# Early Warning Indicators for Banking Crises: A Conditional Moments Approach

by

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**Abstract**

This paper presents a novel methodology to calculate thresholds in an early warning signalling framework for extracting signals useful to predict the occurrence of banking crises. The conditional moments based methodology does not rely on assumptions on an objective function trading off Type I and Type II errors and leads to the identification of zones corresponding to different intensities of the signal. The signalling performance of these signalling zones is similar to that of the traditional early warning method based on the optimisation of a policymaker's loss function; our methodology in fact outperforms the latter for a number of indicators. The methodology is then extended to allow for country specificities, which leads to a substantial improvement of the signalling power. On average, across all indicators, the country-specific signalling zones outperform the pooled approach, resulting in a larger average true positive rate and a lower false alarms rate.

## 1. INTRODUCTION

The recent financial crisis resulted in increased attention for macro-prudential policy to maintain financial stability. The translation of the Basel III framework[2] into European legislation[3] provided national authorities with a range of macro-prudential policy instruments. A number of countries are in fact already applying such macro-prudential policy instruments, such as countercyclical capital buffers, additional capital requirements on real estate exposures or caps on loan-to-value or debt service-to-income ratios, to dampen systemic risk. The European Systemic Risk Board (ESRB) strongly encourages European countries to develop sound macroprudential policy strategies to frame such actions, which include the identification of leading indicators and associated thresholds signalling excessive developments that may lead to systemic risk.[4]

In recent years, policymakers as well as academics focused on the identification of early-warning indicators signalling excessive developments in credit growth and leverage in the run-up to a banking crisis. One of the most common methodologies used to identify early warning indicators and obtain thresholds is the signalling approach, as introduced in the pioneering study by Kaminsky and Reinhart (1999). The signalling approach results in the computation of a threshold above which an indicator signals the potential occurrence of a banking crisis over the relevant prediction horizon. Such signals could be used by macro-prudential policymakers as an initial trigger for an in depth investigation of systemic risk and potential policy actions.

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[2] Basel Committee of Banking Supervision (2011).

[3] The CRD IV Directive 2013/36/EU of the European Parliament and of the Council of 26 June 2013 on access to the activity of credit institutions and the prudential supervision of credit institutions and investment firms, and the CRR Regulation (EU) No. 575/2013 of the European Parliament and of the Council of 26 June 2013 on prudential requirements for credit institutions and investment firms.

[4] See ESRB Recommendation of 4 April 2013 on Intermediate objectives and instruments of macro-prudential policy (ESRB/2013/01) and ESRB (2014).

This paper presents a novel yet intuitive methodology to identify leading indicators and associated thresholds signalling excessive developments, with the aim of extracting signals useful to predict the occurrence of banking crises. A conditional moments approach is proposed, in which for a given prediction horizon, the first moment of the indicator observations in pre-crisis periods in crisis countries is compared to the first moment of observations consistent with normal times. Accounting for the uncertainty surrounding the estimates of cross-country first moments, the methodology provides thresholds that determine zones, which correspond to different intensities of the signal issued by the indicator for the given prediction horizon.

This study contributes to the great body of literature that aims at identifying useful early warning indicators for the occurrence of banking crises. This strand of research relies heavily on the signalling approach, following the seminal study of Kaminsky and Reinhart (1999). Compared to the existing signalling approach, our methodology has several advantages. First, the thresholds obtained are not dependent on arbitrary assumptions on, for example, the objective function to be optimized for obtaining thresholds (e.g., the noise to signal ratio or a policymaker's loss function), but rely only on the empirical properties of the indicators for the countries considered. Second, in contrast to the standard methodology, our framework leads to identify, for each prediction horizon preceding a crisis, zones corresponding to different intensities of the signal issued by an indicator. Hence, instead of obtaining a single threshold resulting in a binary outcome of the signal, we identify areas that convey information on the intensity of warning released by indicators. Third, our methodology can be extended to account for country specificities, structural features and state dependencies. As such, the methodology provides more flexibility than the traditional early warning approaches, which is important in a world where country specificities are still important.

Using panel data for 15 EU countries, we consider a number of potential early warning indicators for banking crises and evaluate the properties of our signalling zones in terms of extracting signals for predicting crises while minimizing the issuance of false alarms. In particular, a comparison is made to the signalling performance of binary early warning thresholds obtained through standard methodologies that obtain thresholds on the basis of the optimization of an assumed policymaker's loss function. In addition, the value added of allowing for country specificities in improving signalling ability is explored.

Our findings are the following. First, we show that different assumptions on the specification of the policymaker's loss function (i.e., varying the relative weight assigned to Type 1 and Type 2 errors) may lead to substantial differences in binary early warning thresholds and their signalling performance. Second, when comparing our conditional moments approach to the binary early warning thresholds based on a policymaker's loss function with equal weight assigned to Type 1 and Type 2 errors, we find that on average, the signalling performance of our methodology is more or less similar to that of the traditional early warning method. In particular, the conditional moments approach results in a slightly lower true positive rate (56 vs. 60 percent) and false positive rate (33 vs. 38 percent), resulting in an average noise to signal ratio close to 0.60 for both methods. For a number of indicators,7 out of 44, the conditional moments framework actually outperforms (both at least as large true positive rate and at least as low false alarms rate) the traditional early warning method. Third, allowing for country specificities substantially improves signalling power of the conditional moments approach. When evaluated at the level of the entire sample of 15 EU countries, the average true positive rate increases from 56 to 62 percent and the false alarms rate drops from 33 to 28 percent. The country-specific approach outperforms the pooled approach for 29 out of 44 indicators; the reverse is true in only 5 cases. The average noise to signal ratio falls from 60 to 47 percent. When evaluating signalling performance at the individual country level, the improvement in terms of average true positive rates and false alarms rates shows the same picture. Similarly, the average noise to signal ratio fell from 58 percent to 51 percent. However, the dominance of the country-specific approach seems to be somewhat less strong: the country-specific conditional moments approach outperforms the pooled one for 214 out of 646 country-indicator combinations, whereas the reverse is true in 138 cases.

The remainder of the paper is organised as follows. In Section 2 an overview is provided of the signalling approach in the existing early warning literature. Section 3 outlines our novel approach for determining zones corresponding to different intensities of the signal issued by an indicator. In Section 4 we present the data and evaluation method used in the empirical evaluation of the signalling performance of our methodology in Section 5. Finally, Section 6 concludes.

## 2. THE SIGNALLING APPROACH IN THE EXISTING LITERATURE

A great body of literature has been produced aiming at identifying useful early-warning indicators (EWIs) for the occurrence of crises. While the pioneering studies focused on leading indicators of currency crises in emerging economies (e.g. Frankel and Rose 1996, Kaminski et al. 1998 and more recently Crespo Cuaresma and Slacik 2008), later studies encompassed developing as well as developed countries and considered a wider spectrum of events, including banking crises (Demirgüç-Kunt and Detragiache 1997, Babecky et al. 2012 and 2013, Drehmann and Juselius 2013, Behn et al. 2013) and busts in asset prices (Agnello and Schuknecht 2009, Alessi and Detken 2011, Crespo Cuaresma 2010, Gerdesmeier et al. 2012). In recent years, a special attention has been devoted to EWI models as starting point for the operationalization of macro-prudential policies, such as countercyclical capital buffers (Detken et al., 2014), sectorial capital requirements, limits to the loan-to-value, loan-to-income and debt-service to-income ratios (ESRB 2013 and Ferrari et al. (forthcoming)).

A number of variables have been identified as useful EWIs of banking crises. First of all, indicators related to the supply of credit, such as the deviation of credit to GDP from its long-run trend (Borio and Lowe, 2002, Babecky et al. 2012, Drehmann and Juselius 2013) and credit growth (Repullo and Saurina 2011 and Schularick and Taylor 2012). Developments in other macro-financial variables such as GDP growth, interest rates (Demirgüç and Detragiache 1997, Babecky et al. 2012), current account balance, banking sector profitability and capitalization (Behn et al. 2013) have also been found to influence the probability of banking sector distress. Furthermore, studies affirm the importance of global development in association with the occurrence of banking crises (Behn et al. 2013), as well of variables related to developments in the real estate sector (Borio and Drehmann 2009, Claessens et al. 2011 among others).

From a statistical standpoint, studies on EWIs primarily rely on signal extraction methods. The signalling approach, pioneered by Kaminsky and Reinhart (1999) and extended by Demirgüç-Kunt and Detragiache (2000), Alessi and Detken (2011) and Lo Duca and Peltonen (2013), focus on issuing signals whenever one (or more) indicators breach a pre-defined threshold during the relevant prediction horizon. Then, the predictive abilities of the models can be evaluated by comparing the signal issued with actual observations.

Once a signal is issued by an indicator, four possible outcomes can occur, classified in the so-called “Confusion Matrix” presented in Table 1 here below. A signal is classified as correct if a crisis follows within the relevant horizon (A); if a crisis does not follow, then the signal results in a false alarm (B). A non-issued signal (i.e., an indicator or model output not breaching a threshold) is correct when a crisis does not follow (D) and it is incorrect when a crisis occurs (C).

**Table 1: Confusion Matrix**

| | *Crisis* | *No crisis* |
|---|---|---|
| Signal is issued | A | B |
| Signal is not issued | C | D |

On the basis of the Confusion Matrix, a number of key ratios can be calculated. The fraction of correctly predicted crises represented by the ratio $\left(\frac{A}{A+C}\right)$ is called the true positive rate (TPR). Similarly the ratio $\left(\frac{C}{A+C}\right)$ or 1-TPR is denoted as the Type I error rate, which represents the fraction of missed crises. The noise or false positive ratio (FPR) represents the fraction of false alarms, i.e., signals wrongly issued $\left(\frac{B}{B+D}\right)$. The FPR is also referred to as the Type II error rate.

Signal extraction methodologies can then be distinguished on the basis of the approach used to calculate the threshold. On one hand, distribution-based methods define the threshold as a percentile of the distribution of the indicator over time and across the country sample considered. Objective function-based methods[5] obtain the threshold optimizing an objective function, which specifies the trade-off between Type I and Type II errors. Examples of such objective functions are the noise-to signal ratio (defined as $\left(\frac{TPR}{FPR}\right)$) or a policymaker's loss function

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

where parameter θ represents the policymaker's relative preference for missing crises (Type I error) versus issuing false alarms (Type II error). The optimal threshold can then be determined as that minimizing the chosen objective function. Optimal threshold identification involves a trade-off between missing crises (Type I error) and issuing false alarms (Type II error): a lower threshold decreases the Type I error rate but at the same time increases the Type II error rate.

The signalling approach has been applied in a variety of settings. Non-parametric applications involve grid searching for the optimal threshold over the set of possible values, determined by the cross-sectional and/or the time series distribution of the indicator.[6] Univariate or multivariate grid searches can be performed, but the latter face dimensionality problems. In a multivariate setting, Manasse and Roubini (2009) pioneered the use of classification and regression trees to predict financial crisis, while Alessi and Detken (2014) extend this approach to a "random forest" framework. The parametric or regression approach, implemented inter alia[7] by Demirgüç-Kunt and Detragiache (1997)

[5] Alessi and Detken (2011) and Lo Duca and Peltonen (2013).

[6] See Borio and Lowe (2002), Borio and Drehmann (2008), Drehmann, Borio and Tsatsaronis (2011), Alessi and Detken (2009), Drehmann and Juselius (2013). Ferrari et al. (forthcoming) provide a comparison between non-parametric and parametric approaches.

[7] Cfr Babecky et al. (2012 and 2013) for an application in a Bayesian model averaging framework and Ferrari et al. (forthcoming) in the context of real estate-related banking crises.

and more recently by Behn et al. (2013), usually involves the regression of a binary dependent variable, equal to 1 in the relevant prediction horizon, on a set of explanatory variables. The resulting predicted probabilities are then used to assess the early warning properties of the model.

The methodology presented in this paper is set within the signal extraction framework and relies on a distribution-based setting for the computation of thresholds. In this article, the binary signalling approach is extended to a multi-threshold framework allowing for different intensities of the signal. While our approach can be applied also in a non-parametric context (see Ferrari and Pirovano, 2014), here we opt for an econometric framework. Contrary to the standard regression approach, the binary variables defining the relevant crisis and pre-crisis samples are on the right side of the regression equation and potential indicators are the dependent variables. While we exploit all information derived by the pooled set of time series for our sample of countries, the methodology is easily extended to obtain country-specific thresholds, which constitutes an important value added of our approach.

# 3. A CONDITIONAL MOMENTS APPROACH FOR EARLY WARNING INDICATORS

## 3.1. Intuition

Like the traditional early warning approach, the method of conditional moments relies on cross-country information, as this yields a sufficient coverage of crisis events in the sample.[8] The conditional moments approach then builds on the simple comparison of, for a given prediction horizon, the average level of an indicator in pre-crisis periods in crisis countries and the average level of the indicator in normal times. In a next step, the method then accounts for the dispersion around these average indicator levels both across countries and over time in order to determine the bounds of a “danger zone” and a “normal zone”.

In the remainder of the paper, we consider as the relevant prediction horizon a period of 1 to 3 years before a banking crisis. This window is situated sufficiently close to historical crisis events so that the early warning information contained in the indicators can be extracted, while at the same time providing sufficiently timely signals, which leave the policy maker sufficient time to take remedial action.

### 3.1.1. **Relevant subsamples for calculation of moments: pre-crisis vs normal times**

Observations in a window of 5 to 12 quarters before the onset of a banking crisis in those countries that actually experienced a banking crisis are classified as “pre-crisis” observations.

The sample of observations consistent with normal times consists of two subsamples. A first subsample, denoted as “non-crisis countries”, contains observations for countries that did not experience a banking crisis in periods that are marked as “pre-crisis” for countries actually experiencing a crisis. The second subsample consistent with normal times consists of observations for periods in which no country is in a pre-crisis situation, which we refer to as “tranquil periods”.

[8] In case a sufficient amount of crisis events were available for an individual country, the method could obviously also be applied to that individual country.

The comparison between the first moment of the “pre-crisis” and the “tranquil periods” sample shows whether an indicator assumes, on average, higher levels before an imminent banking crisis than in tranquil times. The comparison between the first moment of the “pre-crisis” and the “non-crisis countries” subsample shows whether an indicator assumes, on average, higher levels before an imminent banking crisis in crisis countries than at the same points in time in countries where a banking crisis was not imminent. The latter comparison is key to account for potential false alarms. In fact, if an indicator shows, on average, a similar behaviour in countries that subsequently experience a crisis and in countries that do not, it leads to a signal scarcely informative on the vulnerabilities peculiar to a run-up to a distress event. This can result, for example, when countries are hit by a common shock, which brings an indicator to rise above levels considered consistent with “tranquil periods”, but that do not necessarily lead to the occurrence of a crisis in the near future.

### 3.1.2. **Determining thresholds**

In a next step, the dispersion around the first moments of the three subsamples (“pre-crisis”, “non-crisis countries” and “tranquil periods”) is accounted for. In particular, bootstrapped confidence intervals around the three first moments are obtained.

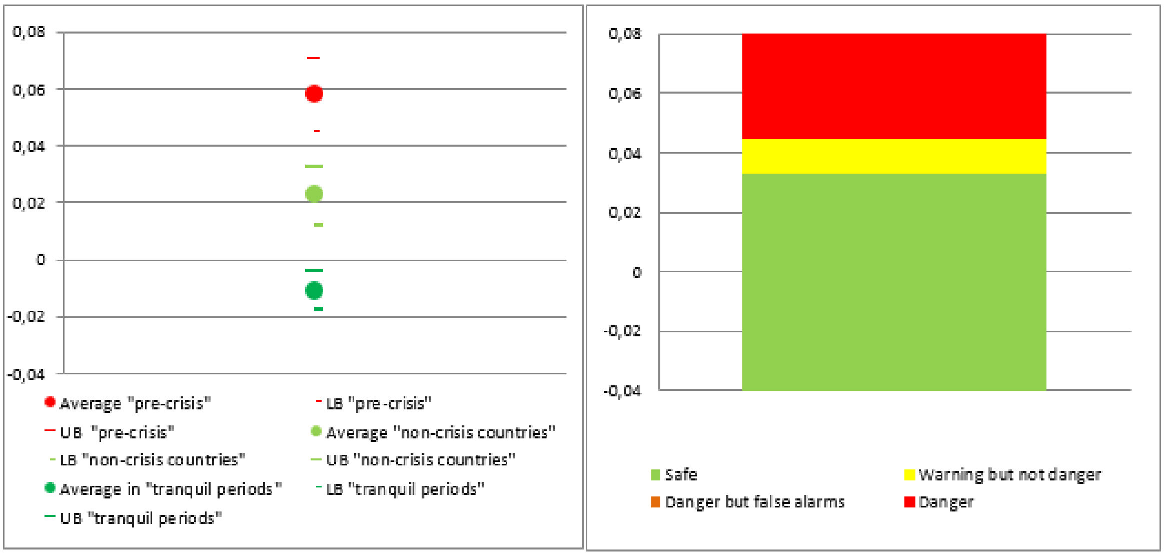
These bootstrapped confidence intervals serve as the basis for determining zones which indicate the intensity of the signal for a particular time horizon. We consider as the “normal zone” those indicator levels below the maximum of the upper confidence bounds for “non-crisis countries” and “tranquil periods”. We consider as the “danger zone” those indicator levels above the lower confidence bound for the “pre-crisis” sample. Depending on whether or not the “normal zone” and the “danger zone” overlap, 4 signalling zones can be identified, as summarised in Table 2.

**Table 2**: Colour coding of signalling zones

| | Not in danger zone | In danger zone |
|---|---|---|
| In normal zone | Safe | Danger, but false alarms |
| Not in normal zone | Warning, but not danger | Danger |

Figure 1 illustrates the above described mapping of bootstrapped confidence bounds around the first moments of the three subsamples into the signalling zones.

**Figure 1**: From conditional moments to signalling zones




**Signals of different intensity**

Indicator levels in the green zone (i.e., *below* the lower confidence bound for “pre-crisis” and *below* the maximum of the upper confidence bounds for “non-crisis countries” and “tranquil periods”) can be considered as “safe”, as the indicator value is situated in the “normal zone” and not in the “danger zone”. When indicators lie in the green zone, no signal is issued.

The indicator is in the red zone when its value is *above* the lower confidence bound for “pre-crisis” and *above* the maximum of the upper confidence bounds for “non-crisis countries” and “tranquil periods”. Here, the indicator assumes values consistent with being in the “danger zone” and at the same time not in the “normal zone”, leading to the issuance of a strong signal.

Two zones are identified in which an intermediate signal is issued. An indicator is in the yellow zone when its level is *above* the maximum of the upper confidence bounds for “non-crisis countries” and “tranquil periods” but still *below* the lower confidence bound for “pre-crisis”. The orange zone corresponds to a situation in which the indicator level is *above* the lower confidence bound for “pre-crisis” and *below* the maximum of the upper confidence bounds for “non-crisis countries” and “tranquil periods”. In the yellow zone, a warning is issued as the value of the indicator is no longer in the “normal zone”, but it is not in the “danger zone” either. In the orange zone, the indicator is in the “danger zone”, but the risk of false alarms is likely to be high, as the indicator value is also still situated in the “normal zone”.[9]

**Policy implications**

[9] In general, indicators with a yellow instead of an orange zone can be expected to have stronger signalling capabilities; when the danger zone is situated above the normal zone, the indicator levels in pre-crisis periods are more distinct from those in normal times as compared to when there is overlap between the normal and the danger zone.

The above framework of signalling zones of different signal intensity differs from the binary early warning thresholds (see Section 3.2). In the latter, there are only two states, as no signal is issues when the indicator is below the threshold and a signal is issued when the indicator is above the threshold. A policymaker can then decide whether or not to act on this signal.

In contrast, our approach of intensity zones results in three states: no signal is issued when the indicator is in the green zone, an intermediate signal is issued when the indicator is no longer in the green zone but not yet in the red zone, and a strong signal results when the indicator is in the red zone. While a policymaker is unlikely to act upon an intermediate signal, as the false alarms rate is still large, the signal issued at this earlier stage nevertheless provides the policymaker with relevant information on developments no longer being necessarily safe. When the indicator moves to the red zone, the probability that the issued signal is not a false alarm but in fact announcing a potential banking crisis is increasing, providing more grounds for the policymaker to act.

Hence, this framework of different signalling zones combines a potentially larger true positive rate of no longer being in the green zone with a potentially lower false positive rate when moving into the red zone. Therefore, it may improve on signalling performance as it incorporates more flexibility than binary threshold methods, in which the trade-off between Type 1 and Type 2 errors is to be managed by only one instead of two thresholds.

### 3.2. **Empirical implementation**

In principle, the above methodology can be performed in a non-parametric setting, i.e. by simply calculating the means of the three subsamples and obtaining bootstrapped confidence intervals around these means.[10]

A parametric (regression) approach has several important advantages, however. In particular, it allows us to easily extend the conditional moments approach to account for country specificities, structural features and state dependencies. Therefore, we implement the above described methodology by estimating the following linear regression:

$$Y_{k,t} = \alpha_1 \text{pre-crisis}_{k,t} + \alpha_2 \text{non-crisis}_{k,t} + \alpha_3 \text{tranquil}_{k,t} + \varepsilon_{k,t} \qquad (1)$$

where $Y_{k,t}$ is level of the early warning indicator under consideration at time t in country k, $\text{pre-crisis}_{k,t}$ $\text{non-crisis}_{k,t}$ $\text{tranquil}_{k,t}$ are dummy variables equal to 1 when the observation at time t in country k is in the pre-crisis, non-crisis countries or tranquil periods subsample, respectively, and zero otherwise, and $\varepsilon_{k,t}$ is an error term.

The (pooled) conditional moments are obtained as follows:

$$\begin{aligned} E\left[Y_{k,t} | \text{pre-crisis}_{k,t} = 1\right] &= \alpha_1 \\ E\left[Y_{k,t} | \text{non-crisis}_{k,t} = 1\right] &= \alpha_2 \\ E\left[Y_{k,t} | \text{tranquil}_{k,t} = 1\right] &= \alpha_3 \end{aligned} \qquad (2)$$

10 Cfr. Ferrari and Pirovano (2014) for an implementation of the methodology in a non-parametric framework.

Bootstrapped confidence intervals on $\alpha_1$, $\alpha_2$ and $\alpha_3$ are then obtained by running regression (1) on 1,000 bootstrapped data samples, resulting in thresholds for the normal and danger zone.

The method is easily extended to account for country specificities by adding country-specific constant terms as well as other control variables. The simple extension of allowing for country specificities amounts to the following regression:

$$Y_{k,t} = \alpha_1 \text{pre-crisis}_{k,t} + \alpha_2 \text{non-crisis}_{k,t} + \alpha_3 \text{tranquil}_{k,t} + \sum_k \beta_k \text{country}_k + \varepsilon_{k,t} \qquad (3)$$

where $\text{country}_k$ is a dummy variable equal to 1 for observations in country k and zero otherwise.

The conditional moments for country k are obtained as follows:

$$\begin{aligned} E\left[Y_{k,t} | \text{pre-crisis}_{k,t} = 1, \text{country}_k = 1\right] &= \alpha_1 + \beta_k \\ E\left[Y_{k,t} | \text{non-crisis}_{k,t} = 1, \text{country}_k = 1\right] &= \alpha_2 + \beta_k \\ E\left[Y_{k,t} | \text{tranquil}_{k,t} = 1, \text{country}_k = 1\right] &= \alpha_3 + \beta_k \end{aligned} \qquad (4)$$

Bootstrapped confidence intervals on $\alpha_1 + \beta_k$, $\alpha_2 + \beta_k$ and $\alpha_3 + \beta_k$ are then obtained by running regression (1) on 1,000 bootstrapped data samples, resulting in country specific thresholds for the normal and danger zone.

A more general model with country specificities, structural features and state dependencies amounts to:

$$\begin{aligned} Y_{k,t} = {} & \left(\alpha_1 + \sum_i X_{k,t}^i \gamma_i^{\text{pre-crisis}}\right) \text{pre-crisis}_{k,t} + \left(\alpha_2 + \sum_i X_{k,t}^i \gamma_i^{\text{non-crisis}}\right) \text{non-crisis}_{k,t} + \\ & \left(\alpha_3 + \sum_i X_{k,t}^i \gamma_i^{\text{tranquil}}\right) \text{tranquil}_{k,t} + \sum_k \beta_k \text{country}_k + \sum_i X_{k,t}^i \gamma_i + \varepsilon_{k,t} \end{aligned} \qquad (5)$$

where $X_{k,t}^i$ are control variables reflecting the countries' structural macro-financial features. Signalling zones will in this case be time-varying, depending on the evaluation of $X_{k,t}^i$ at some point in time within a given country.

## 4. DATA AND EVALUATION METHOD

### 4.1. Data

In terms of country coverage, the database used in this study balances the desire to have as broad a sample as possible with both data availability and the increased reliability of thresholds when applied to a more homogeneous set of countries. Therefore, the analysis is based on 15 EU countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden and the United Kingdom) in the period 1970 to 2014.

#### 4.1.1. Identification of banking crises

The information on banking crises comes from a database compiled by Babecky et al. (2012), which provides quarterly data on the occurrence of banking crises in the EU from

1970 to 2012. The dataset is based on information on the timing of banking crises gathered from various sources: influential papers, the authors' own survey and country experts' opinions (mostly from national central banks).[11] The database reports crisis periods distinguishing whether "at least one source" or "at least two sources" confirmed the occurrence of a crisis[12]. We combine this information considering as banking crises all episodes confirmed by at least one source. As for marking the starting date of the identified banking crises, we give priority over the starting dates confirmed by at least two sources, when these deviate from the starting dates confirmed by at least one source.

This methodology leads us to identify 26 banking crisis episodes involving each of the 15 EU countries of our sample, as summarized in Table 3. There are 13 banking crises in the context of the recent financial crisis, and 13 banking crises during earlier episodes.

**Table 3**: List of banking crises

| **country** | **start** | **end** | **country** | **start** | **end** |
|---|---|---|---|---|---|
| Austria | 2008Q1 | 2008Q4 | Italy | 1994Q1 | 1995Q4 |
| Belgium | 2008Q1 | 2008Q4 | Luxembourg | 2008Q1 | 2008Q4 |
| Denmark | 1987Q1 | 1992Q4 | Netherlands | 2008Q1 | 2008Q4 |
| | 2008Q3 | 2008Q4 | Portugal | 2008Q1 | 2008Q4 |
| Finland | 1991Q1 | 1995Q4 | Spain | 1977Q1 | 1985Q4 |
| France | 1994Q1 | 1995Q4 | | 2008Q1 | 2008Q4 |
| | 2008Q1 | 2008Q4 | Sweden | 1991Q1 | 1994Q4 |
| Germany | 1974Q2 | 1974Q4 | | 2008Q3 | 2008Q4 |
| | 1977Q1 | 1979Q4 | United Kingdom | 1974Q1 | 1976Q4 |
| | 2008Q1 | 2008Q4 | | 1984Q1 | 1984Q4 |
| Greece | 1991Q1 | 1995Q4 | | 1991Q1 | 1995Q2 |
| | 2008Q1 | 2008Q4 | | 2007Q1 | 2007Q4 |
| Ireland | 1985Q1 | 1985Q1 | | | |
| | 2008Q1 | 2008Q4 | | | |

Source: Babecky et al. (2012).

### 4.1.2. Potential early warning indicators

We consider a broad set of macro-financial variables as potential leading indicators of banking crises. Data were collected for the aforementioned 15 EU countries from various sources, among which the ECB, OECD, BIS and Eurostat databases. The data are at a quarterly frequency and range from 1970Q1 to 2014Q2 for the series with the longest coverage.

The dataset consists of 4 categories of variables: credit variables (both structural and cyclical), real estate variables (both price and quantities), interest rates and other

[11] The Babecky et al. (2012) database can be freely downloaded at http://ies.fsv.cuni.cz/cs/node/372 (March 2014).

[12] In the papers surveyed by Babecky et al. (2012), banking crises are identified according to a systemic loss of bank capital, bank runs or the size of public intervention in the banking sector. The complete database can be freely downloaded at: http://ies.fsv.cuni.cz/cs/node/372.

macroeconomic variables.[13] Table 4 lists all the variables we consider by category; many of these have been found to be useful in predicting banking crises in previous studies.

**Table 4**: Overview of potential early warning indicators

| ***credit variables*** | ***real estate variables*** | ***other macroeconomic variables*** |
|---|---|---|
| Total private credit to GDP | Nominal residential real estate price growth | Nominal GDP growth |
| Household credit to GDP | Real residential real estate price growth | Real GDP growth |
| NFC credit to GDP | Price to income ratio | Unemployment rate |
| Bank credit to GDP | Price to rent ratio | Inflation rate |
| Non-bank credit to GDP | Price to income ratio growth | Current account deficit to GDP |
| Total private credit to GDP gap | Price to rent ratio growth | Real effective exchange rate |
| Household credit to GDP gap | Investment in dwellings to GDP | Government debt to GDP |
| NFC credit to GDP gap | Investment in other buildings to GDP | Government debt to GDP growth |
| Bank credit to GDP gap | Value added construction to GDP | Nominal stock market growth |
| Non-bank credit to GDP gap | **interest rates** | Real stock market growth |
| Total private credit growth | Nominal government 10y bond yield | |
| Household credit growth | Real government 10y bond yield | |
| NFC credit growth | Nominal 3m money market rate | |
| Bank credit growth | Real 3m money market rate | |
| Non-bank credit growth | Mortgage market rate | |
| Bank credit share | Floating mortgage market rate | |
| Non-bank credit share | Fixed mortgage market rate | |

Notes: Gaps are calculated as the deviation from the one-sided Hodrick-Prescott filter with λ=400,000. Price to income and price to rent levels are expressed as the percentage deviation of the all-sample average.

### 4.2. Evaluation method

For each of the indicators in Table 4, we obtain two thresholds based on the conditional moments approach outlined above as well as the commonly used binary early warning threshold derived from the policymaker's loss function. The policymaker's loss function trades off Type 1 and Type 2 errors and is of the following form: $L = \theta \times Type\ 1\ error + (1-\theta) \times Type\ 2\ error$, where the Type 1 error is the probability of not issuing a signal when a crisis follows, and the Type 2 error is the probability to issue a wrong signal. The higher the preference parameter $\theta$, the more importance is attached to correctly predicting crises (true positive rate or one minus Type 1 error) compared to avoiding false alarms (Type 2 error).

We evaluate the signalling power of the signals obtained from our conditional moments approach and from binary early warning thresholds. In particular, we consider (in-sample) true positive rates, false alarms rates and noise to signal ratios; lower false alarm rates and higher true positive rates result in lower noise to signal ratios.

[13] While it would be very interesting to consider indicators related to credit conditions (e.g., loan to value and debt service to income ratios) and the characteristic of the banking sector (e.g., leverage, profitability), these data are not available in sufficient time coverage for many countries.

## 5. RESULTS

In this section we present the results of the empirical approach outlined above. In particular, we first show the sensitivity of binary early warning thresholds and their signalling power for different assumptions on the policymaker's loss function (different $\theta$). Next, we compare the signalling power of the signals obtained from our pooled conditional moments approach to that from binary early warning thresholds. Finally, we investigate to what extent country-specific conditional moments-based signalling zones improve the signalling power compared to that of the pooled conditional moments approach.

For reasons of space constraints, we show results for the 5 indicators with the highest AUROC[14] for each of the 4 indicator categories in Table 4, as well as aggregate results across all indicators. Detailed results on all individual indicators are available from the authors upon request.

### 5.1. Sensitivity of binary early warning thresholds

The binary early warning thresholds derived from a policymaker's loss function are not only dependent on the empirical properties of the indicators for the countries considered, but also on assumptions on the objective function to be optimized for obtaining thresholds. Such objective functions could rely on different functional forms on the trade-off between Type 1 and Type 2 errors, such as the noise to signal ratio or a policymaker's loss function.

In the commonly used loss function-based approach, the functional form is determined by the value of the preference parameter $\theta$. Higher (lower) values of $\theta$ imply that more (less) importance is attached to correctly predicting crises compared to avoiding false alarms, thereby resulting in lower (higher) threshold values. Table 5 illustrates how threshold values, and consequently signalling power, differ for a range of values of $\theta$ between 0.3 and 0.7.

As expected, a low value of the preference parameter ($\theta$ =0.3) results in low false alarm rates (3 percent on average), but generally also in low ability of signalling crises (indicating 12 percent of pre-crisis quarters on average). In contrast, a high value of the preference parameter ($\theta$ =0.7) implies good crisis signalling performance (indicating 98 percent of pre-crisis quarters on average), but also a large false alarms rate (90 percent on average). In some cases, higher values of $\theta$ result in implausibly low threshold values (e.g., -3.79 for the total private credit to GDP gap).

[14] Area Under the Receiver Operating Characteristic curve, see Drehmann and Juselius (2013) and references therein. The ROC curve plots the indicator's TPR against the FPR for every possible value of the threshold. The area under the ROC-curve or AUROC ranges from 0 to 1: a value larger than 0.5 indicates that an indicator issues informative signals, while for a fully informative indicator the AUROC is 1. The AUROC is a robust evaluation criterion, as it assesses the indicator for all possible thresholds. Therefore, it does not rely on favourable values of the evaluation metrics for one specific potentially very narrow threshold range.

**Table 5**: Sensitivity of binary early warning thresholds

| | | ***θ* =0.3** | | | ***θ* =0.5** | | | ***θ* =0.7** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | AUROC | **threshold** | TPR | FPR | **threshold** | TPR | FPR | **threshold** | TPR | FPR | #crises |
| **credit variables** | | | | | | | | | | | |
| Household credit to GDP gap | 0.71 | **7.19** | 0.23 | 0.07 | **0.37** | 0.85 | 0.48 | **-0.26** | 0.94 | 0.66 | 21 |
| Household credit to GDP | 0.70 | **107.89** | 0.10 | 0.00 | **33.31** | 0.92 | 0.58 | **32.82** | 0.93 | 0.59 | 21 |
| Total private credit to GDP gap | 0.65 | **26.16** | 0.14 | 0.02 | **5.41** | 0.51 | 0.28 | **-3.79** | 0.95 | 0.81 | 24 |
| Bank credit to GDP gap | 0.65 | **18.40** | 0.15 | 0.02 | **5.86** | 0.40 | 0.18 | **-2.50** | 0.93 | 0.78 | 24 |
| Bank credit to GDP | 0.65 | **111.68** | 0.22 | 0.05 | **93.31** | 0.43 | 0.16 | **36.79** | 1.00 | 0.98 | 24 |
| **Real estate variables** | | | | | | | | | | | |
| Price to income ratio | 0.73 | **19.96** | 0.41 | 0.06 | **13.81** | 0.48 | 0.11 | **-23.50** | 0.98 | 0.83 | 20 |
| Price to rent ratio | 0.70 | **16.56** | 0.50 | 0.14 | **10.41** | 0.57 | 0.18 | **-29.92** | 0.96 | 0.83 | 23 |
| Price to income ratio growth | 0.66 | **8.59** | 0.33 | 0.10 | **7.43** | 0.39 | 0.15 | **-8.60** | 0.99 | 0.93 | 20 |
| Real residential real estate price growth | 0.62 | **17.47** | 0.11 | 0.03 | **7.82** | 0.45 | 0.20 | **-7.22** | 0.98 | 0.92 | 23 |
| Nominal residential real estate price growth | 0.60 | **32.29** | 0.06 | 0.02 | **10.25** | 0.53 | 0.33 | **-2.81** | 1.00 | 0.96 | 23 |
| **Interest rates** | | | | | | | | | | | |
| Nominal government 10y bond yield (-) | 0.70 | **4.05** | 0.60 | 0.07 | **4.05** | 0.60 | 0.07 | **15.01** | 1.00 | 0.94 | 19 |
| Real government 10y bond yield (-) | 0.68 | **1.83** | 0.49 | 0.16 | **2.44** | 0.68 | 0.27 | **2.48** | 0.99 | 1.00 | 17 |
| Fixed mortgage market rate (-) | 0.66 | **2.34** | 0.01 | 0.00 | **4.87** | 0.72 | 0.33 | **6.30** | 1.00 | 0.92 | 11 |
| Floating mortgage market rate (-) | 0.61 | **1.82** | 0.00 | 0.00 | **4.59** | 0.82 | 0.54 | **5.36** | 0.98 | 0.75 | 12 |
| Real 3m money market rate (-) | 0.59 | **-3.27** | 0.00 | 0.00 | **0.90** | 0.53 | 0.28 | **11.97** | 1.00 | 0.99 | 13 |
| **Other macroeconomic variables** | | | | | | | | | | | |
| Nominal stock market growth | 0.64 | **1.58** | 0.00 | 0.00 | **7.62** | 0.83 | 0.53 | **-5.59** | 0.95 | 0.71 | 20 |
| Real stock market growth | 0.64 | **1.50** | 0.00 | 0.00 | **4.20** | 0.88 | 0.55 | **-18.44** | 0.99 | 0.79 | 17 |
| Real effective exchange rate | 0.62 | **114.71** | 0.00 | 0.00 | **98.30** | 0.97 | 0.43 | **98.30** | 0.97 | 0.43 | 13 |
| Inflation rate | 0.60 | **13.51** | 0.00 | 0.00 | **1.64** | 0.84 | 0.67 | **1.27** | 0.96 | 0.80 | 17 |
| Nominal GDP growth | 0.59 | **23.12** | 0.00 | 0.00 | **3.77** | 0.88 | 0.69 | **2.97** | 0.95 | 0.79 | 19 |
| **Average all indicators** | 0.60 | - | 0.12 | 0.03 | - | 0.60 | 0.38 | - | 0.98 | 0.90 | 19.34 |

Notes: AUROC=Area Under the Receiver Operating Characteristic curve, TPR=true positive rate, FPR=false positive rate, #crises=the number of crises covered in the data sample available for the indicator. Indicators indicated with (-) have the opposite interpretation: the lower the indicator level, the higher the risk of an imminent banking crisis.

An intermediate value of the preference parameter ($\theta$ =0.5), where equal weight is attached to Type 1 and Type 2 errors, generally results in intermediate levels of crisis signalling performance (indicating 60 percent of pre-crisis quarters on average) and false alarm rates (0.38 percent on average). Substantial variation exists across indicators, however. Whereas some indicators (e.g., household credit to GDP variables, other macroeconomic variables) show a high true positive rate in combination with a relative large false positive rate, others (e.g., total private credit and bank credit variables, real estate variables) show lower false positive rates in combination with relatively low true positive rates.

### 5.2. **Pooled conditional moments approach vs. binary early warning thresholds**

Table 6 compares the signalling performance of our pooled conditional moments approach given by equations (1) and (2) to that of the binary early warning thresholds with equal weight attached to Type 1 and Type 2 errors ($\theta$ =0.5).

The second and third column ("not green" and "red") report the thresholds above which the indicator value is no longer in the green zone and entering the red zone, respectively. For example, a bank credit to GDP gap up to 2.05 is assumed to be safe; for values between 2.05 and 5.55 an intermediate signal is issued and for values above 5.55 a strong signal is issued. For indicators denoted with "-", the interpretation is the opposite; the lower the value of the indicator, the larger the risk of an imminent banking crises. For example, a floating mortgage market rate above 4.22 is consistent with the green zone; for rates between 3.60 and 4.22 an intermediate signal is issued, and for rates below 3.60 a strong signal is issued.

The threshold values determining the signalling zones compare with the binary early warning thresholds in the seventh column (threshold). The latter can be situated either in the green, red or intermediate signal zones of the conditional moments approach. For example, the binary early warning threshold on the household credit to GDP gap (0.37) is still in the green zone, which only ends above a level of 1.34. For the total private credit to GDP gap, the binary early warning threshold (5.41) is situated in the intermediate signals zone: indicators values above 3.74 are no longer in the green zone and the red zone only starts above 7.65. Finally, the bank credit to GDP binary early warning threshold (93.31) is situated in the red zone, which starts above 83.60.

The conditional moments signalling zone in which the binary early warning threshold is situated determines the relative signalling performance of the two approaches. If the binary early warning threshold is situated in the green (red) zone, it will have a higher (lower) true positive rate but also a higher (lower) false alarms rate, so there will be a trade-off between Type 1 and Type 2 errors when comparing the conditional moments framework to the binary early warning thresholds. If the latter are situated in the intermediate signals zone, this trade-off may still be there, but cases where either one of the methods in fact outperforms the other may also exist.

**Table 6**: Pooled conditional moments approach vs. binary early warning thresholds

| | *conditional moments* | | | | | ***θ* =0.5** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **notgreen** | **red** | TPR | FPR | NTS | **threshold** | TPR | FPR | NTS | #crises |
| **credit variables** | | | | | | | | | | |
| Household credit to GDP gap | **1.34** | **3.07** | 0.68 | 0.22 | 0.32 | **0.37** | 0.85 | 0.48 | 0.57 | 21 |
| Household credit to GDP | **47.27** | **56.28** | 0.52 | 0.24 | 0.46 | **33.31** | 0.92 | 0.58 | 0.62 | 21 |
| Total private credit to GDP gap | **3.74** | **7.65** | 0.55 | 0.22 | 0.40 | **5.41** | 0.51 | 0.28 | 0.56 | 24 |
| Bank credit to GDP gap | **2.05** | **5.55** | 0.53 | 0.19 | 0.36 | **5.86** | 0.40 | 0.18 | 0.45 | 24 |
| Bank credit to GDP | **75.38** | **83.60** | 0.59 | 0.25 | 0.43 | **93.31** | 0.43 | 0.16 | 0.37 | 24 |
| **real estate variables** | | | | | | | | | | |
| Price to income ratio | **-4.60** | **10.54** | 0.74 | 0.14 | 0.19 | **13.81** | 0.48 | 0.11 | 0.23 | 20 |
| Price to rent ratio | **-3.96** | **11.54** | 0.71 | 0.18 | 0.25 | **10.41** | 0.57 | 0.18 | 0.32 | 23 |
| Price to income ratio growth | **2.52** | **4.45** | 0.61 | 0.29 | 0.48 | **7.43** | 0.39 | 0.15 | 0.38 | 20 |
| Real residential real estate price growth | **4.31** | **5.57** | 0.55 | 0.32 | 0.58 | **7.82** | 0.45 | 0.20 | 0.44 | 23 |
| Nominal residential real estate price growth | **9.38** | **10.54** | 0.57 | 0.32 | 0.56 | **10.25** | 0.53 | 0.33 | 0.61 | 23 |
| **interest rates** | | | | | | | | | | |
| Nominal government 10y bond yield (-) | **6.64** | **6.58** | 0.68 | 0.51 | 0.75 | **4.05** | 0.60 | 0.07 | 0.12 | 19 |
| Real government 10y bond yield (-) | **3.35** | **2.88** | 0.74 | 0.37 | 0.50 | **2.44** | 0.68 | 0.27 | 0.40 | 17 |
| Fixed mortgage market rate (-) | **4.81** | **4.57** | 0.68 | 0.24 | 0.34 | **4.87** | 0.72 | 0.33 | 0.46 | 11 |
| Floating mortgage market rate (-) | **4.22** | **3.60** | 0.61 | 0.27 | 0.45 | **4.59** | 0.82 | 0.54 | 0.66 | 12 |
| Real 3m money market rate (-) | **2.47** | **2.21** | 0.70 | 0.53 | 0.76 | **0.90** | 0.53 | 0.28 | 0.54 | 13 |
| **other macroeconomic variables** | | | | | | | | | | |
| Nominal stock market growth | **16.39** | **18.65** | 0.59 | 0.35 | 0.60 | **7.62** | 0.83 | 0.53 | 0.63 | 20 |
| Real stock market growth | **15.64** | **15.97** | 0.56 | 0.36 | 0.65 | **4.20** | 0.88 | 0.55 | 0.62 | 17 |
| Real effective exchange rate | **99.79** | **101.20** | 0.51 | 0.24 | 0.46 | **98.30** | 0.97 | 0.43 | 0.45 | 13 |
| Inflation rate | **2.71** | **3.51** | 0.46 | 0.19 | 0.42 | **1.64** | 0.84 | 0.67 | 0.79 | 17 |
| Nominal GDP growth | **6.63** | **7.36** | 0.43 | 0.30 | 0.68 | **3.77** | 0.88 | 0.69 | 0.79 | 19 |
| **average all indicators** | **-** | **-** | 0.56 | 0.33 | 0.60 | **-** | 0.60 | 0.38 | 0.59 | 19.34 |
| **#higher TPR** | 24 | **#higher TPR and lower FPR** | | | | 7 | **# lower NTS** | | 27 | |
| **#lower FPR** | 27 | **#lower TPR and higher FPR** | | | | 0 | **# indicators** | | 44 | |

Notes: TPR=true positive rate, FPR=false positive rate, NTS=noise to signal ratio, #crises=the number of crises covered in the data sample available for the indicator, #higher TPR=number of cases where the pooled conditional moments approach has a true positive rate as least as large as that of the binary early warning threshold, #lower FPR=number of cases where the pooled conditional moments approach has a false positive rate as least as low as that of the binary early warning threshold, #higher TPR and lower TPR=number of cases where the pooled conditional moments approach has a true positive rate as least as large as that of the binary early warning threshold as well as a false positive rate a least as low as that of the binary early warning threshold, #lower TPR and higher FPR=number of cases where the pooled conditional moments approach has a true positive rate as least as low as that of the binary early warning threshold as well as a false positive rate a least as large as that of the binary early warning threshold, #lower NTS=number of cases where the pooled conditional moments approach has noise to signal ratio at least as low as that of the binary early warning threshold. “Notgreen” indicates the indicator level above which it is no longer in the green zone, “red” indicates the indicator level above which it is in the red zone. Indicators indicated with “-“ have the opposite interpretation: the lower the indicator level, the higher the risk of an imminent banking crisis. Hence, “notgreen” indicates the indicator level below which it is no longer in the green zone, “red” indicates the indicator level below which it is in the red zone.

The bottom two rows of Table 6 provide aggregate statistics comparing the signalling performance of the two methods. In 24 (27) out of 44 cases, the conditional moments framework has a true (false) positive rate at least as high (low) as the binary early warning threshold. In 27 out of 44 cases this results in a lower noise to signal ratio for the conditional moments approach. In 7 out of 44 cases, the conditional moments framework actually outperforms the traditional method. This is for example the case for the total private sector credit to GDP gap; the conditional moments approach results in a true positive rate of 55 percent and a false alarms rate of 22 percent, comparing to 51 and 28 percent for the binary early warning threshold.

On average, the conditional moments approach results in a slightly lower true positive rate (56 vs. 60 percent) and false positive rate (33 vs. 38 percent) than the binary early warning thresholds. The average noise to signal ratio is close to 0.60 for both methods.

In terms of indicators performance, the price to income and the price to rent ratio clearly outperform the other variables in terms of noise to signal ratio. These indicators are followed by credit variables, mortgage market rate variables[15] and the inflation rate. The latter correctly classifies less than half of the pre-crisis quarters, however.

### 5.3. The value added of accounting for country specificities

While signals obtained from the pooled conditional moments approach given by equations (1) and (2) may perform reasonably well for a number of indicators at the level of the entire sample of 15 EU countries, this may not necessarily be the case for signalling performance at the individual country level. In this subsection we therefore assess whether a country-specific conditional moments approach, as given by equations (3) and (4) improves signalling power, not only at the level of the entire sample of 15 EU countries (pooled evaluation), but also at the individual country level.

#### 5.3.1. Pooled evaluation

Table 7 presents the signalling performance at the level of the entire sample of 15 EU countries for country-specific conditional moments-based signalling zones based on equations (3) and (4). As for the thresholds marking the different zones, the mean, min and max across the 15 countries in our sample are shown. With a few exceptions, the average thresholds marking the end of the green zone and the start of the red zone are of broadly the same order of magnitude as the pooled conditional moments thresholds in Table 6. The min and max show that quite some variation may be observed across countries, however. For example, whereas for some countries bank credit to GDP levels over 100 percent are considered to be safe, bank credit to GDP levels around 70 percent may already mark a strong signal in other countries.

[15] The data sample for mortgage rates only covers crisis episodes from the recent financial crisis, which may positively affect signalling performance.

**Table 7**: Country-specific conditional moments approach

| | ***notgreen*** | | | ***red*** | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **mean** | min | max | **mean** | min | max | TPR | FPR | NTS | #crises |
| **credit variables** | | | | | | | | | | |
| Household credit to GDP gap | **1.09** | -2.43 | 4.93 | **3.02** | -0.12 | 6.53 | 0.87 | 0.19 | 0.22 | 21 |
| Household credit to GDP | **50.83** | 25.22 | 96.23 | **55.14** | 31.28 | 99.72 | 0.80 | 0.20 | 0.25 | 21 |
| Total private credit to GDP gap | **3.97** | -7.03 | 12.64 | **7.70** | 4.02 | 14.24 | 0.64 | 0.19 | 0.30 | 24 |
| Bank credit to GDP gap | **2.50** | -1.56 | 10.75 | **5.54** | 1.38 | 12.15 | 0.72 | 0.18 | 0.24 | 24 |
| Bank credit to GDP | **76.15** | 56.74 | 116.46 | **80.97** | 62.25 | 120.92 | 0.61 | 0.20 | 0.33 | 24 |
| **real estate variables** | | | | | | | | | | |
| Price to income ratio | **-2.58** | -7.52 | 7.22 | **10.52** | 4.44 | 19.14 | 0.70 | 0.15 | 0.23 | 20 |
| Price to rent ratio | **-1.79** | -9.30 | 3.89 | **11.86** | 4.67 | 18.97 | 0.67 | 0.16 | 0.60 | 23 |
| Price to income ratio growth | **2.95** | -1.42 | 6.09 | **3.70** | -0.13 | 6.10 | 0.54 | 0.32 | 0.58 | 20 |
| Real residential real estate price growth | **4.37** | -0.18 | 7.37 | **4.94** | 0.74 | 7.95 | 0.57 | 0.35 | 0.62 | 23 |
| Nominal residential real estate price growth | **9.05** | 1.76 | 14.20 | **9.59** | 2.54 | 14.25 | 0.55 | 0.33 | 0.61 | 23 |
| **interest rates** | | | | | | | | | | |
| Nominal government 10y bond yield (-) | **6.81** | 5.13 | 9.16 | **6.27** | 4.75 | 8.46 | 0.68 | 0.41 | 0.60 | 19 |
| Real government 10y bond yield (-) | **3.03** | 1.68 | 3.98 | **2.91** | 1.55 | 3.86 | 0.72 | 0.43 | 0.60 | 17 |
| Fixed mortgage market rate (-) | **4.78** | 3.58 | 5.72 | **4.60** | 3.43 | 5.46 | 0.72 | 0.23 | 0.32 | 11 |
| Floating mortgage market rate (-) | **4.32** | 3.70 | 4.95 | **3.58** | 2.90 | 4.37 | 0.72 | 0.18 | 0.25 | 12 |
| Real 3m money market rate (-) | **2.76** | 1.03 | 5.57 | **1.83** | 0.27 | 2.85 | 0.73 | 0.46 | 0.62 | 13 |
| **other macroeconomic variables** | | | | | | | | | | |
| Nominal stock market growth | **14.61** | 4.22 | 19.87 | **19.82** | 7.84 | 31.72 | 0.65 | 0.37 | 0.56 | 20 |
| Real stock market growth | **11.33** | 0.81 | 17.51 | **19.24** | 6.62 | 34.72 | 0.71 | 0.35 | 0.49 | 17 |
| Real effective exchange rate | **95.74** | 88.53 | 107.70 | **104.36** | 100.04 | 112.05 | 0.86 | 0.06 | 0.07 | 13 |
| Inflation rate | **2.62** | 1.57 | 4.99 | **3.36** | 2.09 | 6.41 | 0.48 | 0.20 | 0.42 | 17 |
| Nominal GDP growth | **5.91** | 3.06 | 9.90 | **7.90** | 4.97 | 12.85 | 0.57 | 0.28 | 0.48 | 19 |
| **average all indicators** | - | - | - | - | - | - | 0.62 | 0.28 | 0.47 | 19.34 |
| **#higher TPR** | 37 | **#higher TPR and lower FPR** | | | 29 | **# lower NTS** | | 36 | | |
| **#lower FPR** | 37 | **#lower TPR and higher FPR** | | | 5 | **# indicators** | | 44 | | |

Notes: TPR=true positive rate, FPR=false positive rate, NTS=noise to signal ratio, #crises=the number of crises covered in the data sample available for the indicator, #higher TPR=number of cases where the country-specific conditional moments approach has a true positive rate as least as large as that of the pooled approach, #lower FPR=number of cases where the country-specific conditional moments approach has a false positive rate as least as low as that of the pooled approach, #higher TPR and lower TPR=number of cases where the country-specific conditional moments approach has a true positive rate as least as large as that of the pooled approach as well as a false positive rate a least as low as that of the pooled approach, #lower TPR and higher FPR=number of cases where the country-specific conditional moments approach has a true positive rate as least as low as that of the pooled approach as well as a false positive rate a least as large as that of the pooled approach, #lower NTS=number of cases where the country-specific conditional moments approach has noise to signal ratio at least as low as that of the pooled approach. Notgreen indicates the indicator level above which it is no longer in the green zone, red indicates the indicator level above which it is in the red zone. Indicators indicated with (-) have the opposite interpretation: the lower the indicator level, the higher the risk of an imminent banking crisis. Hence, green indicates the indicator level below which it is no longer in the green zone, red indicates the indicator level below which it is in the red zone.

The average true positive rate amounts to 62 percent and the false alarms rate to 28 percent. Therefore, the country-specific conditional moments approach on average outperforms the pooled approach, which has average true and false positive rates of 56 and 33 percent, respectively. 37 out of 44 indicators have a true positive rate that is at least as high in the country-specific approach as in the pooled approach. The false alarms rate is also at least as low for 37 out of 44 indicators. The country-specific approach outperforms (both a at least as high true positive rate and a at least as low false positive rate) the pooled one in 29 out of 44 cases. This is for example the case for the three cyclical credit variables (gaps) in Tables 5 and 6. The country-specific approach is being outperformed by the pooled one for 5 indicators.

The average noise to signal ratio is also lower: 47 percent compared to 60 percent. 36 out of 44 indicators have a lower noise to signal ratio in the country-specific approach than in the pooled approach.

While price to income and price to rent ratios are still among the top performers in terms of noise to signal ratio, the ranking of best-performing indicators changes somewhat when accounting for country specificities. In particular, non-bank credit growth and the real effective exchange rate are now the two indicators with the lowest noise to signal ratio. For the remainder, credit variables and mortgage market rates again perform well, as well as investment in dwellings, investment in other buildings, and government debt related variables (not shown)[16].

#### 5.3.2. Country level evaluation

Table 8 compares the country level signalling performance of the pooled and the country-specific conditional moments approaches. The thresholds underlying the evaluations are given under the headers “notgreen” and “red” in Tables 6 and 7, respectively. For both approaches, the average true positive rate and false positive rate across the 15 countries in our sample is given, as well as the minimum and the maximum true and false positive rates observed across the individual countries.

[16] The latter three again only cover crisis episodes related to the recent financial crisis, however. This is also the case for the real effective exchange rate.

**Table 8**: Country level evaluation of pooled vs. country-specific conditional moments approach

| | *pooled* | | | | | | *country-specific* | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **TPR** | | | **FPR** | | | **TPR** | | | **FPR** | | | #crises |
| | **mean** | min | max | **mean** | min | max | **mean** | min | max | **mean** | min | max | |
| **credit variables** | | | | | | | | | | | | | |
| Household credit to GDP gap | **0.70** | 0.00 | 1.00 | **0.17** | 0.00 | 0.45 | **0.87** | 0.38 | 1.00 | **0.15** | 0.00 | 0.38 | 21 |
| Household credit to GDP | **0.53** | 0.00 | 1.00 | **0.28** | 0.00 | 1.00 | **0.86** | 0.00 | 1.00 | **0.24** | 0.01 | 1.00 | 21 |
| Total private credit to GDP gap | **0.51** | 0.00 | 1.00 | **0.22** | 0.01 | 0.51 | **0.59** | 0.00 | 1.00 | **0.20** | 0.05 | 0.42 | 24 |
| Bank credit to GDP gap | **0.54** | 0.00 | 1.00 | **0.18** | 0.00 | 0.48 | **0.72** | 0.00 | 1.00 | **0.16** | 0.00 | 0.31 | 24 |
| Bank credit to GDP | **0.56** | 0.00 | 1.00 | **0.24** | 0.00 | 1.00 | **0.62** | 0.00 | 1.00 | **0.20** | 0.00 | 0.70 | 24 |
| **real estate variables** | | | | | | | | | | | | | |
| Price to income ratio | **0.73** | 0.00 | 1.00 | **0.11** | 0.00 | 0.31 | **0.68** | 0.00 | 1.00 | **0.12** | 0.00 | 0.23 | 20 |
| Price to rent ratio | **0.79** | 0.50 | 1.00 | **0.14** | 0.00 | 0.34 | **0.71** | 0.00 | 1.00 | **0.12** | 0.00 | 0.28 | 23 |
| Price to income ratio growth | **0.55** | 0.00 | 1.00 | **0.28** | 0.00 | 0.69 | **0.51** | 0.00 | 1.00 | **0.31** | 0.00 | 0.69 | 20 |
| Real residential real estate price growth | **0.52** | 0.00 | 1.00 | **0.30** | 0.00 | 0.72 | **0.56** | 0.00 | 1.00 | **0.32** | 0.00 | 0.52 | 23 |
| Nominal residential real estate price growth | **0.54** | 0.00 | 1.00 | **0.29** | 0.00 | 0.62 | **0.56** | 0.00 | 1.00 | **0.30** | 0.00 | 0.45 | 23 |
| **interest rates** | | | | | | | | | | | | | |
| Nominal government 10y bond yield (-) | **0.73** | 0.00 | 1.00 | **0.53** | 0.31 | 0.86 | **0.73** | 0.00 | 1.00 | **0.43** | 0.26 | 0.61 | 19 |
| Real government 10y bond yield (-) | **0.78** | 0.00 | 1.00 | **0.37** | 0.13 | 0.73 | **0.75** | 0.00 | 1.00 | **0.41** | 0.14 | 0.71 | 17 |
| Fixed mortgage market rate (-) | **0.71** | 0.00 | 1.00 | **0.28** | 0.00 | 1.00 | **0.74** | 0.25 | 1.00 | **0.21** | 0.00 | 0.40 | 11 |
| Floating mortgage market rate (-) | **0.56** | 0.00 | 0.88 | **0.28** | 0.00 | 1.00 | **0.74** | 0.13 | 1.00 | **0.21** | 0.00 | 0.60 | 12 |
| Real 3m money market rate (-) | **0.72** | 0.00 | 1.00 | **0.53** | 0.18 | 0.71 | **0.75** | 0.00 | 1.00 | **0.44** | 0.24 | 0.61 | 13 |
| **other macroeconomic variables** | | | | | | | | | | | | | |
| Nominal stock market growth | **0.64** | 0.33 | 0.88 | **0.35** | 0.18 | 0.50 | **0.70** | 0.38 | 1.00 | **0.36** | 0.26 | 0.50 | 20 |
| Real stock market growth | **0.59** | 0.19 | 0.88 | **0.37** | 0.16 | 0.51 | **0.74** | 0.50 | 1.00 | **0.35** | 0.28 | 0.47 | 17 |
| Real effective exchange rate | **0.51** | 0.25 | 0.88 | **0.23** | 0.02 | 0.71 | **0.86** | 0.00 | 1.00 | **0.06** | 0.00 | 0.22 | 13 |
| Inflation rate | **0.46** | 0.00 | 1.00 | **0.19** | 0.00 | 0.64 | **0.47** | 0.00 | 1.00 | **0.19** | 0.06 | 0.38 | 17 |
| Nominal GDP growth | **0.40** | 0.00 | 1.00 | **0.30** | 0.00 | 0.83 | **0.58** | 0.00 | 1.00 | **0.27** | 0.16 | 0.35 | 19 |
| **average all indicators** | **0.56** | 0.00 | 1.00 | **0.33** | 0.00 | 1.00 | **0.62** | 0.00 | 1.00 | **0.27** | 0.00 | 1.00 | 19.34 |
| **#higher TPR** | 507 | | | **#higher TPR and lower TPR** | | | | | 214 | | **#country-indicator combinations** | | 646 |
| **#lower FPR** | 376 | | | **#lower TPR and higherTPR** | | | | | 138 | | | | |

Notes: TPR=true positive rate, FPR=false positive rate, NTS=noise to signal ratio, #crises=the number of crises covered in the data sample available for the indicator, #higher TPR=number of cases where the country-specific conditional moments approach has a true positive rate as least as large as that of the pooled approach, #lower FPR=number of cases where the country-specific conditional moments approach has a false positive rate as least as low as that of the pooled approach, #higher TPR and lower TPR=number of cases where the country-specific conditional moments approach has a true positive rate as least as large as that of the pooled approach as well as a false positive rate a least as low as that of the pooled approach, #lower TPR and higher FPR=number of cases where the country-specific conditional moments approach has a true positive rate as least as low as that of the pooled approach as well as a false positive rate a least as large as that of the pooled approach, #lower NTS=number of cases where the country-specific conditional moments approach has noise to signal ratio at least as low as that of the pooled approach. Notgreen indicates the indicator level above which it is no longer in the green zone, red indicates the indicator level above which it is in the red zone. Indicators indicated with (-) have the opposite interpretation: the lower the indicator level, the higher the risk of an imminent banking crisis. Hence, green indicates the indicator level below which it is no longer in the green zone, red indicates the indicator level below which it is in the red zone.

The average true and false positive rates across countries resulting from the country level evaluations in Table 8 are of similar orders of magnitude as the true and false positive rates of the pooled evaluations in Tables 6 and 7. At the same time, the min and max across countries shows that quite some variation exists in both signalling crises and issuing false alarms.

When comparing the signalling performance of the pooled conditional moments framework to that of the country-specific conditional moments framework, we find that on average (across all indicators), the country-specific signalling zones outperform the pooled approach; the average true positive rate is larger (62 compared to 56 percent) and the false alarms rate is lower (27 compared to 33 percent). When looking at averages across countries, this is also the case for all credit variables, the mortgage and money market rates, and the other macroeconomic variables.

Shifting to the country level, the country-specific conditional moments approach results in a true positive rate that is as least as large as that of the pooled approach in 507 out of 646 country-indicator combinations. In 376 out of 646 cases the false alarms rate is at least as low. Overall, the country-specific approach dominates (at least as large true positive rate and at least as low false alarms rate) the pooled one in 214 out of 646 cases. The reverse is true in 138 cases.

Hence, while allowing for country specificities improves signalling performance for a substantial amount of cases when evaluating performance at the pooled level, there seems to be more of a trade-off involving larger true positive rate but also larger false alarms rates at the individual country level. In the majority of cases in which a noise to signal ratio could be computed (315 out of 452), this trade-off resulted in a lower noise to signal ratio when country specificities where allowed for. The average noise to signal ratio amounted to 51 percent in the country-specific conditional moments approach, compared to 58 percent in the pooled conditional moments approach.

## 6. **CONCLUSIONS**

Sound macroprudential policy strategies includes the identification of leading indicators and associated thresholds signalling excessive developments that may lead to systemic risk. This paper presents a novel yet simple methodology to identify leading indicators and associated thresholds, with the aim of extracting signals useful to predict the occurrence of banking crises. Our methodology substantially improves on existing ones on three main grounds. First, the thresholds obtained are not dependent on arbitrary assumptions on the objective function to be optimized, but are based solely on the time and cross-country distribution of indicators. Secondly, our methodology results in the identification of signalling zones associated with different intensities of the warning issued. This provides an additional layer of information to the policymaker, which can be informed of a situation no longer consistent with “normal times” and as such worth monitoring closer, and receive a stronger signal associated with a lower risk of false alarms when indicators assume levels consistent with pre-crisis periods. Finally, the methodology can easily be extended to account for country specificities, structural features and state dependencies, allowing exploiting the entire cross-country information in the dataset while obtaining thresholds specific to a given country.

Comparing our conditional moments approach to the binary early warning thresholds based on a policymaker’s loss function with equal weight assigned to Type 1 and Type 2 errors, we find that on average, the signalling performance of our methodology is more or less similar to that of the traditional early warning method. Furthermore, allowing for country specificities improves signalling power of the conditional moments approach. While this generally holds at the individual country level, in many cases there nevertheless seems to be a trade-off involving larger true positive rates but also larger false alarms rates at the individual country level.

Therefore, we are currently extending the analysis with the aim of further improving the signalling performance at the level of individual countries, by controlling for structural features and state dependencies along the lines suggested in this paper.

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