year ahead forecasts. Next section explains about HP filter which was applied to estimate the Credit-to-GDP ratio gap after augment each series. The final part of this topic includes signaling method for evaluation early warning indicator (EWI).

2.1. Systemic and macroprudentially-relevant crises

Historical data indicates that the marks of crisis are shown well in advance, as imbalances build up over time and leave the financial system vulnerable to shocks. Therefore, it is important to regularly supervise signals of EWIs, which tracks early imbalances of the financial cycle because it gives policymakers enough time to implement corrective or adjust new policy measures. Systemic instability during unprecedented the global financial crisis in 2007/2009 led policymakers to develop macroprudential approaches to financial supervision and regulation, such as countercyclical capital buffer to protect the banking system against potential losses that may be incurred due to the pro-cyclical growth of systemic risk, thereby contributing to sustainable crediting of the real economy during a financial cycle.

To evaluate one-sided HP filter augmented with random walk forecast method ability to identify periods of increased cyclical systemic risk, first need to define the crisis which will be predicted. All start dates of systemic crises were sourced from the European Central Bank (ECB) European Union crises database[2].

		Countries	1970s	1980s	1990s	2000s	2010s
1	AT	Austria				2007q4	
2	BE	Belgium				2007q4	
3	CY	Cyprus				2000q1	2011q2
4	DE	Germany	1974q2			2001q1, 2007q3	
5	EE	Estonia			1998q2		
6	ES	Spain	1978q1			2009q1	
7	FI	Finland			1991q3		
8	FR	France			1991q2	2008q2	
9	GR	Greece					2010q2
10	IE	Ireland				2008q3	
11	IT	Italy			1991q3		2011q3
12	LT	Lithuania				2008q4	
13	LU	Luxembourg				2008q1	
14	LV	Latvia				2008q4	
15	MT	Malta					

[2] M. L. Duca et al. A new database for financial crises in European countries, 2017. Crisis dates: https://www.esrb.europa.eu/pub/fcdb/esrb.fcdb20170731.en.xlsx

16	NL	Netherlands			2008q1
17	PT	Portugal	1983q1		2008q4
18	SE	Sweden		1991q1	2008q3
19	SI	Slovenia		1991q2	2009q4
20	SK	Slovakia		1997q4	

Table 1: All systemic and macroprudentially-relevant crises start date independently of their origination.

From the beginning of the crisis table, there is a visible trend - in every decade systemically risk crisis starts in any country. Moreover, obvious similarities, in 2007/2009 most countries faced with the global financial crisis. It was unexpected, so countries were not ready for it.

2.2. Indicators of systemic risk

Financial crises are regularly related with rapid credit growth and imbalanced property prices. In order to ensure financial stability in the country, the Bank of Lithuania regularly monitors six EWIs closely related to the financial cycle: Credit-to-Gross domestic product (GDP) ratio gap (also called the Basel gap), Credit-to-GDP ratio gap using simple forecasts, MFI loans-to-GDP ratio gap, Loans-to-deposits ratio, House price-to-household income ratio gap, and Current account deficit-to-GDP ratio. First four are credit indicators, fourth indicates asset prices and last one is macroeconomic indicator.

According researchers[3], the Credit-to-GDP ratio gap is main and very useful EWI indicator for financial crises. It reveals difference between the Credit-to-GDP ratio gap and its long-term trend. The Credit-to-GDP ratio gap was choose as main indicator for one-sided HP filter augmented with random walk forecast method evaluation, because various studies have shown[4] that the Credit-to-GDP ratio gap is a useful measure of cyclical systemic risk, as it provides good aggregate early warning signals for systemic banking crises and calculated in three steps[5]:

1. Calculated the aggregated non-financial private sector credit-to-GDP ratio,
2. Calculated the credit-to-GDP gap (the gap between the ratio and its trend),
3. Transformed the credit-to-GDP gap into the guide buffer add-on.

$$GAP_t = RATIO_t - TREND_t,$$

here t is end-period date, the period being one quarter, $RATIO_t$ reflect the deviation of the ratio of Credit-to-GDP from its long-term trend, $Credit_{\,t}$ is broad measure of the stock of credit to the private non-financial sector in the Member State of the designated authority outstanding at the end of quarter t; $GDP_{\,t}$ is gross domestic product of the Member State of the designated authority in quarter t; $TREND_t$ is recursive Hodrick-Prescott filtered trend of the $RATIO$ with a smoothing parameter, $\lambda = 400{,}000$.

However, the Credit-to-GDP ratio gap has shortcomings when it comes to measuring cyclical systemic risk. First, the Credit-to-GDP ratio gap can be biased downward after prolonged credit booms, because the longer periods of unwarranted excessive credit developments last, the greater will be the portion of the credit excesses contained in the calculation of the statistical trend and thereby lead the trend away from sustainable Credit-to-GDP ratios[6]. This could lead to underestimation of the size of the credit-to-GDP gap in the build-

3 Borio and Drehmann (2009), Behn et al (2013), Drehmann and Juselius (2013).
4 Borio and Lowe (2002), Borio and Drehmann (2009), Alessi and Detken (2011), Detken et al. (2014), Aldasoro, Borio and Drehmann (2018).
5 European Systemic Risk Board. Recommendation of the European Systemic Risk Board on guidance for setting countercyclical buffer rates, 2014.
6 J. H. Lang and P. Welz. Measuring credit gaps for macroprudential policy, 2017.

up phase of financial imbalances. Likewise, when a deleveraging phase starts, credit-to-GDP gaps might be persistently biased downward, as the credit-to-GDP ratio may fall rapidly but the very persistent trend will likely remain elevated for a prolonged period, as past excesses will still be partially incorporated into the trend. Second, the level of the Credit-to-GDP ratio gap can be highly sensitive to the length of the underlying time series, which reduces the robustness of the risk signals for many euro area countries owing to short credit series of 10-15 years[7]. Even if the HP-filter smoothing parameter of 400,000 used for computing the Credit-to-GDP ratio gap assigns considerable weight to observations from the distant past to estimate the trend component. Third, issues of interpretation and communication may arise with the Credit-to-GDP ratio gap, as it can decrease in situations where the credit-to-GDP ratio increases strongly but does so at a slower pace than the trend component. Such situations could possibly cause problems for communicating risk signals in a policy context.

As a long time strongest EWI for banking crises was nominated the Credit-to-GDP ratio gap (suggested by the Basel Committee on Banking Supervision). However, estimation faces uncertainty as the long-term trend is unobservable. In 2015, N. Valinskytė and G. Rupeika discovered most suitable alternative. They found out that the Credit-to-GDP ratio gap using simple forecasts is a suitable EWI of financial crises in Baltic countries. To deal with the uncertainty, the estimation of the long-term trend was augmented with forecasts.

Small signaling exam was made for six the Bank of Lithuania's EWIs with only Lithuania data and only one financial crisis (appendix A.1.). It is assumed that systemic crises have higher values. As results showed, no surprise that House price-to-household income ratio gap had the strongest signal about systemic crisis (AUROC=0.99) because crisis in 2008 was closely related to real estate sector. Second as the best signaling indicator was the Credit-to-GDP ratio gap using simple forecasts (AUROC=0.91), it has slightly better early warning properties than the Credit-to-GDP ratio gap (AUROC=0.85) although at the first glance the graphical representation of their time series looks very similar. Sadly but MFI Loans-to-deposits ratio and Current account deficit-to-GDP ratio does not look like a good EWI (respectively AUROC=0.57, AUROC=0.51).

All three Baltic countries are small open economies. For this reason, it was decided to explore how this method fits to other countries, how it predicts cyclical systemic risk. Because of this, in this research to estimate the Credit-to-GDP ratio gap each series of twenty countries with quarter data from 1970q4-2008q1 to 2017q3 (appendix A.2.) was augment with simple 5-year ahead random walk forecasts. As Gerdrup in 2013 research showed, augmenting historical data with simple forecasts of the Credit-to-GDP ratio makes trend estimation at the end of the series more robust and it improves signalling quality.

2.3. Hodrick–Prescott filter

In 1981 the HP filter was created by Hodrick and Prescott to analyze fluctuations in economic activity easier and event nowadays the method still remains popular and widely use in academic research, policy studies and analysis[8].

The authors proposed a method for decomposing a data series into trend and cycle components, i.e. removing the high-frequency cycle-error residual from the actual data (y_t) and retrieving smooth low frequency series (μ_t).

$$\min_{\{\mu_t\}_{t=0}^{T}} \sum_{t=0}^{T}(y_t-\mu_t)^2+\lambda\sum_{t=1}^{T-1}\left((\mu_{t+1}-\mu_t)-(\mu_t-\mu_{t-1})\right)^2,$$

[7] J. H. Lang et al . Anticipating the bust: a new cyclical systemic risk indicator to assess the likelihood and severity of financial crises, 2019.

[8] According to the October 2017survey of the European Union Independent Fiscal Institutions, 10 of 20 uses the HP filter method to estimate potential output.

$$\lambda = \frac{\sigma_1^2}{\sigma_2^2} \geq 0,$$

here σ_1^2 is the variance of the growth cycle, σ_2^2 is the variance of the trend growth dynamics, and λ is a non-negative penalty parameter for the smoothness of the output series.

Equation shows, if the penalty parameter λ approaches to zero, potential output estimates are forced to cling to the actual output because with lower values of λ, the trend becomes more volatile as it will contain more of high-frequency spectrum approaching the original data when the penalty value drops to zero. On the contrary, if the smoothness penalty λ tends to infinity, the HP filter approaches a regression on a linear time trend for which the second difference is exactly zero, i.e. higher value of parameter λ, shift the gain function of trend closer to zero, hence the latter becomes smoother and approaches linear trend in the limit. Besides, the choice of λ affects not only the volatility of the trend but also the size of the cycle, only a cycle component has the opposite effects as a residual of the trend cycle decomposition. Therefore, the most difficult question is what size of the penalty parameter for the smoothness researcher should choose.

The Bank of Lithuania made comparison of EWI with different values of the smoothing parameter λ on one-sided HP filter and two sided HP filter. Values of parameter λ were 1,600, 26,000, 130,000 and 400,000. The findings was one-sided HP filter with smoothing parameter $\lambda =$ 400,000 had best signalling qualities when applied to quarterly data. Moreover, the European Systemic Risk Board and the Basel Committee on Banking Supervision[9] also suggests to use $\lambda =$ 400,000 for measuring the cyclical dimension of systemic risk, because penalty parameter λ should reflect length of a cycle for a particular dataset and for a specific period of time, therefore this choice of value corresponds to assumption that a financial cycle is 4 times length of the real business cycle[10].

Like most of methods, HP filter is criticized in academic literature. Strongest criticism could be found in Hamilton (2017) research paper. He suggests not using HP filter because:

- the HP filter produces series with false dynamic relations that have no basis in the underlying data-generating process,
- filtered values has heavy end-of-sample distortions, i.e. at the end of the sample are very different from those in the middle,
- the smoothing penalty parameter size crucial question and selection choice must be made by researcher.

Following EU IFIs guide and its literature review, additional issue with HP filter that it is unable to detect and reflect a sudden structural break in trend, unless lower values of penalty parameter λ are chosen.

Furthermore, recently J. H. Lang et al (2019) showed how different time series availability can affect the estimate of the HP-filtered credit gap, even if the underlying credit-to-GDP data is exactly the same. Result may vary significantly. The reason for the aforementioned shortcomings is that the statistical properties of the HP filter are far from optimal for the time series used in macroeconomics, including credit. Studies have highlighted that the HP filter is optimal only if the persistence of the cycle is low. However, in practice the filter is used to extract highly persistent cycles, by setting the smoothing parameter λ to arbitrary high values in order to accommodate prior views about the length of the cycles.

---

[9] European Systemic Risk Board. Recommendation of the European Systemic Risk Board on guidance for setting countercyclical buffer rates, 2014.

[10] C. Detken et al .Operationalising the countercyclical capital buffer: indicator selection, threshold identification and calibration options, 2014.

This implies various shortcomings, as estimates of cycles may be biased, in particular in real time application. In case of the Basel gap in particular, a very high value of λ = 400,000 is chosen, to accommodate the prior view that credit cycles are of a medium-term nature. As a result, the filter adapts very slowly to any structural shifts in the time series and is therefore highly sensitive to the length of the time series, as noted above. Further features of relevant cyclical dynamics may simply be missed. For instance, the conclusion of Drehmann et al. (2012) that GDP and financial (credit, house price) cycles are independent is largely driven by their choice of filters, while subsequent studies based on different methods come up with different conclusions. A further consequence is the well-known bias in real-time estimates: on average, the volatility of the cycle is substantially under-estimated in real-time.

The forecast augmented HP filter is a simple variant of the traditional Basel gap which serves particularly well for countries with short time series. Using this approach the trend is constructed by recursively taking historical the Credit-to-GDP series at each point of time and right before the application of the HP filter, each vintage is extended with simple five year ahead forecasts.

In this research after augment each of twenty country series vintage with simple 5-year ahead forecasts, a one-sided HP filter was applied to estimate the Credit-to-GDP gap. Method was implemented on a common dataset to the extent possible encompassing the largest possible sample of countries.

2.4. Signaling approach

The most important requirement of EWI is that it should generate correct signals. To investigate if method is useful in predicting growing crisis, the univariate EWIs will be evaluated based on a combination of their in-sample and out-of-sample signalling performance, because the occurrence of a crisis can be easily represented with a binary state variable where binary indicator that equals one during pre-crisis periods and zero otherwise.

2.4.1. In-sample signalling performance

To evaluate one-sided HP filter augmented with random walk forecast method ability to identify periods of increased cyclical systemic risk, in the baseline exercise, the "vulnerable period" is defined as the quarters comprised between the 12th and the 5th quarter prior to the start of a financial crisis.

All systemic crises with at least partly domestic origin and considered by European national authorities as relevant from a macroprudential perspective are considered in the baseline estimations. In addition, one-sided HP filter augmented with random walk forecast method was also estimated considering broadening the crises sample to encompass all systemic and macroprudentially relevant crises independently of their origination, and lengthening the prediction horizon to the period comprised between the 20th and the 5th quarter before the start of financial crises.

The in-sample early warning properties are evaluated based on the AUROC. It tells about the indicator's ability to discriminate between cases (positive examples) and non-cases (negative examples), i.e. the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one.

The outcomes for each indicator are categorized from a prediction and the actual value (Table 2):

- TP (true positive) – number of correct signals and the crisis occurs.
- FN (false negative) – number of negative signals about the crisis, if the crisis occurs.
- FP (false positive) – number of false alarms, when crisis does not occur, although the alarm is present.
- TN (true negative) – number of negative signals about the crisis, if the crisis does not occur.

	Crisis	No crisis
Signal	TP	FP
No signal	FN	TN

Table 2: The outcomes categories from a prediction and the actual value in-sample signalling.

The numbers of dedicated outcomes to each category can be used to estimate the true positive rate of classifier as in T. Fawcett:

$$TPR = \frac{Positives\ correctly\ classified}{Total\ positives} = \frac{TP}{P} = \frac{TP}{TP+FN} = 1 - FNR\ .$$

Also, the false positive rate of the classifier:

$$FPR = \frac{Negatives\ incorrectly\ classified}{Total\ negatives} = \frac{FP}{N} = \frac{FP}{FP+TN} = 1 - TNR\ .$$

Finally, the AUROC is calculated by:

$$\begin{aligned} AUROC &= \int_{x=0}^{1} TPR\big(FPR^{-1}(x)\big)\mathrm{d}x \\ &= \int_{\infty}^{\infty} TPR(T)FPR'(T)\mathrm{d}T \\ &= \iint_{-\infty}^{\infty} I(T' > T)f_1(T')f_0(T)\mathrm{d}T'\mathrm{d}T \\ &= P(X_1 > X_0), \end{aligned}$$

here X_1 is the score for a positive instance, X_0 is the score for a negative instance, and f_0 and f_1 are probability densities of false and true positive rates.

In general, AUROC measure predictive quality signals with ranges from 0 to 1. An AUROC of less than 0.5 shows that indicator is useless, the signals have no predictive value, having no class separation capacity whatsoever. Greater than 0.8 means that the indicator has strong discriminatory ability and if it equals to 1 – predictions are 100 percent correct, in other words for each threshold EWI generates only accurate signals TP=1 and FP=0.

For comparison the AUROC signaling method was applied on outcomes with two pre-crisis horizons of late (12-5 quarters) and early (20-5 quarters) to see how indicator predicts in short and long term.

2.4.2. Out-of-sample signalling performance

The out-of-sample early warning properties are evaluated using the relative usefulness measure defined by Alessi and Detken (2011), Sarlin (2013), based on a recursive quasi real-time exercise starting in 2000q1 for the benchmark crisis definition and pre-crisis horizon of 12-5 quarters.

The pre-crisis periods can be represented with a binary state variable with a specified forecast horizon h: $\mathrm{I}_j(h) \in \{0,1\},\ j = 1,2,\dots,N$. A binary indicator that equals one during pre-crisis periods and zero otherwise. A binary probability point forecast P_j that equals one if p_j exceeds a specified threshold λ and zero otherwise. The correspondence between P_j and I_j summarized in contingency matrix (Table 3):

		Actual class I_j	
		Crisis	**No crisis**
Predicted class P_j	**Signal**	TP	FP
	No signal	FN	TN

Table 3: The outcomes categories from a prediction and the actual value out-sample signalling.

The goal is to avoid two types of errors: issuing false alarms and missing crises. Type 1 errors represent the probability of not receiving a warning conditional on a crisis occurring can be represented by false negative rate, also called Type 1 error rate:

$$T_1 = P\left(p_j \leq \lambda \mid I_j(h) = 1\right) .$$

Probability of false positive ratio, also called type 2 errors shows receiving a warning conditional on no crisis occurring:

$$T_2 = P\left(p_j > \lambda \mid I_j(h) = 0\right),$$

here λ is threshold. ECB recommends to choose $\lambda = 0.2$ or such that loss is minimized.

By accounting for unconditional probabilities of crises $P_1 = P\left(I_j(h) = 1\right)$ and calm periods $P_2 = P\left(I_j(h) = 0\right) = 1 - P_1$, a loss function can be written as follows:

$$L(\mu) = \mu T_1 P_1 + (1 - \mu) T_2 P_2 .$$

The absolute usefulness of an indicator calculated by the loss generated by the indicator subtracted from the loss of ignoring it

$$U_a(\mu) = min\left(\mu P_1, P_2(1 - \mu)\right) - L(\mu) .$$

To calculate relative usefulness, which informs $U_a(\mu)$ on a percentage of the usefulness that would be obtained with a perfectly performing model:

$$U_r(\mu) = \frac{U_a(\mu)}{min\left(\mu P_1, P_2(1-\mu)\right)} .$$

This relative usefulness criterion flags whether the EWI is more useful for the policy maker when a naive benchmark. The relative usefulness criterion can have values between -1 and 1. If values below zero, it says EWI is uninformative. If criterion is equal to zero, it means the policymaker disregards the model and either always or never issues an alarm. Perfect value of the relative usefulness criterion is 1 because it suggests that EWI correctly predicts all crises and never issues a false alarm.

3. RESULTS AND KEY MESSAGES

One-sided HP filter augmented with random walk forecast is implemented on a common dataset to the extent possible encompassing the largest possible sample of countries. The approach is evaluated both at the pooled and specific country level, thereby allowing to assess overall performance and usefulness for identifying cyclical systemic risks in individual countries.

This section shows that the filter contains useful information about both the likelihood and severity of financial crises. The use of output in the form of tables and charts facilitates the comparison across the countries.

3.1. Assessing the likelihood of financial crises

One-sided HP filter augmented with random walk forecast is a tractable cyclical systemic risk indicator that displays long cycles across nineteen euro area countries and Sweden over time. Analysis covering data from twenty countries (appendix A.2., total 2,651 observations).

Assuming that shape of indicators shows phase of credit cycle and high values of the Credit-to-GDP indicators show increasing systemic risk (as opposed to low values). As Figure 1 shows, method displays rather long swings. Since the early 1970s, the cross country distribution of the forecast augmented HP filter exhibits three peaks in 1991q3, 2001q1, 2008q3.

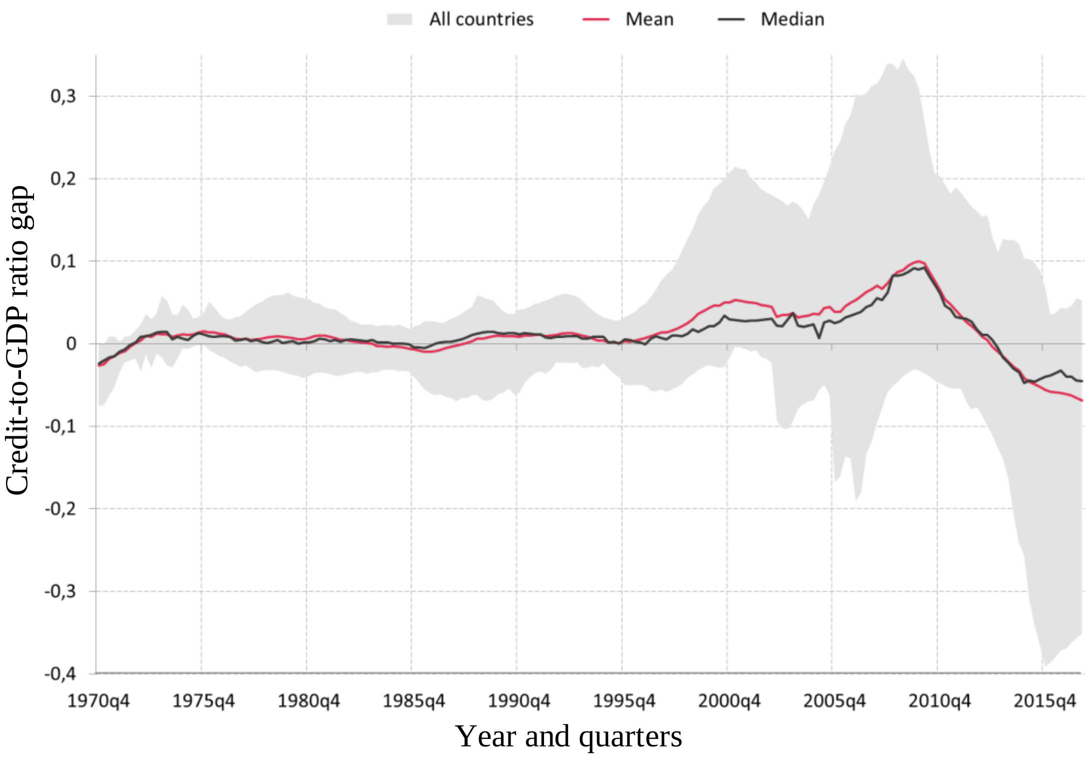


Figure 1: Cyclical systemic risk ratio across twenty countries over time.

Appendix A.4. shows how every country looks like in pooled data set and how the Credit-to-GDP ratio gap trend line looks in timeline around systemic crisis beginning. Graphical analysis shows that Estonia, Malta and Slovakia did not have financial crisis period because of short time series.

As country level distribution in boxplots shows (Figure 2), top three minimum and maximum values are in Cyprus, Portugal and Ireland. In the interquartile range of Cyprus and Latvia values is much higher than in other countries, in Sweden – the smallest. In all counties median is around zero, but in Cyprus median is 0.11 (indicates about most of time risky cyclical systemic situation).

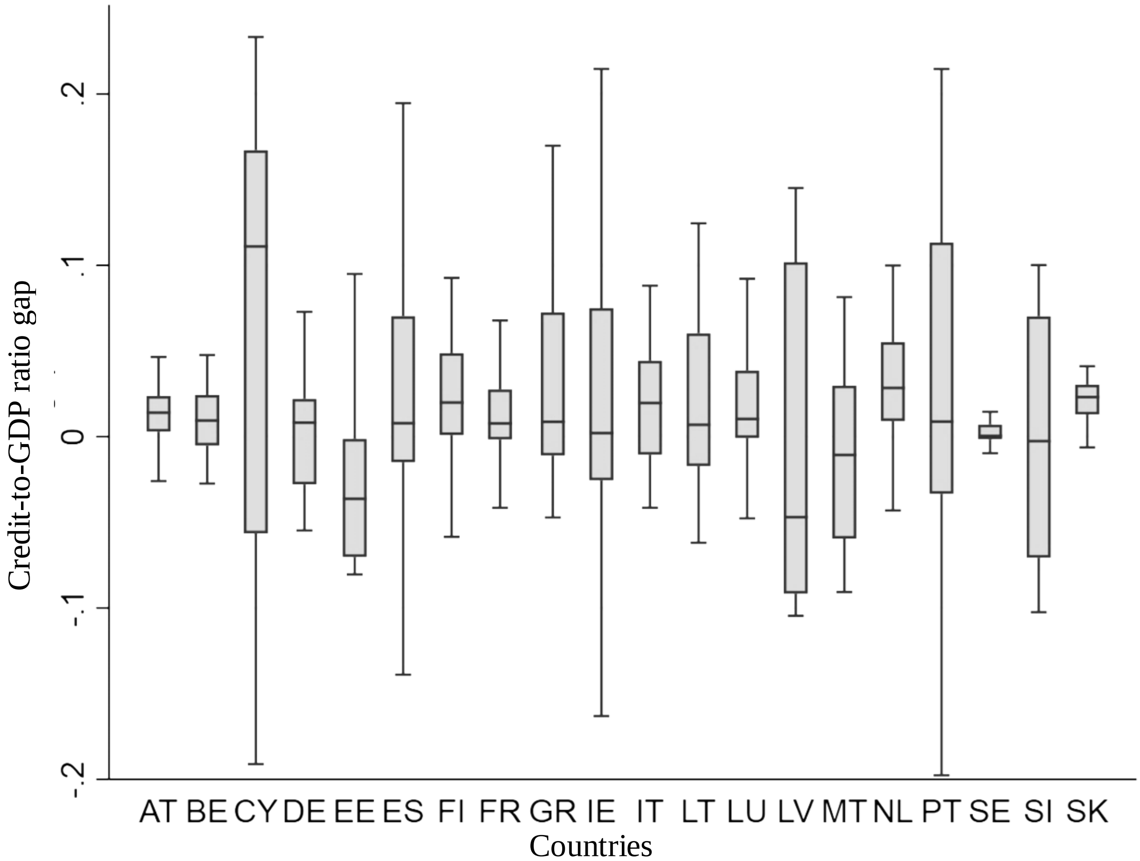


Figure 2: Cyclical systemic risk ratios of twenty countries over time.

3.2. Financial cycle length

According to Y. S. Schüler et al. research on 2015[11], on average financial cycles in Europe last 7.2 years (shortest being around 4 and longest around 17 years).

One-sided HP filter augmented with random walk forecast displays short and long cycles. It presents cycles around 19.27 till 26.07 quarter (respectively 4.8 years and 6.5 years) length.

	Countries	Cycle length - min	Cycle length - max	Cycle length - peak
1	AT	19.66	28.83	23.38
2	BE	14.29	17.13	15.58
3	CY	10.16	13.92	11.75
4	DE	36.60	64.68	46.75
5	EE	7.76	12.24	9.50
6	ES	33.52	77.23	46.75
7	FI	19.80	24.13	21.75
8	FR	20.89	26.53	23.38
9	GR	38.96	58.42	46.75
10	IE	18.87	29.85	23.12
11	IT	33.67	58.54	42.75

[11] Y. S. Schüler, P. P. Hiebert, T. A. Peltonen. Characterising the financial cycle: a multivariate and time-varying approach, 2015.

12	LT	18.48	26.43	21.75
13	LU	6.57	8.09	7.25
14	LV	12.76	16.79	14.50
15	MT	11.04	14.40	12.50
16	NL	20.61	27.00	23.38
17	PT	36.22	65.90	46.75
18	SE	21.43	25.71	23.38
19	SI	11.98	15.47	13.50
20	SK	4.93	6.89	5.75
	Pooled set	**19.27**	**26.07**	**22.44**

Table 4: Financial cycle length (minimum, maximum and peak) in quarters

Closer inspect at the individual country level shows lowest cycle length at Slovakia (5 quarters), Luxembourg (6,6 quarters) and Estonia (7,7 quarters). Possible cause – small amount of time series. Three highest cycle lengths are in Spain (19,3 years), Portugal (16,5 years) and Germany (16 years).

3.3. Distribution around systemic crises

A key desirable property of every EWI is that signals flare up well before crisis events hit the economy. The forecast augmented HP filter starts to increase around five years ahead of systemic financial crises with a clear pattern of increasing imbalances. The median value of the gap during pre-crisis times is always greater than that during normal times for all countries. On average, the gaps tend to start increasing more sharply twelve quarters. From four to six quarters before start of crisis signals especially high (Figure 3).

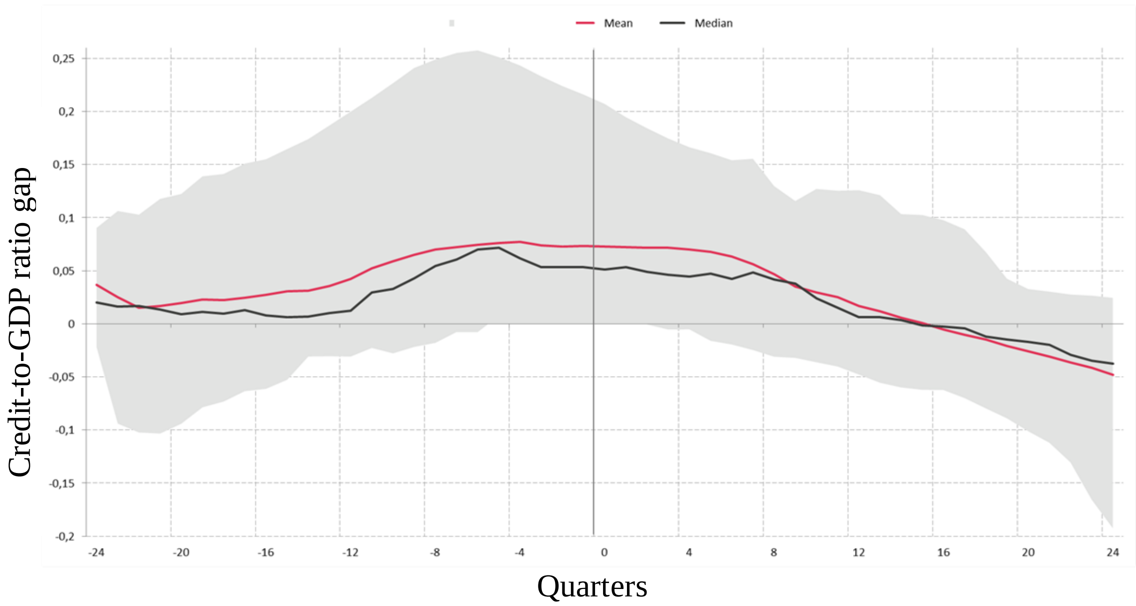


Figure 3: Twenty four quarters before and after systemic financial crises.

Figure 3 shows, that crisis signals usually starts decline already during the year ahead of the crisis start. For that reason declines in the method from high levels may not necessarily indicate that vulnerabilities are receding, but rather that a turning point in the cycle is approaching, with stretched financial conditions and therefore a heightened risk of a crisis.

3.4. Signalling about systemic risk

The resulting one sided HP filter augmented with random walk forecast displays good early warning properties (AUROC – 0.83; quasi-out-of-sample usefulness – 0.41). The share of countries with AUROC bigger than 0.8 is 82 %, 59 % of countries with AUROC higher than 0.85 and the share with quasi out of sample usefulness higher than 0.1 is 75 %.

	Countries	AUROC (12-5)	AUROC (20-5)	Quasi out of sample usefulness (starting in 2000q1)
1	AT	0.59	0.65	0.18
2	BE	0.83	0.74	0.66
3	CY	1.00	0.88	0.88
4	DE	0.74	0.78	1.00
5	EE			0.67
6	ES	0.85	0.82	0.00
7	FI	0.69	0.69	0.18
8	FR	0.87	0.79	0.19
9	GR	1.00	1.00	0.03
10	IE	1.00	0.99	0.00
11	IT	0.99	1.00	0.06
12	LT	0.99	0.95	0.64
13	LU	0.81	0.76	0.64
14	LV	0.95	0.60	0.71
15	MT			0.61
16	NL	0.82	0.86	0.13
17	PT	0.81	0.86	0.00
18	SE	0.92	0.88	0.98
19	SI	1.00	1.00	0.75
20	SK			0.59
	Pooled set	**0.83**	**0.74**	**0.41**

Table 5: Method signals in late horizon (12-5), early horizon (20-5) and relative usefulness.

Method exhibit good signalling properties at the individual country level. Late (12-5) horizon has better signaling than early (20-5) horizon. Ten countries has AUROC higher than 0.85. Four countries with perfect signalization in the prediction horizon to the period comprised between twelfth and fifth quarter: Cyprus, Greece, Ireland, and Slovenia. In longer period – twentieth and fifth quarter before the start of financial crises three countries with perfect signalization: Greece, Italy, Slovenia. Observations of Estonia, Malta and Slovakia did not have financial crisis period data because of short time series. Interesting that countries with bigger standard deviation had a better AUROC signaling values when countries with smaller. Countries who had till 60 quarters time series either good signals about crisis (AUROC values for short horizon was $0.81 \geq AUROC \geq 1$) or did not had financial crisis period data because of short time series. Countries with long time series had similar values in signaling short or long horizon.

From results of quasi out of sample usefulness, seems like the EWI for Spain, Ireland and Portugal always or never issues an alarm about crisis that would help policymaker to take correct actions. Unlikely, for Germany the EWI fits perfectly, correctly predicts all crises and never issues a false alarm.

It appears, method serves particularly well for countries with short time series between twelfth and fifth quarter.

4. SUMMARY AND RECOMMENDATIONS

The main goal of this master's thesis was to test one-sided HP filter augmented with random walk forecast method on all nineteen euro area countries and Sweden's data (in total 2,651 observations), provide strengths and weaknesses of the method. For this purpose, performance of the measures of cyclical systemic risk were evaluated both for the pooled set of countries and on an individual country basis, using a common set of quantitative criteria.

The traditional ratio of total credit to the non-financial private sector to GDP was augment with simple 5-year ahead random walk forecasts and de-trended using a HP filter with a smoothing parameter of λ = 400,000. As results showed, indicator serves particularly well for countries with short time series. On average, the gaps tend to start increasing more sharply twelve quarters and peak five quarters before the start of a systemic crisis. Besides, on average signals decrease during the year ahead of the crisis start.

Method exhibit good signalling properties at the individual country level – 59 % of countries with AUROC higher than 0.85, 82 % of countries with AUROC higher than 0.8, and 75 % of countries with quasi out of sample usefulness higher than 0.1. This method might be not the best for all countries because of 3 of 17 countries had AUROC lower then 0.7, but comparisons of results for individual countries have to be interpreted carefully because of the small number of crisis events per country (1 or 2) and because of the different macroeconomic vulnerabilities.

According to results, length of resulting cycles from around 4.82 till 6.52 years and it does not contradict with ECB findings.

Research shows the main strengths of this method:

- it is available for many countries,
- it is simple to estimate and easy to communicate,
- it is persistent, has good signalling properties and correlates with crisis severity,
- makes trend estimation at the end of the series more robust,
- estimates are available in real time and do not change,
- gives acceptable early warning performance (82 % of countries with AUROC > 0.8).

While the main disadvantages of the method:

- accuracy of forecasts and random walk projections are not precise. The prediction of random wandering is naive because it predicts that tomorrow will be the same as today. It would be interesting to test if simple moving average in this case yields significantly better signaling than the random walk.
- discussions about statistical shortcomings of the HP filter and selection of penalty parameter size, because here is no definitive way to choose or calibrate the optimal value of λ. Fascinating findings could be discovered if smoothness parameter λ would be linked with specific countries business and credit cycles. Moreover, test results if parameter λ is equal to the inverse signal-to-noise variance ratio.
- the Credit-to-GDP ratio gap indicator is strong, although it should be consolidated with other indicators to reduce the number of false signals or for further research need to develop complementary measures of cyclical systemic risk.

Eventually, the Credit-to-GDP ratio gap indicator is strong. it is the difference between the Credit-to-GDP ratio and the estimated forecast augmented HP trend. This approach at least partly covers three the Basel gap shortcomings. Firstly, the downward bias of the Credit-to-GDP ratio gap during the recovery phase is alleviated by the forecast augmented HP gap with current values ranging from -30 to +5 percentage points. Secondly, the forecast augmented HP filter lengthens the underlying series with forecasts and effectively puts less emphasis on historical time series and more on recent developments as well as the outlook. And thirdly, the forecast augmented HP gap has slightly better early warning properties than the Basel gap. Although, the Credit-to-GDP ratio gap could be improved. It could be consolidated with other indicators to reduce the number of false signals or for further research could be developed complementary measures of cyclical systemic risk.

Summing up, results shows that one-sided HP filter augmented with random walk forecast method is suitable to use for the identification of cyclical systemic risk and to potentially calibrate macroprudential instruments in the future since it is easy to use and interpret, available for many countries and estimates in real time. This supports thesis hypothesis that most of twenty Europe countries are homogenous and one-sided HP filter augmented forecast identifies periods of increased cyclical systemic risk, event for countries with small observations.

5. BIBLIOGRAPHY

1. I. Aldasoro, C. Borio, M. Drehmann. “Early warning indicators of banking crises: expanding the family”, BIS Quarterly Review, 2018, pp. 1-17.
   https://www.bis.org/publ/qtrpdf/r_qt1803e.pdf

2. L. Alessi, C. Detken. Identifying excessive credit growth and leverage, ECB Working Paper Series, 2014, no 1723, pp. 2-51.
   https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1723.pdf

3. L. Alessi, C. Detken. Quasi real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity, European Journal of Political Economy, 2011, vol. 27, pp. 520-533.
   https://www.sciencedirect.com/science/article/abs/pii/S0176268011000048

4. Basel Committee on Banking Supervision. Guidance for national authorities operating the countercyclical capital buffer, BIS, 2010, pp. 7-32.
   https://www.bis.org/publ/bcbs187.pdf

5. M. Behn, C. Detken, T. A. Peltonen, W. Schudel. Setting countercyclical capital buffers based on early warning models: would it work?, ECB Working Paper Series, 2013, no 1604, pp. 6-44.
   https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1604.pdf

6. C. Borio, M. Drehmann. Assessing the risk of banking crises – revisited, BIS Quarterly Review, 2009, pp 29-46.
   https://www.bis.org/publ/qtrpdf/r_qt0903e.pdf

7. C. Borio, P. Lowe. “Asset prices, financial and monetary stability: exploring the nexus”, BIS Working Papers, 2002, no 114, pp. 7-41.
   https://www.bis.org/publ/work114.pdf

8. D. Celov and the Network’s Output Gap Working Group. A practitioner’s guide to potential output and the output gap, European Union Independent Fiscal Institutions, pp. 6-67.
   https://www.euifis.eu/eng/fiscal/228/a-practitioners-guide-to-potential-output-and-the-output-gap

9. C. Detken, O. Weeken, L. Alessi, D. Bonfim, M. M. Boucinha, C. Castro, S. Frontczak, G. Giordana, J. Giese, N. Jahn, J. Kakes, B. Klaus, J. H. Lang, N. Puzanova, P. Welz. Operationalising the countercyclical capital buffer: indicator selection, threshold identification and calibration options, European Systemic Risk Board Occasional Paper Series, 2014, no 5, pp. 3-88.
   https://www.esrb.europa.eu/pub/pdf/occasional/20140630_occasional_paper_5.pdf

10. M. Drehmann, M. Juselius. Evaluating early warning indicators of banking crises: satisfying policy requirements, BIS Working Papers, 2013, no 421, pp.3-37.
    http://www.bis.org/publ/work421.htm

11. M. L. Duca, A. Koban, M. Basten, E. Bengtsson, B. Klaus, P. Kusmierczyk, J. H. Lang. A new database for financial crises in European countries, European Systemic Risk Board Occasional Paper, 2017, no 194, pp. 2-59.
https://www.ecb.europa.eu/pub/pdf/scpops/ecb.op194.en.pdf
Crisis dates: https://www.esrb.europa.eu/pub/fcdb/esrb.fcdb20170731.en.xlsx

12. European Systemic Risk Board. Recommendation of the European Systemic Risk Board on guidance for setting countercyclical buffer rates, 2014, no C293, pp. 1-10.
https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=OJ:C:2014:293:TOC

13. T. Fawcett. An introduction to ROC analysis, Pattern Recognition Letters, 2006, no 27, pp. 861-874.
https://people.inf.elte.hu/kiss/11dwhdm/roc.pdf

14. K. Gerdrup, A. B. Kvinlog, E. Schaanning. Key indicators for a countercyclical capital buffer in Norway - Trends and uncertainty, Norges Bank Staff Memo, 2013, no 13, pp. 3-43.
https://www.norges-bank.no/en/news-events/news-publications/Papers/Staff-Memo/2013/Staff-Memo-132013/

15. J. D. Hamilton. Why you should never use the Hodrick-Prescott filter, National Bureau of Economic Research working paper series, 2017, no 23429, pp. 3-47.
https://www.nber.org/system/files/working_papers/w23429/w23429.pdf

16. J. H. Lang and P. Welz. Measuring credit gaps for macroprudential policy, Financial Stability Review, 2017, pp. 145-158.
https://www.ecb.europa.eu/pub/pdf/other/financialstabilityreview201705.en.pdf

17. J. H. Lang, C. Izzo, S. Fahr, J. Ruzicka. Anticipating the bust: a new cyclical systemic risk indicator to assess the likelihood and severity of financial crises, ECB Occasional Paper Series, 2019, no 219, pp. 5-76.
https://www.ecb.europa.eu/pub/pdf/scpops/ecb.op219~7483083881.en.pdf

18. P. Sarlin. On policymakers’ loss functions and the evaluation of early warning systems, Economics Letters, 2013, vol. 119, pp. 1-7.
https://www.sciencedirect.com/science/article/abs/pii/S0165176513000025

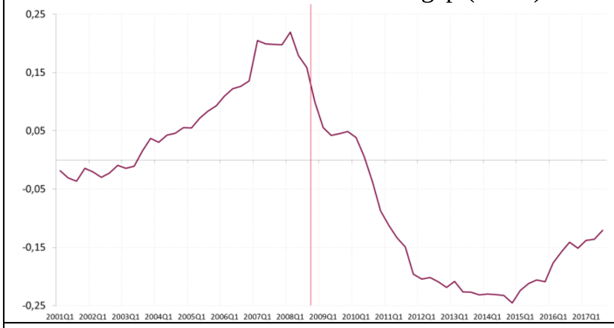
19. Y. S. Schüler, P. P. Hiebert, T. A. Peltonen. Characterising the financial cycle: a multivariate and time-varying approach, ECB Working Paper Series, 2015, no 1846, pp. 3-55.
https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1846.en.pdf

20. N. Valinskytė, G. Rupeika. Leading indicators for the countercyclical capital buffer in Lithuania, Bank of Lithuania Occasional Paper Series, 2015, no 4, pp. 1-26.
https://www.lb.lt/en/publications/no-4-leading-indicators-for-the-countercyclical-capital-buffer-in-lithuania

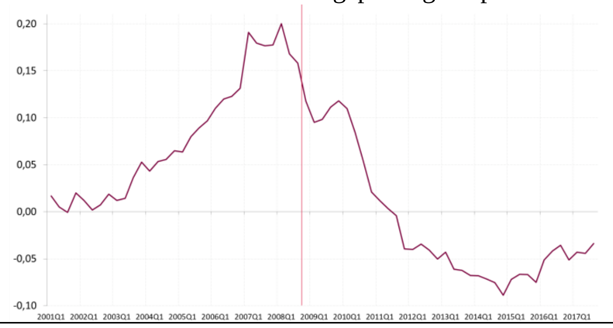
A. APPENDIX

A.1. Six the Bank of Lithuania EWIs

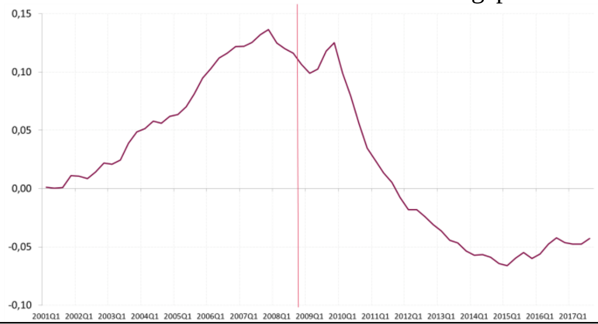
1. Credit-to-GDP ratio gap (Basel)



2. Credit-to-GDP ratio gap using simple forecasts



3. MFI loans-to-GDP ratio gap



4. MFI Loans-to-deposits ratio

5. House price-to-household income ratio gap

6. Current account deficit-to-GDP ratio

Note: quarterly data from 2001q1 till 2017q3 with 67 observations of the Bank of Lithuania EWIs. Red vertical line marks financial crisis start on 2008q4 in Lithuania.

	EWI	Min	Max	Mean	Median	Standard deviation	AUROC (12-5)	AUROC (20-5)	Quasi out of sample usefulness
1	Credit-to-GDP ratio gap (Basel gap)	-0.25	0.22	-0.04	-0.02	0.14	0.85	0.75	0.64
2	Credit-to-GDP ratio gap using simple forecasts	-0.09	0.20	0.03	0.01	0.08	0.91	0.83	0.69
3	MFI loans-to-GDP ratio gap	-0.07	0.14	0.03	0.02	0.07	0.84	0.75	0.63
4	MFI Loans-to-deposits ratio	0.61	2.07	1.26	1.21	0.37	0.57	0.50	0.28
5	House price-to-household income ratio gap	-0.17	0.30	0.01	-0.04	0.12	0.99	0.92	0.79
6	Current account deficit-to-GDP ratio	-0.17	0.03	-0.05	-0.05	0.05	0.51	0.50	0.04

A.2. Time series of observations (quarterly data)

		Countries	First observation	Last observation	No of observations
1	AT	Austria	1970q4	2017q3	187
2	BE	Belgium	1970q4	2017q3	187
3	CY	Cyprus	2005q4	2017q3	47
4	DE	Germany	1970q4	2017q3	187
5	EE	Estonia	2008q1	2017q3	38
6	ES	Spain	1970q4	2017q3	187
7	FI	Finland	1974q1	2017q3	174
8	FR	France	1970q4	2017q3	187
9	GR	Greece	1970q4	2017q3	187
10	IE	Ireland	1971q2	2017q3	185
11	IT	Italy	1974q4	2017q3	171
12	LT	Lithuania	1995q4	2017q3	87
13	LU	Luxembourg	2003q1	2017q3	58
14	LV	Latvia	2003q1	2017q3	58
15	MT	Malta	2005q1	2017q3	50
16	NL	Netherlands	1970q4	2017q3	187
17	PT	Portugal	1970q4	2017q3	187
18	SE	Sweden	1970q4	2017q3	187
19	SI	Slovenia	2004q1	2017q3	54
20	SK	Slovakia	2006q1	2017q3	46
		Pooled set			**2,651**

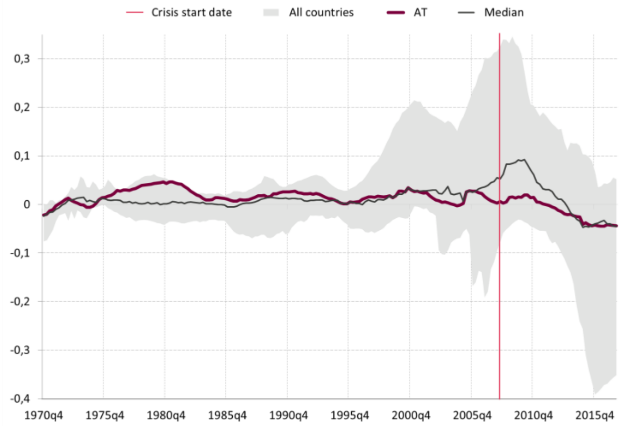
A.3. Descriptive statistics of the observations

	Countries	No of observations	No of crises quarters	Min	Max	Mean	Median	Standard deviation
1	AT	187	35	-0.04	0.05	0.01	0.02	0.02
2	BE	187	20	-0.03	0.05	0.01	0.01	0.02
3	CY	47	20	-0.19	0.23	0.11	-0.16	0.13
4	DE	187	15	-0.05	0.07	0.01	0.01	0.03
5	EE	38		-0.08	0.13	-0.04	0.02	0.06
6	ES	187	51	-0.20	0.26	0.01	0.01	0.09
7	FI	174	22	-0.06	0.09	0.02	0.01	0.04
8	FR	187	23	-0.04	0.07	0.01	0.00	0.02
9	GR	187	27	-0.05	0.17	0.01	0.00	0.06
10	IE	185	22	-0.39	0.35	0.00	0.00	0.14
11	IT	171	10	-0.04	0.09	0.02	0.01	0.04
12	LT	87	5	-0.06	0.12	0.01	0.01	0.06
13	LU	58	11	-0.05	0.12	0.01	0.01	0.04
14	LV	58	8	-0.10	0.15	-0.05	0.01	0.09
15	MT	50		-0.09	0.08	-0.01	0.02	0.05
16	NL	187	21	-0.11	0.10	0.05	0.03	0.04
17	PT	187	29	-0.20	0.21	0.01	0.01	0.09
18	SE	187	26	-0.01	0.01	0.00	0.00	0.01
19	SI	54	21	-0.10	0.10	0.00	-0.07	0.07
20	SK	46		-0.05	0.04	0.02	0.02	0.02
	Pooled set	**2,651**	**335**	**-0.39**	**0.35**	**-0.02**	**0.01**	**0.07**

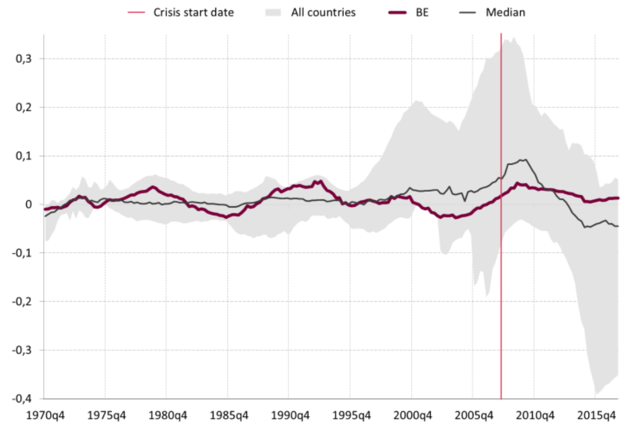
Note: observations of Estonia, Malta and Slovakia did not had financial crisis period data because of short time series.

A.4. Countries over times

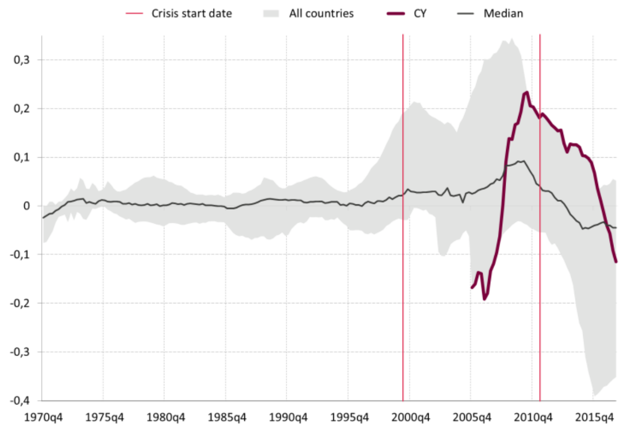
Austria



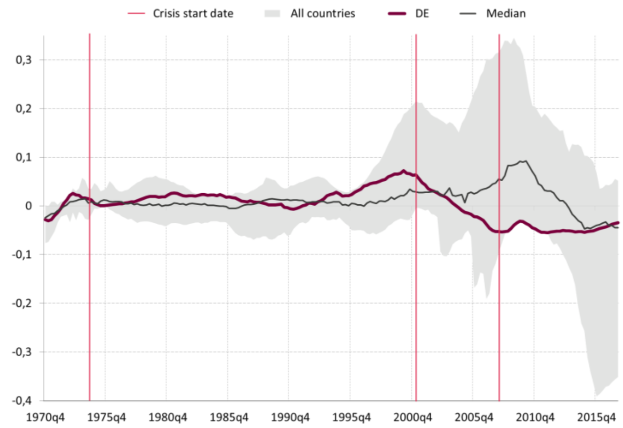
Belgium



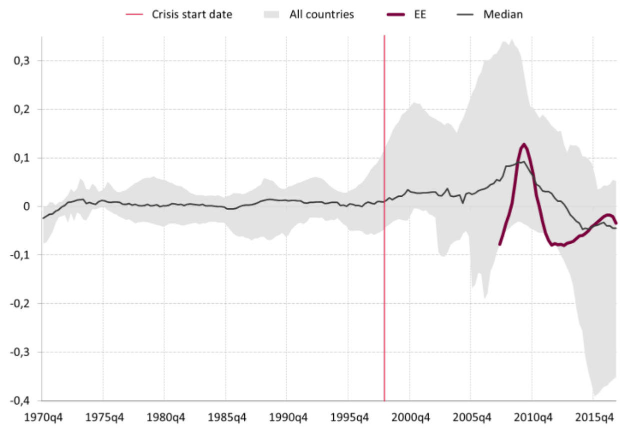
Cyprus



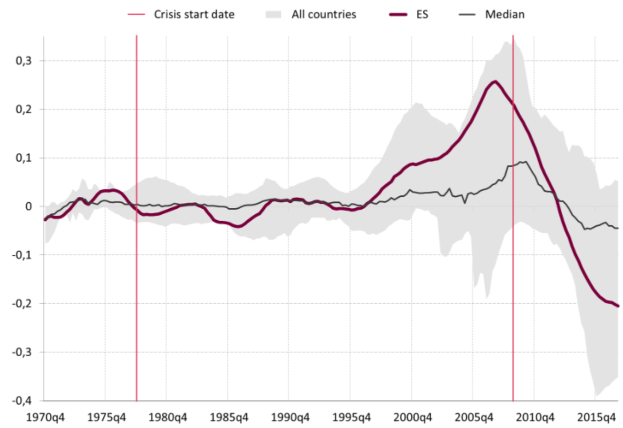
Germany



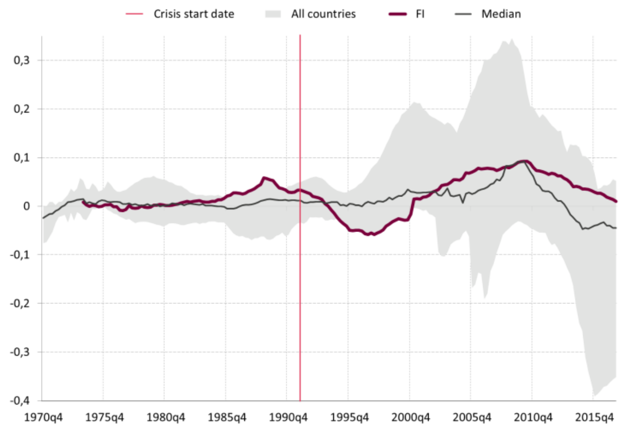
Estonia



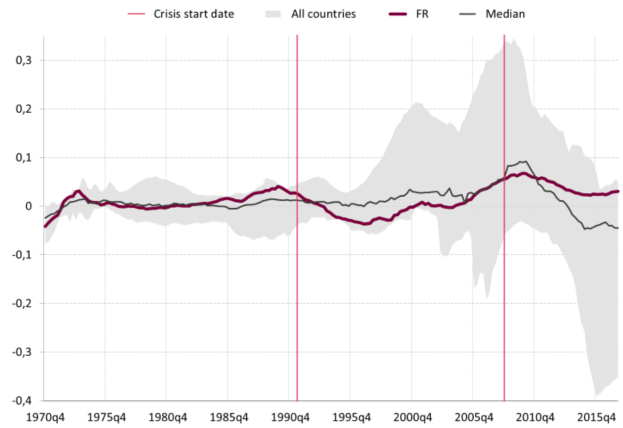
Spain

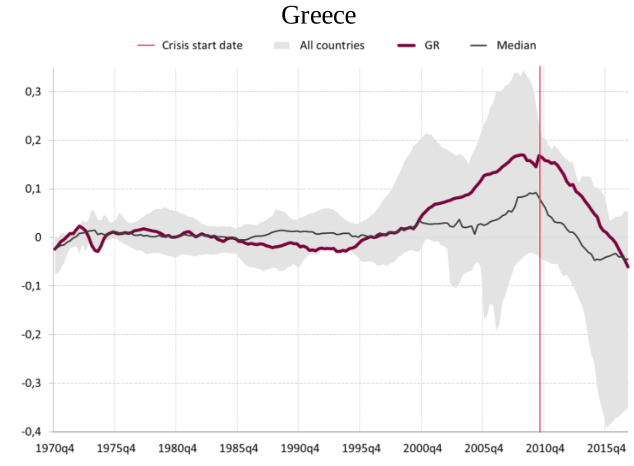


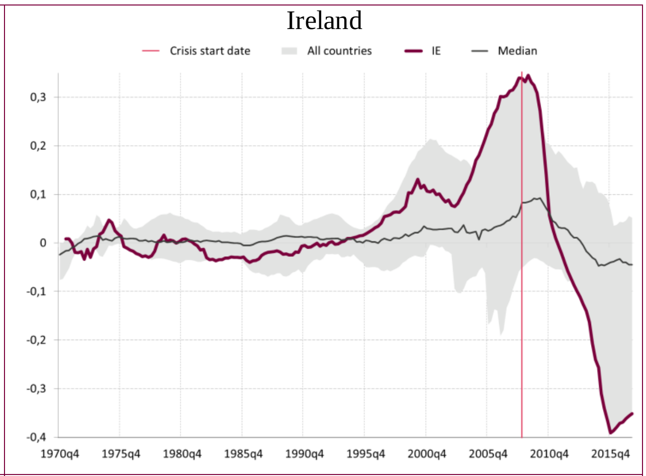
Finland

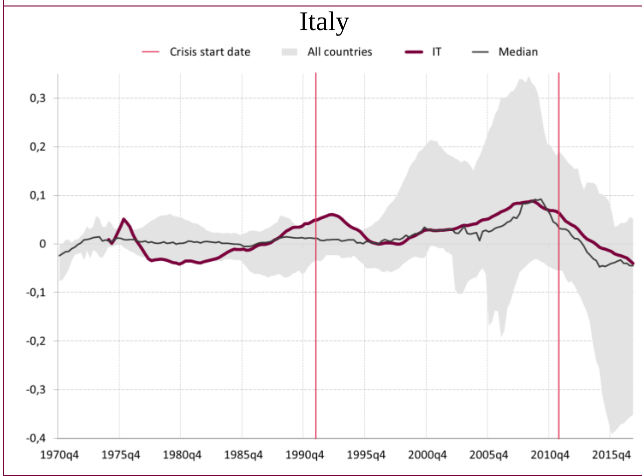


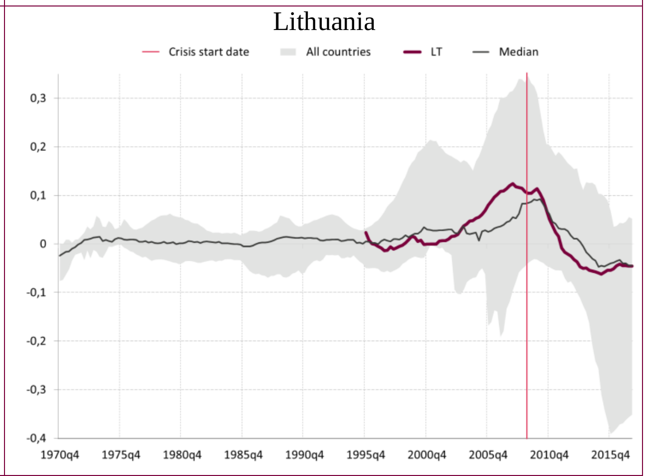
France

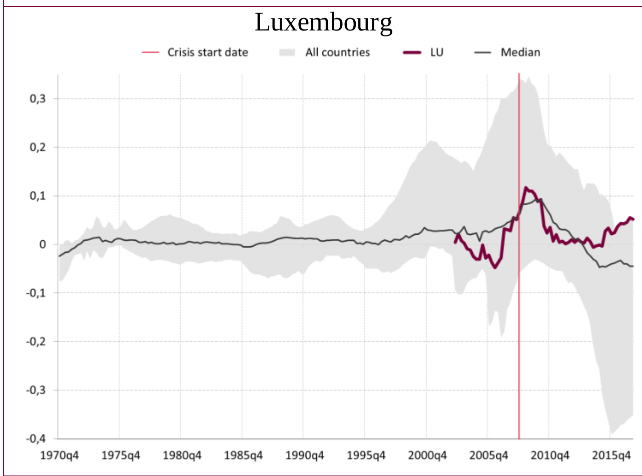


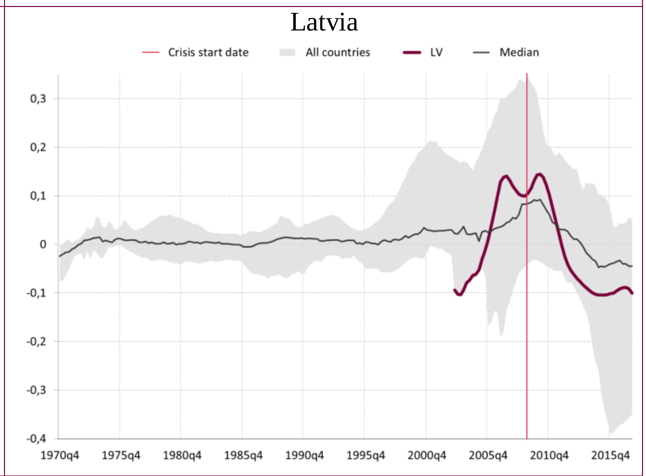

Greece
Crisis start date
All countries
GR
Median
0,3
0,2
0,1
0
-0,1
-0,2
-0,3
-0,4
1970q4
1975q4
1980q4
1985q4
1990q4
1995q4
2000q4
2005q4
2010q4
2015q4

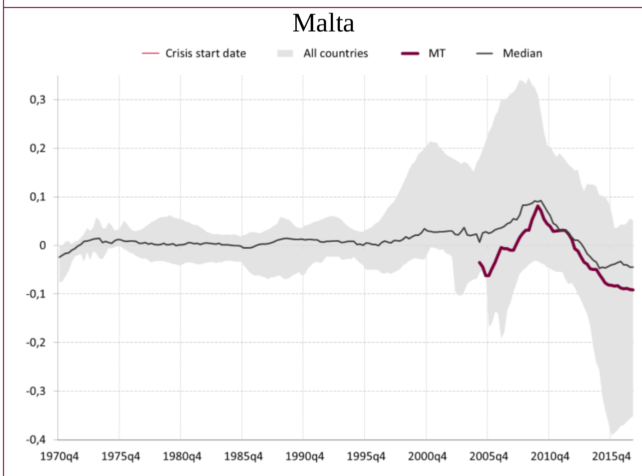

Ireland
Crisis start date
All countries
IE
Median
0,3
0,2
0,1
0
-0,1
-0,2
-0,3
-0,4
1970q4
1975q4
1980q4
1985q4
1990q4
1995q4
2000q4
2005q4
2010q4
2015q4

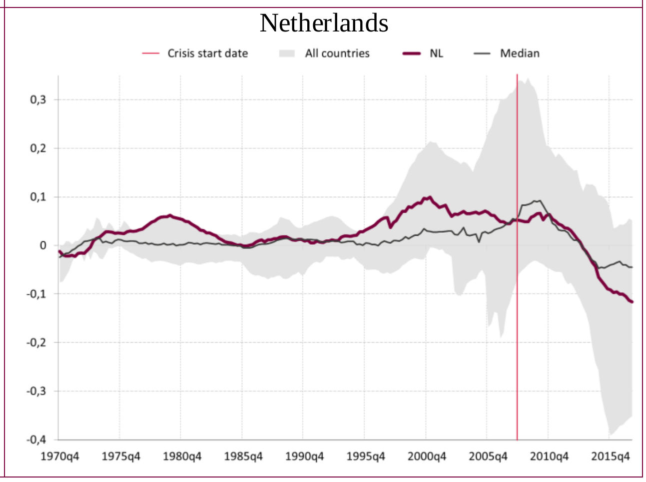

Italy
Crisis start date
All countries
IT
Median
0,3
0,2
0,1
0
-0,1
-0,2
-0,3
-0,4
1970q4
1975q4
1980q4
1985q4
1990q4
1995q4
2000q4
2005q4
2010q4
2015q4


Lithuania
Crisis start date
All countries
LT
Median
0,3
0,2
0,1
0
-0,1
-0,2
-0,3
-0,4
1970q4
1975q4
1980q4
1985q4
1990q4
1995q4
2000q4
2005q4
2010q4
2015q4


Luxembourg
Crisis start date
All countries
LU
Median
0,3
0,2
0,1
0
-0,1
-0,2
-0,3
-0,4
1970q4
1975q4
1980q4
1985q4
1990q4
1995q4
2000q4
2005q4
2010q4
2015q4


Latvia
Crisis start date
All countries
LV
Median
0,3
0,2
0,1
0
-0,1
-0,2
-0,3
-0,4
1970q4
1975q4
1980q4
1985q4
1990q4
1995q4
2000q4
2005q4
2010q4
2015q4

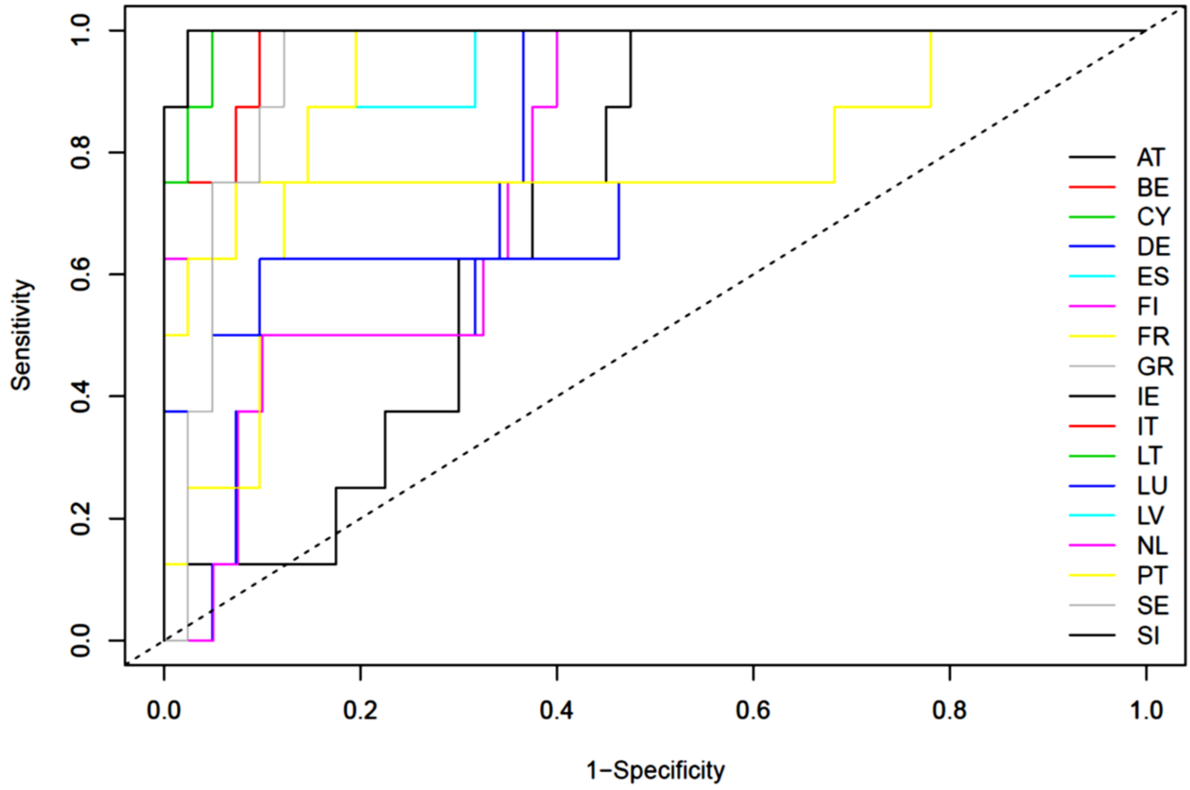

Malta
Crisis start date
All countries
MT
Median
0,3
0,2
0,1
0
-0,1
-0,2
-0,3
-0,4
1970q4
1975q4
1980q4
1985q4
1990q4
1995q4
2000q4
2005q4
2010q4
2015q4


Netherlands
Crisis start date
All countries
NL
Median
0,3
0,2
0,1
0
-0,1
-0,2
-0,3
-0,4
1970q4
1975q4
1980q4
1985q4
1990q4
1995q4
2000q4
2005q4
2010q4
2015q4

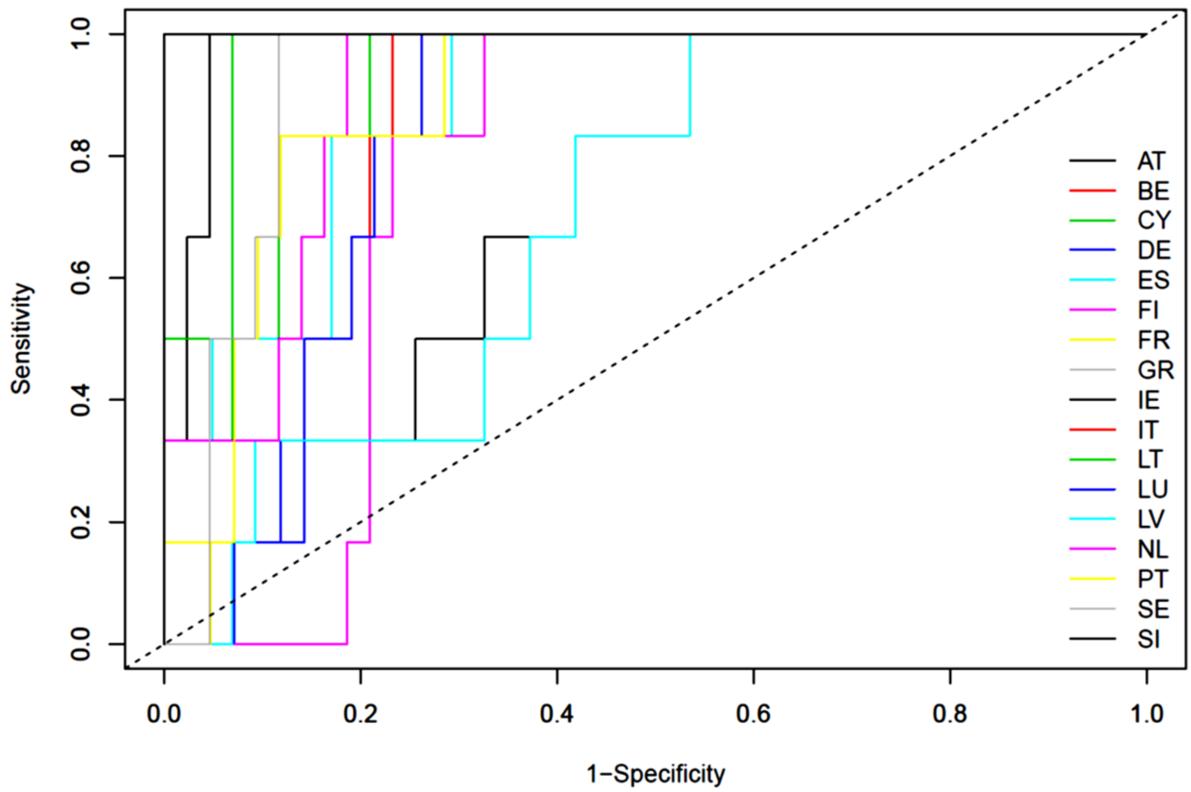
Note: observations of Estonia, Malta and Slovakia did not had financial crisis period data because of short time series.

A.5. Predictive quality of signals for countries

AUROC (12-5)



AUROC (20-5)



Note: observations of Estonia, Malta and Slovakia did not had financial crisis period data because of short time series.