Does one size fit all at all times? The role of country specificities and state dependencies in predicting banking crises

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by Stijn Ferrari and Mara Pirovano

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Abstract

Given the indisputable cost of policy inaction in the run-up to banking crises as well as the negative side effects of unwarranted policy activation, policymakers would strongly benefit from early-warning thresholds that more accurately predict crises and produce fewer false alarms. This paper presents a novel yet intuitive methodology to compute country-specific and state-dependent thresholds for early-warning indicators of banking crises. Our results for a selection of early-warning indicators for banking crises in 14 EU countries show that the benefits of applying the conditional moments approach can be substantial. The methodology provides more robust signals and improves the early-warning performance at the country-specific level, by accounting for country idiosyncrasies and state dependencies, which play an important role in national supervisory authorities' macroprudential surveillance.

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1. INTRODUCTION

Due to the severe repercussions financial crises can have on the real economy, safeguarding financial stability has become a priority for supervisory authorities worldwide. Compared to normal recessions, Jorda et al. (2013) find that the recession path of real GDP per capita in financial recessions is 4% lower. In absolute terms, Cerra and Saxena (2008) and Reinhart and Rogoff (2009a, b) estimate that financial crises lead to output losses in the order of, respectively, 7.5% and 9% of GDP.

The more pronounced costs of financially driven recessions originate from the tight feedback loops between the financial sector and the real economy, which can reinforce the economic dynamics after a negative shock. In particular, as shown by Kindleberger (1978), Schularik and Taylor (2012), Jorda et al. (2013) and Aikman et al. (2015), excessive credit booms have a pivotal role in preceding banking crises and in worsening their effects on the real economy. Strong credit growth drives surges in asset prices[1], and fuels borrowers' leverage. With elevated levels of outstanding debt, the pro-cyclical behaviour of prices leads to debt-deflation effects, which can be detrimental in downturn phases of the cycle. The seminal contributions of Kiyotaki and Moore (1997) and Bernanke et al. (1999) affirmed the pivotal importance of leverage in amplifying economic fluctuations. In fact, Mian and Sufi (2010) find that high leverage is a powerful predictor of the severity of the downturn experienced during the financial crisis of 2007-2009.

Against this background, in the aftermath of the financial crisis increased attention was devoted, from policymakers and academics alike, to the role of macroprudential policies in safeguarding financial stability (e.g. Hanson et al., 2011; Dell'Ariccia et al., 2012). Leading international organisations (e.g. European Systemic Risk Board (ESRB), 2014; International Monetary Fund (IMF), 2014) strongly encourage the development of sound macroprudential policy frameworks, involving the identification of leading indicators and associated thresholds signalling excessive developments that may lead to systemic risk.

Therefore, the recent years saw the flourishing of a growing body of new research on early-warning indicators for the occurrence of banking crises. 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. Several methodologies have been applied to the computation of thresholds in the signalling framework, such as non-parametric univariate and multivariate signalling (e.g. Borio and Drehmann, 2009; Alessi and Detken, 2011; Detken et al., 2014), discrete choice models (e.g., Babecký et al., 2013, 2014; Schularick and Taylor, 2012; Behn et al., 2013; Lo Duca and Peltonen, 2013; Caggiano et al., 2014; Detken et al., 2014; Anundsen et al., 2016; Caballero, 2016), and binary decision trees/random forests (e.g. Manasse and Roubini, 2009; Alessi and Detken, 2014).

[1] On bubbles and crises, see for instance Allen and Gale (2000).

A common trait of all these studies is that, due to the scarcity of crisis events for individual countries, cross-country data is used to compute a single threshold for all countries in the sample. Similarly, there is a tendency towards establishing common rules for the activation of macroprudential policy instruments. For example, the Basel Committee on Banking Supervision (BCBS) suggests that national authorities should activate the countercyclical capital buffer when the deviation of credit to GDP from its backward looking trend (the so-called credit to GDP gap) rises above two percentage points.

But does "one size" fit all? Similarly to the debate on the adequacy of a single monetary policy for a set of heterogeneous countries[2], a single early-warning threshold, considered to be optimal for a set of countries as a whole, could be sub-optimal at the individual country level. Structural differences across countries might warrant that rules for macroprudential policy activation be tailored to individual country needs. In their study on the operationalisation of the countercyclical capital buffer, Detken et al. (2014) highlight the need to further explore ways to account for country idiosyncrasies in early-warning models. Similarly, Davis and Karim (2008) conclude that pooled early-warning models for banking crises cannot be a substitute for country-specific macroprudential surveillance.

Against this backdrop, this paper presents a novel yet intuitive methodology to compute country-specific and state-dependent thresholds for early-warning indicators of banking crises. A conditional moments approach is proposed, which builds on the simple comparison of the average level of an indicator in pre-crisis periods in crisis countries and the average level of the indicator in normal times. Accounting for the dispersion around these average indicator levels both across countries and over time, the method then determines the interval over which the optimal signalling threshold is searched. That is, compared to traditional non-parametric signalling, the conditional moments constrain the interval in which the optimal threshold is situated. This approach makes the thresholds more robust to the specification of the policymaker's loss function (i.e. the objective function used to compute the optimal threshold) compared to the traditional early-warning threshold. Importantly, while relying on cross-country data, the methodology allows the interval and, therefore, the optimal threshold to be country-specific and state-dependent.

Using panel data on a number of potential early-warning indicators for banking crises for 14 EU countries, our results show that the benefits of applying the conditional moments approach with country specificities and state dependencies can be substantial. When evaluated in-sample, the model with country specificities and state dependencies is characterised by a better signalling performance than the traditional early-warning framework. In particular, for balanced preferences for Type I and Type II errors ($\theta=0.5$), relative usefulness increases on average from 0.34 to 0.45. When more weight is attached to missing crises ($\theta=0.7$), relative usefulness is on average 0.24 for the country-specific and state-dependent conditional moments compared to 0.13 for the traditional approach. Similarly, the noise to signal ratio is on average 0.39 compared to 0.44 for balanced preferences, and 0.59 compared to 0.81 when the aversion towards Type I errors is greater. The importance of accounting for country specificities and state dependencies is confirmed at the level of individual countries: country-specific and state-dependent conditional

2 See for instance Pirovano and Van Poeck (2011) and references therein.

moments result in a larger fraction of country/indicator pairs having a strictly positive relative usefulness relative to the traditional approach (80-90% compared to about 70%), and higher levels of relative usefulness for most country/indicator pairs. Similarly, when the aversion towards Type I errors is greater, country-specific and state-dependent conditional moments result in lower noise to signal ratios for almost all country/indicator pairs. More specifically, the fraction of country/indicator pairs with a noise to signal ratio lower than 0.5 amounts to almost 30% for conditional moments, whereas the equivalent figure for the traditional common approach is only about 10%. The role of country specificities and state dependencies is confirmed by an out-of-sample evaluation exercise. Overall, our results further show that the conditional moments-based thresholds and their signalling performance are more robust to the policymaker's relative preference for missing crises versus issuing false alarms than the traditional thresholds. Therefore, this methodology provides more robust signals and improves the early-warning performance at the country-specific level, by accounting for country idiosyncrasies and state dependencies, which play an important role in national authorities' macroprudential surveillance.

The remainder of the paper is organised as follows. Section 2 briefly outlines the signalling approach in the existing early-warning literature. Section 3 presents our novel conditional moments approach for determining country-specific and state-dependent early-warning thresholds. In Section 4 we present the data that are used for 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 for the occurrence of crises. In recent years, a special attention has been devoted to early-warning models as starting point for the operationalization of macroprudential policies, such as countercyclical capital buffers (e.g. Drehmann et al., 2011; Detken et al., 2014) and policy instruments targeting residential real estate (e.g. Ferrari et al. 2015).

From a statistical standpoint, studies on early-warning indicators primarily rely on signal extraction methods. The signalling approach, pioneered by Kaminsky and Reinhart (1999) and extended by, inter alia, Alessi and Detken (2011) focuses on issuing signals $S_{k,t}$ at time t in country k whenever the value $Y_{k,t}$ of a given indicator breaches a pre-defined threshold T:

$$\begin{cases} S_{k,t} = 0 \; if \; Y_{k,t} \leq T \\ \quad\;\; = 1 \; if \; Y_{k,t} > T \end{cases}$$

Then, the predictive abilities of the indicator 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. A signal is classified as correct if a crisis follows within the relevant prediction horizon (A); if a crisis does not follow, then the signal results in a false alarm (B). A non-issued signal 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

In several studies, optimal thresholds have been identified by minimising the noise to signal ratio, defined as the Type II error rate divided by one minus the Type I error rate:

$$NTS = \frac{B/(B + D)}{C/(A + C)}.$$

Given the drawbacks of this approach[3], Alessi and Detken (2011) propose to derive the optimal threshold by minimising 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). Optimal threshold identification involves a trade-off between missing crises and issuing false alarms: a lower threshold decreases the Type I error rate but at the same time increases the Type II error rate.

Given the optimal threshold value, evaluation measures for the signalling performance of the indicator can be calculated. Besides the noise to signal ratio, a commonly used measure is the relative usefulness, which expresses the policymaker's gain from using the indicator or model for predicting crises compared to disregarding it and always (or never) issuing a signal.[4] The relative usefulness measure takes the loss function as input and is defined as:

$$Relus = \frac{min[\theta, (1 - \theta)] - L}{min[\theta, (1 - \theta)]}.$$

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 (e.g. Borio and Drehmann, 2009; Alessi and Detken, 2011; Detken et al., 2014). 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 crises, while Alessi and Detken (2014) extend this approach to a "random forest" framework. The parametric or regression approach, implemented inter alia by Demirgüç-Kunt and Detragiache (1998) and more recently by Babecký et al. (2013, 2014), Behn et al. (2013), Lo Duca and Peltonen (2013), Caggiano et

[3] See for instance Drehmann et al. (2011).

[4] If a policymaker were to always issue a signal, the loss function would equal 1-θ. If a policymaker were to never issue a signal, the loss function would equal θ. Hence, the policymaker can always achieve a loss of $min[\theta, (1 - \theta)]$. The relative usefulness expresses the percentage reduction in the loss function of issuing signals on the basis of the indicator or model compared to the level $min[\theta, (1 - \theta)]$.

al. (2014), Detken et al. (2014), Anundsen et al. (2016) and Caballero (2016), usually involves the regression of a binary dependent variable, equal to one in the relevant prediction horizon before the onset of a financial crisis, on a set of explanatory variables. The resulting predicted probabilities are then used to assess the early-warning properties of the model.[5]

3. THE CONDITIONAL MOMENTS APPROACH FOR COUNTRY-SPECIFIC AND STATE-DEPENDENT EARLY-WARNING THRESHOLDS

3.1. Overview of the conditional moments approach

As mentioned above, optimal threshold identification involves a trade-off between missing crises and issuing false alarms. This trade-off is captured by the policymaker's loss function, and the optimal threshold results from minimizing this loss function. In the traditional early warning approach, this optimization is performed through a grid search over a large number of potential threshold values. As an illustration, the upper left-hand panel of Figure 1 shows, for the credit to GDP gap, the Type I (blue line) and Type II (red line) error rate across all countries in the sample as a function of different potential threshold values, as well as the optimal threshold based on a policymaker's loss function with equal weight on Type I and Type II errors. This optimal threshold for the credit to GDP gap equals 5.62, as denoted by the red dashed vertical line.

Compared to this traditional approach of obtaining early-warning thresholds, the conditional moments approach proceeds in two steps. First, an interval over which the optimal threshold is searched is derived. Second, within this interval of potential threshold values, the optimal threshold is obtained in the same way as in the traditional approach, by trading off Type I and Type II errors across all countries in the sample in the minimization of the policymaker's loss function. That is, compared to traditional non-parametric signalling, the conditional moments approach constrains the interval in which the optimal threshold is situated. This is illustrated in the lower left-hand panel of Figure 1, in which the black dashed vertical lines show that the range of possible values for the optimal threshold on the credit to GDP gap is restricted to the interval spanning from 2.27 to 9.12. The optimal conditional moments-based threshold for the credit to GDP gap amounts to 5.62 (denoted by the black vertical line), which, given that no country specificities or state dependencies were introduced, coincides with the traditional common threshold in the upper left-hand panel of Figure 1.

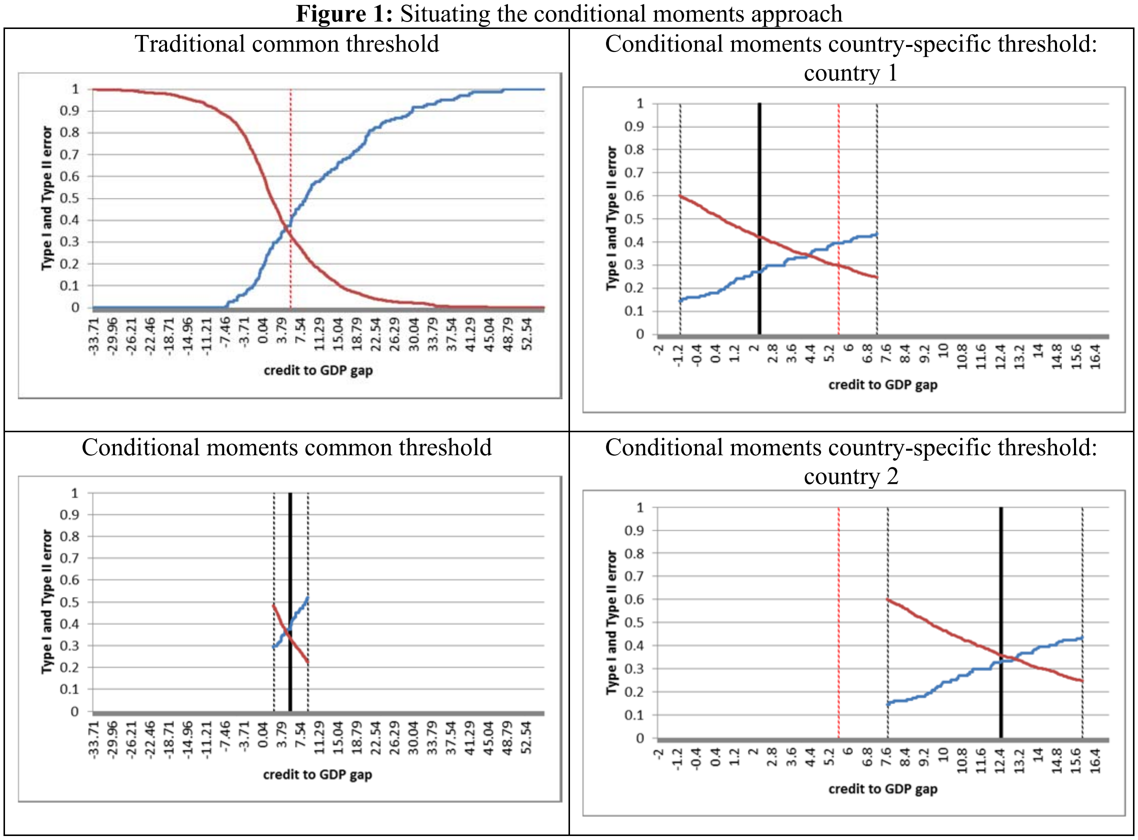
The economic intuition underlying the determination of the interval of potential threshold values in the first step assumes that indicator values (the credit to GDP gap in this example) below the lower bound of the interval (the left-hand black dashed vertical line) are consistent with "normal times". Similarly, indicator values above the upper bound of the interval (the right-hand black dashed vertical line) are consistent with "pre-crisis periods". Indicator values between these two thresholds, i.e. within the interval, may be

[5] Ferrari et al. (2015) compare the performance of the non-parametric and parametric approach in the context of real estate-related banking crises.

associated both with normal times and pre-crisis periods. The optimal threshold is situated in this interval, where there is a trade-off between Type I and Type II errors.

To identify such bounds for the interval, the approach builds on the simple comparison of the average level (or first moment) of an indicator in pre-crisis periods in crisis countries and the average level of the indicator in normal times (i.e. the conditional moments). However, rather than using these conditional moments as bounds for the interval of potential threshold values, the method accounts for the dispersion around these average indicator levels both across countries and over time. More specifically, the distribution of both conditional moments is derived, and the bounds of the interval of potential thresholds are obtained by choosing the percentiles of the two distributions that minimize the policymaker's loss function. In other words, both steps of the conditional moments approach, i.e. determining the interval of potential threshold values and selecting the optimal threshold in this interval, involve an optimization procedure.

Figure 1: Situating the conditional moments approach



Notes: The ascending blue line plots the Type I error as a function of the credit to GDP gap. The descending red line plots the Type II error as a function of the credit to GDP gap. The red dashed vertical line is the traditional early-warning threshold, whereas the black vertical lines are the optimal country-specific conditional moments-based thresholds. The bounds of the interval over which the latter is searched are indicated by the dashed black vertical lines.

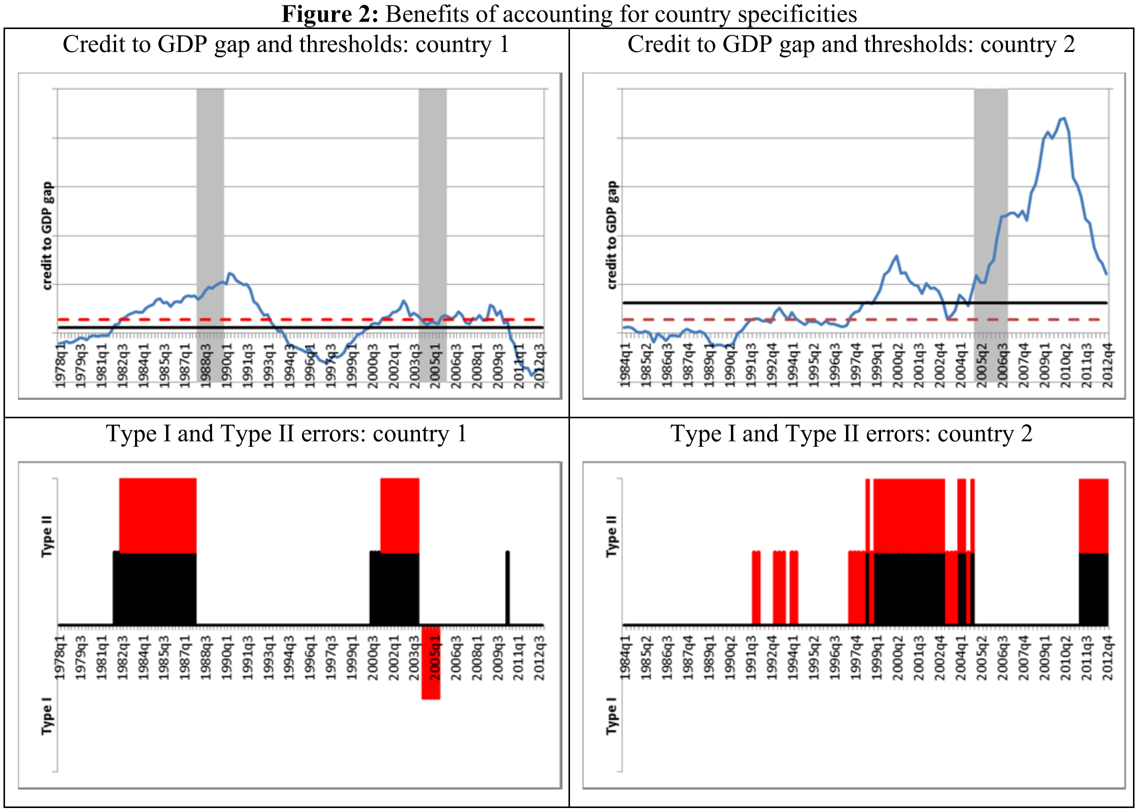
The conditional moments approach has two main advantages. First, constraining the interval over which the optimal threshold is searched makes the optimal threshold more robust to the specification of the policymaker's loss function compared to the traditional early-warning threshold. Second, contrary to existing studies, while relying on cross-country data[6], the methodology allows for deriving country-specific and state-dependent thresholds.

In particular, as illustrated in the right-hand panels of Figure 1, the conditional moments and therefore the interval of potential threshold values can be made country-specific. The upper right-hand panel shows that the interval of potential thresholds for the credit to GDP gap in the country under consideration ranges from -1.06 to 7.25 (black dashed vertical lines). For the second country, the interval of potential thresholds for the credit to GDP gap ranges from 7.68 to 15.90 (black dashed vertical lines in the lower right-hand panel). The optimal country-specific thresholds for the credit to GDP gap are obtained as explained earlier, by trading off Type I and Type II errors across all countries in the sample in the minimization of the policymaker's loss function. However, in this case, the grid of potential threshold values is country-specific. The resulting optimal threshold for the credit to GDP gap in the first country (the black vertical line in the upper right-hand panel) amounts to 2.29, which is lower than the traditional common threshold of 5.62 (indicated by the red dashed vertical line), but the latter is still situated in the interval from which the optimal conditional moments-based threshold is selected. The optimal threshold for the credit to GDP gap in the second country (black vertical line in the lower right-hand panel) amounts to 12.46, which is substantially larger than the traditional common threshold. In fact, the traditional threshold is no longer in the interval from which the optimal threshold is selected.

Figure 2 illustrates the benefits of the country-specific conditional moments-based thresholds in this example. The upper panels plot the credit to GDP gap over time for the two countries considered in the illustration. The values of the credit to GDP gap are considered in relation to two early warning thresholds: the traditional threshold, which is equal to 5.62 (red dashed line) in both cases, and the country-specific threshold obtained from the conditional moments (2.29 in country 1 and 12.46 in country 2, black line). When the credit to GDP gap exceeds the respective thresholds, a signal is issued. This signal is correct when the country is in a pre-crisis period (indicated by the grey shaded areas), and a false alarm if the country is in normal times.

[6] Using cross-country information ensures a sufficient coverage of crisis events in the sample. 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.

Figure 2: Benefits of accounting for country specificities



Notes: The blue line plots the credit to GDP gap over time. The red dashed horizontal line in the upper panels is the traditional early-warning threshold, whereas the black horizontal lines in the upper panels are the optimal country-specific conditional moments-based thresholds. The red areas below (above) the black horizontal line in the lower panels plot Type I (Type II) errors from signals obtained on the basis of the traditional threshold. The black areas below (above) the black horizontal line in the lower panels plot Type I (Type II) errors from signals obtained on the basis of the country-specific conditional moments-based threshold.

The lower panels in Figure 2 classify the signals received from the credit to GDP gap based on the two thresholds. Type I errors are plotted below the horizontal black line, while Type II errors are plotted above the horizontal black line. The left-hand panel shows that the lower country-specific threshold results in false alarms (the black area above the horizontal line) somewhat more often. On the other hand, it does identify both crises, whereas the traditional threshold largely fails to predict the second crisis (the red area below the horizontal line). The right-hand panel illustrates that the higher country-specific threshold for country 2 reduces the Type II error (smaller black than red area above the horizontal line), while at the same time not resulting in a larger Type I error.

Given the indisputable cost of policy inaction in the run-up to banking crises as well as the negative side effects of unwarranted policy activation, policy makers would strongly benefit from early-warning thresholds that more accurately predict crises and produce fewer false alarms. Such thresholds can be obtained by accounting for country specificities and state dependencies. While in principle, thresholds could be estimated on the basis of data for individual countries, crisis events in individual countries are too scarce to derive robust early-warning thresholds.

The conditional moments approach proposed in this paper fulfils the need for early-warning methodologies that identify robust country-specific thresholds in empirical settings that exploit pre-crisis information available in cross-country data. The estimation of thresholds under the conditional moments approach is further explained in the following two subsections. Before detailing the two-step procedure of deriving the optimal threshold, i.e. determining the interval over which the optimal threshold is searched in the first step and obtaining the optimal threshold in the second step, we explain how the conditional moments that are underlying the first step are estimated.

3.2. Estimating the conditional moments

To obtain the conditional moments, the sample of observations is divided in two subsamples: a "pre-crisis sample" and a "normal sample". Given a prediction horizon of 1 to 3 years before a banking crisis[7], observations in a window of 5 to 12 quarters before the onset of a banking crisis in countries that experienced a banking crisis are assigned to the pre-crisis sample. The remaining observations are part of the normal sample. The comparison between the conditional moments, i.e. the first moment of the pre-crisis sample and the normal sample, shows whether an indicator assumes, on average, higher levels before an imminent banking crisis than in normal times.

While these moments can be estimated non-parametrically[8], we apply the method in a linear regression framework. The baseline specification of the linear regression model is:

$$Y_{k,t} = \alpha_0 + \alpha_1 \text{pre-crisis}_{k,t} + \varepsilon_{k,t} \tag{1}$$

where $Y_{k,t}$ is the level of the early-warning indicator under consideration (e.g. the credit to GDP gap)[9] at time t in country k, $\textit{pre-crisis}_{k,t}$ is a dummy variable equal to 1 when the observation at time t in country k is in the pre-crisis subsample and zero otherwise, and $\varepsilon_{k,t}$ is an error term. The pooled conditional moments are then obtained as follows:

$$E\left[Y_{k,t} | \text{normal}_{k,t} = 1\right] = \alpha_0$$
$$E\left[Y_{k,t} | \text{pre-crisis}_{k,t} = 1\right] = \alpha_0 + \alpha_1$$

Note that the estimated coefficients α_0 and α_1 do not have a country-specific subscript, i.e. the pooled conditional moments are common across countries and time-invariant, estimated using pooled information only, relying on both cross-country and time variation

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[7] 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.

[8] See Ferrari and Pirovano (2014) for an implementation of an embryonic version of the methodology in a non-parametric framework.

[9] The methodology can also be implemented in a discrete choice framework. In this case, $Y_{k,t}$ would be the predicted probability of an estimated logit model regressing a dummy equal to 1 in the 5th to 12th quarter before the onset of a banking crisis on a series of potential early-warning indicators. The methodology can then be used to compute signalling thresholds for the predicted logit probabilities.

in the data. Hence, the pooled approach would result in common threshold for all countries and time periods in the sample.

The method is easily extended to account for country-specificities and/or state dependencies by adding country-specific and/or time-varying control variables $X_{k,t}^{i}$:

$$Y_{k,t} = \left(\alpha_0 + \sum_i X_{k,t}^{i}\, \gamma_{i,k}^{\text{normal}}\right) + \left(\alpha_1 + \sum_i X_{k,t}^{i}\, \gamma_{i,k}^{\text{pre-crisis}}\right) \text{pre-crisis}_{k,t} + \varepsilon_{k,t} \quad (2)$$

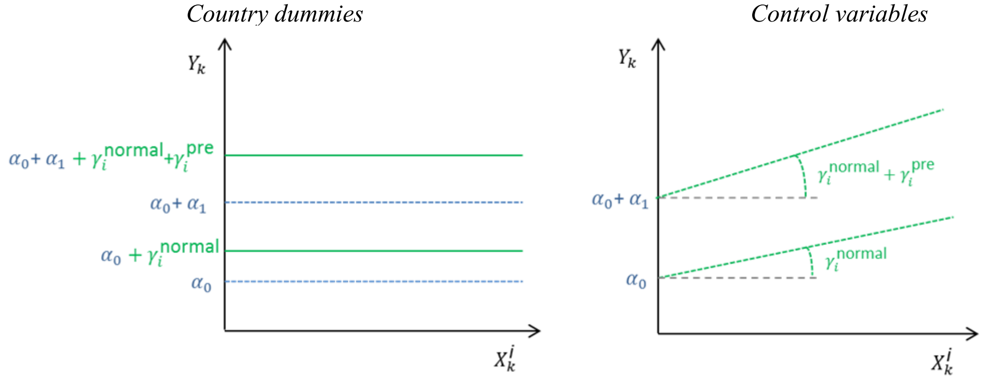
The country-specific and state-dependent conditional moments for country k at time t are obtained as follows:

$$E\left[Y_{k,t} | \text{normal}_{k,t} = 1, X_{k,t}^{i}\right] = \alpha_0 + \sum_i X_{k,t}^{i}\, \gamma_{i,k}^{\text{normal}}$$

$$E\left[Y_{k,t} | \text{pre-crisis}_{k,t} = 1, X_{k,t}^{i}\right] = \left(\alpha_0 + \sum_i X_{k,t}^{i}\, \gamma_{i,k}^{\text{normal}}\right) + \left(\alpha_1 + \sum_i X_{k,t}^{i}\, \gamma_{i,k}^{\text{pre-crisis}}\right)$$

Hence, the control variables $X_{k,t}^{i}$ make the conditional moments country-specific and/or time-varying, resulting in country-specific and/or time-varying signalling thresholds. Country dummy variables are the most straightforward way of accounting for country-specificities. In particular, the simple country dummy variables, resulting in the parameter estimates $\gamma_{i,k}^{\text{normal}}$, account for differences in the average level of $Y_{k,t}$ across countries. The country dummies capture structural cross-country differences that may lead to different average levels in the early-warning indicator (e.g. the credit to GDP gap) under consideration. The interactions of these dummy variables with the pre-crisis dummy, resulting in the parameter estimates $\gamma_{i,k}^{\text{pre-crisis}}$, account for differences in the average level of $Y_{k,t}$ in pre-crisis periods in countries that experienced a crisis. These effects are illustrated in the left-hand panel of Figure 3: the dashed blue lines correspond to the estimated coefficients of model (1), while the solid green lines correspond to the estimated coefficients of model (2) where $X_{k,t}^{i}$ is a dummy variable equal to 1 for country k. The country dummies do not result in time variation in the thresholds, but do result in different levels across countries.

Figure 3: Effect of country dummies and control variables on Y_k



Notes: The blue dashed horizontal lines present the pooled conditional moments. The green lines show the effect of introducing country dummies and continuous control variables, respectively, in the conditional moments equation.

Continuous control variables, on the other hand, account for the fact that the average effect of $Y_{k,t}$ might differ according to developments in countries' macro-financial features. When $X_{k,t}^i$ is a control variable, the parameter estimate $\gamma_{i,k}^{\text{normal}}$ represents the marginal effect of the control variable $X_{k,t}^i$ when it assumes a specific value $x_{k,t}^i$. A value $\gamma_{i,k}^{\text{normal}}>0$, as assumed in the right-hand panel of Figure 3, implies that the average level of $Y_{k,t}$ increases for larger values of $X_{k,t}^i$. The interactions of these control variables with the pre-crisis dummy, resulting in the parameter estimates $\gamma_{i,k}^{\text{pre-crisis}}$, account for differences in the average level of $Y_{k,t}$ for different values of $X_{k,t}^i$ in pre-crisis periods in countries that experienced a crisis. It is important to note that when time-varying control variables are included in the model, the estimated conditional moments will be time-varying, depending on the specific point in time chosen for evaluating $X_{k,t}^i$. That is, the derived early-warning thresholds will not only be country-specific, but are also state-dependent.

Note that, in contrast to α_0 and α_1, the estimated coefficients $\gamma_{i,k}^{\text{normal}}$ and $\gamma_{i,k}^{\text{pre-crisis}}$ can be country-specific. This is obviously the case for country dummies, but country-specific coefficients may also be identified for time-varying control variables from the country-specific time variation in the data. In the remainder of the paper, $X_{k,t}^i$ consists of either country dummies only or country dummies in combination with time-varying control variables that capture the countries' business cycle. As robust identification of country-specific coefficients of control variables (both country dummies and time-varying control variables) interacted with the pre-crisis dummy is only possible if the sample contains a sufficient number of crises in the individual countries, we do not consider the interaction of control variables with the pre-crisis dummy in our empirical application. Instead, the reported results will be on the basis of the following model:

$$Y_{k,t} = \left(\alpha_0 + \textstyle\sum_i X_{k,t}^i \gamma_{i,k}^{\text{normal}}\right) + \alpha_1 \text{pre-crisis}_{k,t} + \varepsilon_{k,t} \qquad (3)$$

This model allows for country-specific and time-varying levels of the conditional moments, but the difference between the moment for the "pre-crisis" sample and the one for the "normal" sample is common across countries and time-invariant.

3.3. Determining thresholds

As explained above, thresholds are determined in two steps. First, the method accounts for the dispersion around the conditional moments (the first moments of the pre-crisis and normal subsamples) in order to determine the interval of potential threshold values. Second, the optimal threshold is selected from the values in this interval.

3.3.1. Interval of potential threshold values

For the derivation of the interval of potential thresholds in the first step we introduce the concepts of the "pre-crisis zone" and the "normal zone"; the bounds of the pre-crisis zone and the normal zone will in fact determine the bounds of the interval of potential threshold values.

The bounds of the pre-crisis zone and the normal zone are derived from the distributions of the respective conditional moments, i.e. the distribution of the first moment of the normal sample and the distribution of the first moment of the pre-crisis sample. These distributions are obtained by applying the delta method to equation (1) or (3).[10] We consider as the normal zone those indicator levels $Y_{k,t}$ below the p^{normal}-th percentile of the distribution of the first moment of the normal sample. We consider as the pre-crisis zone those indicator levels $Y_{k,t}$ above the $p^{pre-crisis}$-th percentile of the distribution of the first moment of the pre-crisis sample. That is, the upper bound of the normal zone, $U_{k,t}^{normal}$, coincides with the p^{normal}-th percentile of the distribution of the first moment of the normal sample and the lower bound of the pre-crisis zone, $L_{k,t}^{pre-crisis}$, coincides with the $p^{pre-crisis}$-th percentile of the distribution of the first moment of the pre-crisis sample.

The interval of potential threshold values is given by $[T_{k,t}^1, T_{k,t}^2]$. Indicator levels below $T_{k,t}^1 = min(U_{k,t}^{normal}, L_{k,t}^{pre-crisis})$ are situated in the normal zone and not in the pre-crisis zone, and therefore, consistent with "normal times". Indicator values that are situated above $T_{k,t}^2 = max(U_{k,t}^{normal}, L_{k,t}^{pre-crisis})$ are in the pre-crisis zone and at the same time not in the normal zone, and therefore, consistent with "pre-crisis periods". Values between $T_{k,t}^1$ and $T_{k,t}^2$ may be associated with both normal times and pre-crisis periods.

As mentioned, the bounds of the interval of potential threshold values $T_{k,t}^1$ and $T_{k,t}^2$ are determined by the p^{normal}-th percentile of the distribution of the first moment of the normal sample and the $p^{pre-crisis}$-th percentile of the distribution of the first moment of the pre-crisis sample (also see Figure 4 in Section 3.4). While the levels p^{normal} and $p^{pre-crisis}$ could be set to ad-hoc levels based on economic intuition (e.g. 95 and 5, respectively), we opt for selecting them optimally by minimizing the policymaker's loss function.

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[10] The delta method allows computing the standard errors of the conditional moments on the basis of the standard errors of the estimated regression coefficients in equation (1) or (3), which, under the normality assumption, can be used to derive the distributions of the conditional moments. The less significant the regression coefficients in equation (1) or (3), the wider will be the distribution of the conditional moments. Alternatively, a bootstrap procedure could be applied, in which equation (1) or (3) is estimated many times on random samples to obtain the distributions of the conditional moments.

To this end, the bounds of the interval for potential threshold values, $T^1_{k,t}$ and $T^2_{k,t}$, are mapped into three signalling zones for the indicator. In particular, for indicator levels below $T^1_{k,t}$, which are consistent with normal times, no signal is issued. Indicator values that are situated above $T^2_{k,t}$, which are consistent with pre-crisis periods, lead to the issuance of a strong signal. Values between $T^1_{k,t}$ and $T^2_{k,t}$ may be associated with both normal times and pre-crisis periods, trigger the issuance of an intermediate signal, with the strength of the signal increasing linearly when moving from $T^1_{k,t}$ to $T^2_{k,t}$. Compared to levels above $T^2_{k,t}$, which trigger a strong signal, levels between $T^1_{k,t}$ and $T^2_{k,t}$ will provide an earlier signal (smaller Type I error), but also with the risk of more false alarms (larger Type II error). Therefore only an intermediate signal is issued between $T^1_{k,t}$ and $T^2_{k,t}$. In particular, the strength of the signal $S_{k,t}$ for country k received at time t is

$$\begin{cases} S_{k,t} = 0 \; if \; Y_{k,t} \leq T^1_{k,t} \\ \quad = \frac{Y_{k,t} - T^1_{k,t}}{T^2_{k,t} - T^1_{k,t}} \; if \; T^1_{k,t} \leq \; Y_{k,t} \leq T^2_{k,t} \\ \quad = 1 \; if \; Y_{k,t} \geq T^2_{k,t} \end{cases} \qquad (4)$$

Given the strength of the signal in expression (4), the thresholds $T^1_{k,t}$ and $T^2_{k,t}$ can be chosen optimally by minimizing the policymaker's loss function in function of p^{normal} and $p^{pre-crisis}$. Note that the search for the optimal percentiles results in an optimal p^{normal} and $p^{pre-crisis}$ that is common to all countries and time periods in the sample. However, the distributions from which these optimal percentiles are taken may be country-specific and state-dependent, thereby resulting in country-specific and time-varying bounds ($T^1_{k,t}$ and $T^2_{k,t}$) of the interval from which the optimal threshold will be selected. That is, the interval of potential threshold can vary across countries and over time.

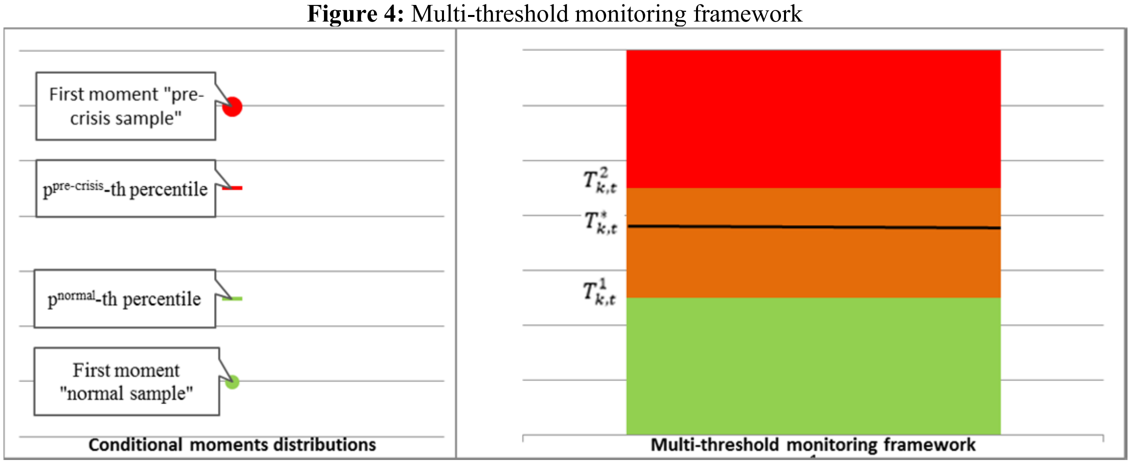
3.3.2. Optimal threshold

In the next step, the optimal threshold $T^*_{k,t}$ is derived by minimizing the policymaker's loss function, conditional on $T^*_{k,t}$ being situated between $T^1_{k,t}$ and $T^2_{k,t}$. That is, while the method follows exactly the same approach as used for determining the traditional threshold, in this case the range of values over which the optimal threshold is searched is limited to the area $[T^1_{k,t}, T^2_{k,t}]$ rather than the entire range of indicator levels. As shown in Section 5, this has the advantage of resulting in an optimal signalling threshold that is more robust to the choice of the preference parameter θ in the policymaker's loss function. Furthermore, as explained above, country-specificities and state dependencies can be introduced, resulting in an optimal threshold that is allowed to vary across countries and over time.

3.4. Multi-threshold monitoring framework

While an optimal threshold $T^*_{k,t}$ is derived in the conditional moments approach, the methodology results in a multi-threshold early-warning monitoring framework. In the traditional approach, the single threshold identifies two states: a signal is issued when the indicator exceeds the threshold, and no signal is issued otherwise. In contrast, the presence of three signalling zones determined by thresholds $T^1_{k,t}$ and $T^2_{k,t}$ provides policymakers with more granular signals of different intensity. In particular, for indicator levels below $T_{k,t}^{1}$, which are consistent with normal times, no signal is issued. Indicator values that are situated above $T_{k,t}^{2}$, which are consistent with pre-crisis periods, lead to the issuance of a strong signal. Values between $T_{k,t}^{1}$ and $T_{k,t}^{2}$ may be associated with both normal times and pre-crisis periods, trigger the issuance of an intermediate signal, with the strength of the signal increasing linearly when moving from $T_{k,t}^{1}$ to $T_{k,t}^{2}$. Hence, as illustrated in the right-hand panel of Figure 4, an indicator breaching the lower threshold $T_{k,t}^{1}$ could be a signal for policymakers to start an in-depth analysis of the identified vulnerability and consider policy options for potential implementation when a stronger signal, in the form of breaching the optimal threshold $T_{k,t}^{*}$, is received. Furthermore, the strength of the signal received once the optimal threshold is breached, i.e. being in the orange zone (between $T_{k,t}^{*}$ and $T_{k,t}^{2}$) or in the red zone (above $T_{k,t}^{2}$), could be used as input in the calibration of the policy measure.

Figure 4: Multi-threshold monitoring framework



4. DATA

The empirical analysis is based on 14 countries: 12 euro area countries (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal and Spain) and three EU countries (Denmark, Sweden and the United Kingdom) in the period ranging from 1970 to 2015. Two types of variables are needed to perform the analysis: a set of potential leading indicators whose early-warning properties are tested, and information on the onset of banking crises in the relevant countries.

4.1. Early-warning indicators and control variables

As the aim of the paper is to illustrate the benefits of our new methodology rather than to provide an exhaustive analysis of potential early-warning indicators for banking crises, we opt for a limited set of indicators that is known to have relatively good signalling performance: indicators related to the supply of credit and indicators related to residential real estate prices.

Credit supply indicators, sourced from the BIS database, encompass broad credit to the private sector, bank credit and credit granted to households (HH), expressed as a percentage of GDP. For the indicators of real estate prices, we rely on OECD data on nominal real estate prices and the nominal real estate price-to-income ratio (the latter expressed in percentage deviations from the all-sample average). Data on the total debt service ratio and the debt service ratio of households are sourced from the dataset used by Detken et al. (2014) for their analysis on indicator selection and threshold identification for the operationalisation of the countercyclical capital buffer. Other than the levels of indicators, we consider the year-on-year growth rate and the gap from the backward-looking trend, referred to as "gap"[11]. The data for the 14 countries are at a quarterly frequency ranging from 1970Q1 to 2015Q3 for the series with the longest coverage. One quarter lags are implemented for all variables (except for market variables), to account for publication lags. The top panel of Table 2 provides summary statistics of the 14 selected indicators.

Table 2: Summary statistics of early-warning indicators (***Y***) and control variables (***X***)

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Early-warning indicators					
Bank credit to GDP gap	1645	3.45	9.79	-41.20	42.84
Broad credit to GDP gap	1645	5.87	13.38	-33.71	88.14
Broad HH credit to GDP gap	1465	1.30	4.71	-22.80	15.53
Nominal bank credit growth	1643	0.09	0.07	-0.22	0.42
Nominal broad credit growth	1643	0.09	0.06	-0.10	0.40
Nominal broad HH credit growth	1437	0.10	0.08	-0.07	0.41
Debt service ratio	1610	18.13	5.62	8.53	43.72
Debt service ratio growth	1598	0.33	1.42	-8.53	6.73
HH debt service ratio	1229	13.05	5.23	4.87	29.25
HH debt service ratio growth	1186	0.32	0.95	-3.60	4.03
Nominal RRE price gap	1586	1.86	9.29	-51.77	32.64
Nominal RRE price growth	1579	0.06	0.08	-0.21	0.71
Price to income	1464	100.84	21.51	60.75	177.34
Change in price to income	1441	0.01	0.07	-0.20	0.33
Control variables					
real GDP growth	1645	2.26	2.74	-10.20	15.60
inflation rate	1645	3.54	3.16	-6.11	21.80
3 month money market rate	1645	6.12	4.49	0.16	45.66
equity price growth	1645	0.10	0.28	-0.65	1.91

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

Similarly, the aim of this paper is not to find the optimal set of control variables for each indicator in the sample, but rather to show that, for a given set of control variables, the conditional moments approach that incorporates country specificities and state dependencies may improve signalling performance. When estimating the model as specified in equation (2), the following control variables are considered: the year-on-year

[11] Gaps are calculated as the deviation from the one-sided Hodrick-Prescott filter with λ=400,000.

growth of real GDP, inflation, nominal equity prices growth and the nominal 3-month market rate[12]. These variables aim at capturing the business cycle, developments on financial markets as well as the stance of monetary policy. Summary statistics are provided in the bottom panel of Table 2.

4.2. Identification of banking crises

The starting dates of banking crises reported in Table 3 are based on a combination of several recent sources, including Laeven and Valencia (2008, 2012), Behn et al. (2013), Babecký et al. (2014), Detken et al. (2014) and Anundsen et al. (2016). After controlling for the availability of data for the control variables in Table 2, our sample covers 19 banking crisis episodes.

Table 3: List of banking crises

Start date	***Countries***
1974Q2	Germany
1987Q1	Denmark
1990Q3	Sweden
1991Q1	Finland, United Kingdom
1994Q1	France, Italy
2007Q1	United Kingdom
2008Q1	France, Germany, Greece, Ireland, Netherlands,
2008Q3	Austria, Belgium, Denmark, Portugal, Spain, Sweden

Source: The starting dates of banking crises are based on a combination of several recent sources, including Laeven and Valencia (2008, 2012), Behn et al. (2013), Babecký et al. (2014), Detken et al. (2014) and Anundsen et al. (2016).

Of these 19 crisis episodes, two thirds are clustered around the 2007-2008 global financial crisis, while seven crisis episodes occurred before the global financial crisis and tend to be clustered in the period from the late eighties to the mid-nineties. While banking and financial crises tend to share a number of similarities in terms of economic growth patterns, asset price inflation, credit growth and debt accumulation in the run-up, each one presents distinctive features regarding specific causes, nature and severity (e.g. Reinhart and Rogoff, 2008; Connolly, 2009). This heterogeneity is reflected in our crisis sample, which contains both systemic banking crises affecting large parts of countries' banking systems (e.g., the Nordic crisis in the early nineties, the global financial crisis) and less systemic more isolated events (e.g., Germany in the seventies, the Danish crisis at the end of the eighties, the crises in France, Italy and the United Kingdom in the nineties).

The information on the starting dates of the crises is used to generate the "pre-crisis" dummy variable, which is equal to 1 in the 12 to 5 quarters prior to the onset of a crisis, set to missing during the 4 quarters prior to a crisis and the 12 quarters starting from the onset

[12] Data on control variables is sourced from the OECD database.

of the crisis[13], and to 0 in all remaining quarters. Consequently, the "normal" sample includes all observations for which the "pre-crisis" dummy is set to zero.

5. RESULTS

In this section we present the results of the empirical approach outlined above. Based on an in-sample exercise, we compare the signalling performance of the optimal thresholds obtained with our novel methodology to that of the traditional common thresholds and show how country-specificities and state dependencies can improve early-warning performance. Furthermore, we show that conditional moments-based thresholds are more robust to the choice of the preference parameter θ in the policymaker's loss function. Finally, we perform an out-of-sample exercise to assess the robustness of the main findings.

5.1. In-sample evaluation

In the in-sample case, the conditional moments and associated optimal thresholds are estimated over the sample ranging from 1970Q1 to 2012Q4, and their signalling performance is evaluated over the aforementioned prediction sample. Results are provided on the signalling performance computed both across all countries in the sample (Tables 4-6) and at the level of the individual countries in the sample (Figure 5).

Table 4 compares, for balanced preferences for Type I and Type II errors (θ=0.5), the relative usefulness of thresholds based on different versions of the conditional moments to the traditional common threshold. The columns under "CM pooled" show the results when the conditional moments of the pre-crisis sample and the normal sample are estimated on the basis of equation (1); the results in the columns named "CM country dummies" and "CM country dummies and controls" are based on conditional moments obtained from equation (3), estimated respectively with country dummies and country dummies plus control variables capturing the state of the business cycle.

[13] The behavior of economic indicators is markedly different in crisis times than in normal times. Since the objective is to compare the average evolution of indicators in pre-crisis and normal times, crisis quarters are dropped from the sample.

Table 4: Traditional vs conditional moments: relative usefulness (θ=0.5)

	Observations		Traditional		CM pooled		CM country dummies		CM country dummies and controls	
Indicator	**Pre-crisis**	**Normal**	**Thres-hold**	**Relus**	**Thres-hold**	**Relus**	**Thres-hold**	**Relus**	**Thres-hold**	**Relus**
Bank credit to GDP gap	144	1182	8.03	0.31	8.03	0.31	1.49	0.36	4.79	0.49
Broad credit to GDP gap	144	1182	5.62	0.29	5.62	0.29	4.42	0.34	5.53	0.39
Broad HH credit to GDP gap	144	1015	1.05	0.38	1.05	0.38	1.45	0.42	1.65	0.53
Nominal bank credit growth	144	1180	0.11	0.26	0.11	0.26	0.13	0.34	0.13	0.43
Nominal broad credit growth	144	1180	0.14	0.23	0.13	0.23	0.14	0.24	0.11	0.26
Nominal broad HH credit growth	141	990	0.10	0.34	0.10	0.31	0.12	0.29	0.14	0.38
Debt service ratio	136	1155	19.44	0.31	19.44	0.31	17.88	0.44	16.50	0.46
Debt service ratio growth	136	1147	0.63	0.43	0.63	0.43	0.39	0.43	0.29	0.44
HH debt service ratio	128	829	11.83	0.29	11.83	0.29	11.65	0.42	12.37	0.55
HH debt service ratio growth	128	786	0.69	0.43	0.69	0.43	0.38	0.45	0.59	0.45
Nominal RRE price gap	144	1123	8.71	0.43	8.71	0.43	3.60	0.45	4.01	0.53
Nominal RRE price growth	144	1116	0.10	0.31	0.10	0.31	0.09	0.32	0.09	0.41
Price to income	136	1026	111.78	0.39	111.80	0.39	115.68	0.45	105.98	0.63
Price to income growth	135	1004	0.06	0.32	0.06	0.32	0.01	0.32	0.03	0.36
Average	**139**	**1065**		**0.34**		**0.34**		**0.38**		**0.45**

Notes: "Traditional" shows the results for the traditional common threshold. "CM pooled" shows the results when the conditional moments of the pre-crisis sample and the normal sample are estimated on the basis of equation (1); the results in the columns named "CM country dummies" and "CM country dummies and controls" are based on conditional moments obtained from equation (3), estimated respectively with country dummies and country dummies plus control variables capturing the state of the business cycle. "Observations" is the number of quarterly observations in the evaluation sample. "Relus" is relative usefulness.

For balanced preferences, thresholds derived from the pooled conditional moments approach are identical to the traditional common thresholds, resulting in the same early-warning performance. This is not surprising, since whereas the traditional approach searches for the optimal threshold over the entire data range, the conditional moments approach constrains the interval in which the optimal threshold is situated. Therefore, when conditional moments do not include country specificities and are time-invariant, we do not expect to obtain thresholds much different from the traditional ones.

Adding country dummies in the estimation of the conditional moments of the pre-crisis sample and the normal sample in equation (3) improves the relative usefulness on average from 0.34 to 0.38. The improvement is quite substantial for the debt service ratio variables (in levels), bank credit growth, price to income and the credit gap variables. When adding to the country dummies in equation (3) state dependencies as captured by the four control variables discussed in Section 4, relative usefulness shows an even stronger average improvement (from 0.34 to 0.45). State dependencies result in a further improvement of the relative usefulness for almost all variables compared to the case with only country dummies.

Table 5: Traditional vs conditional moments: noise to signal (θ=0.5)

	Observations		Traditional		CM pooled		CM country dummies		CM country dummies and controls	
Indicator	**Pre-crisis**	**Normal**	**Thres-hold**	**NTS**	**Thres-hold**	**NTS**	**Thres-hold**	**NTS**	**Thres-hold**	**NTS**
Bank credit to GDP gap	144	1182	8.03	0.36	8.03	0.36	1.49	0.58	4.79	0.36
Broad credit to GDP gap	144	1182	5.62	0.53	5.62	0.53	4.42	0.56	5.53	0.47
Broad HH credit to GDP gap	144	1015	1.05	0.53	1.05	0.53	1.45	0.50	1.65	0.39
Nominal bank credit growth	144	1180	0.11	0.57	0.11	0.57	0.13	0.41	0.13	0.23
Nominal broad credit growth	144	1180	0.14	0.48	0.13	0.51	0.14	0.45	0.11	0.54
Nominal broad HH credit growth	141	990	0.10	0.59	0.10	0.59	0.12	0.57	0.14	0.30
Debt service ratio	136	1155	19.44	0.42	19.44	0.42	17.88	0.40	16.50	0.52
Debt service ratio growth	136	1147	0.63	0.40	0.63	0.40	0.39	0.47	0.29	0.49
HH debt service ratio	128	829	11.83	0.57	11.83	0.57	11.65	0.53	12.37	0.36
HH debt service ratio growth	128	786	0.69	0.37	0.69	0.37	0.38	0.49	0.59	0.37
Nominal RRE price gap	144	1123	8.71	0.20	8.71	0.20	3.60	0.41	4.01	0.31
Nominal RRE price growth	144	1116	0.10	0.44	0.10	0.43	0.09	0.49	0.09	0.39
Price to income	136	1026	111.78	0.30	111.80	0.30	115.68	0.19	105.98	0.19
Price to income growth	135	1004	0.06	0.38	0.06	0.38	0.01	0.63	0.03	0.48
Average	**139**	**1065**		**0.44**		**0.44**		**0.48**		**0.39**

Notes: "Traditional" shows the results for the traditional common threshold. "CM pooled" shows the results when the conditional moments of the pre-crisis sample and the normal sample are estimated on the basis of equation (1); the results in the columns under "CM country dummies" and "CM country dummies and controls" are based on conditional moments estimated on the basis of equation (3), with country dummies respectively country dummies and control variables capturing the state of the business cycle included. "Observations" is the number of quarterly observations in the evaluation sample. "NTS" is the noise to signal ration.

In Table 5 the signalling performance of the conditional moments is compared (for θ=0.5) to that of the traditional common threshold in terms of noise to signal ratio. Adding country-specificities in the form of country dummies results in an improvement of the noise to signal ratio for about half of the indicators (most substantially for bank credit growth, price to income, broad credit growth and the HH debt service ratio). However, despite a status quo or improvement in relative usefulness, noise to signal ratios deteriorate dramatically for a number of variables, such as price to income growth, bank credit to GDP gap and RRE price gap. This is due to the fact that the trade-off between Type I and Type II errors is different in the noise to signal ratio than in the relative usefulness specification. On average, the country-specific conditional moments result in a substantially smaller Type I error (26% compared to 39%, not reported) than the traditional threshold, but at the same time in a larger Type II error (36% compared to 27%, not reported). While this improves the average relative usefulness from (0.34 to 0.38, see Table 4), the average performance in terms of noise to signal ratios (from 0.44 to 0.48) in fact worsens.

When also adding control variables, the improvement in relative usefulness compared to the traditional threshold is accompanied by a reduction of the average noise to signal ratio (from 0.44 to 0.39). Compared to the conditional moments with country dummies only, state dependencies reduce the Type II error on average from 36% to 29% (not reported).

The noise to signal ratio particularly improves for bank and HH credit growth, the household credit gap and the price to income ratio.

The results presented so far clearly show that the benefits of applying the conditional moments approach with country specificities and state dependencies can be substantial, albeit signalling performance is not improved for all indicators considered. The preference parameter θ set at 0.5 implies that the policymaker is indifferent between incurring a Type I and a Type II error. However, with the recent financial crisis still fresh in their memory, policymakers might be more averse towards missing crises, since they might consider the cost of banking crises to be larger than the cost society would incur in case of macroprudential policies unwarrantedly implemented. Table 6 shows the results of a robustness check against a higher preference parameter (θ=0.7), i.e. imposing more weight on the risk of missing crises than on false alarms in the policymaker's loss function.

Table 6: Robustness to choice of preference parameter: θ=0.7

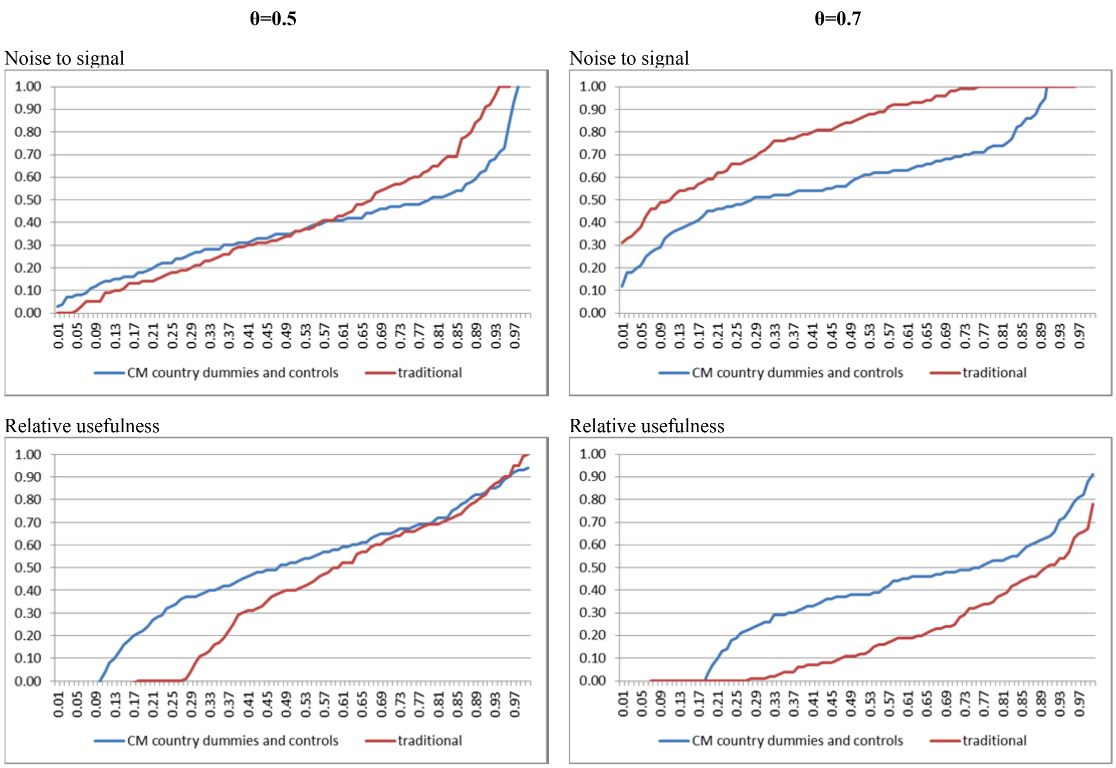
	Observations		Traditional common		CM pooled		CM country dummies		CM country dummies and controls	
Indicator	**Pre-crisis**	**Normal**	**NTS**	**Relus**	**NTS**	**Relus**	**NTS**	**Relus**	**NTS**	**Relus**
Bank credit to GDP gap	144	1182	0.79	0.08	0.65	-0.19	0.65	0.21	0.57	0.22
Broad credit to GDP gap	144	1182	0.88	0.12	0.65	-0.15	0.65	0.07	0.54	0.12
Broad HH credit to GDP gap	144	1015	0.61	0.23	0.59	0.16	0.58	0.29	0.43	0.38
Nominal bank credit growth	144	1180	0.95	0.05	0.72	-0.26	0.81	-0.18	0.69	0.07
Nominal broad credit growth	144	1180	0.98	0.02	0.53	-0.47	0.90	-0.39	0.80	-0.11
Nominal broad HH credit growth	141	990	0.71	0.13	0.59	-0.01	0.73	-0.02	0.69	0.02
Debt service ratio	136	1155	0.90	0.10	0.67	-0.18	0.58	0.24	0.57	0.41
Debt service ratio growth	136	1147	0.60	0.28	0.59	0.23	0.61	0.27	0.61	0.31
HH debt service ratio	128	829	0.94	0.06	0.59	-0.10	0.60	0.29	0.42	0.46
HH debt service ratio growth	128	786	0.59	0.29	0.56	0.21	0.59	0.35	0.64	0.32
Nominal RRE price gap	144	1123	0.95	0.05	0.58	0.00	0.60	0.25	0.51	0.35
Nominal RRE price growth	144	1116	0.92	0.06	0.65	-0.21	0.68	-0.07	0.74	0.15
Price to income	136	1026	0.65	0.22	0.55	0.11	0.58	0.27	0.30	0.45
Price to income growth	135	1004	0.82	0.12	0.70	-0.15	0.68	0.13	0.76	0.18
average	**139**	**1065**	**0.81**	**0.13**	**0.62**	**-0.07**	**0.66**	**0.12**	**0.59**	**0.24**

Notes: "Observations" is the number of quarterly observations in the evaluation sample. "NTS" is the noise to signal ratio and "Relus" is relative usefulness

The table shows that the conditional moments approach results in substantially lower noise to signal ratios (60-65% on average, compared to 81%) than traditional common thresholds when the aversion towards Type I errors is greater. As traditional thresholds are relatively sensitive to the preference parameter θ, they strongly reduce Type I errors (4% on average, not reported) but also suffer from a very large false alarms rate (78% on average, not reported). In contrast, the conditional moments-based thresholds are more robust to the specification of the loss function. While they do not bring the Type I error rate down to very low levels (on average ranging from 10% in the country-specific and state-dependent version to 27% in the pooled version, not reported), they result, at the same time, in more reasonable Type II error rates (on average between 45 and 55%, not reported).

The larger robustness to the choice of the preference parameter in terms of noise to signal ratios comes at a cost of pooled conditional moments resulting in a lower relative usefulness than the traditional common approach for θ=0.7. However, the flexibility introduced by the country specificities and state dependencies substantially improves signalling performance. In fact, the country-specific and state-dependent conditional moments again strongly outperform the traditional approach (an average relative usefulness of 0.24 compared to 0.13). Hence, accounting for country specificities and state dependencies results in better and more robust signalling performance than the traditional common thresholds.

Figure 5: Distribution of noise to signal ratios and relative usefulness across country/indicator pairs



Notes: The blue (red) lines plot the distribution of noise to signal ratios or relative usefulness of the country-specific and state-dependent conditional moments (traditional common threshold) across all 196 country/indicator pairs.

While the results presented above focus on the average improvements in signalling performance across all countries in the sample, they do not provide information on how these improvements are distributed across countries. Figure 5 therefore plots the distribution of noise to signal ratios and relative usefulness across all 196 country/indicator pairs. For example, the bottom left-hand panel shows that for θ=0.5, the fraction of country/indicator pairs that have a relative usefulness larger than 0.2 exceeds 80% under the country-specific and state-dependent conditional moments approach, while this fraction is less than 65% for the traditional common approach. Similarly, the top right panel shows that, for θ=0.7, the fraction of country/indicator pairs with a noise to signal ratio lower than 0.5 amounts to almost 30% for conditional moments, whereas the equivalent figure for the traditional common approach is only about 10%.

The top right panel shows that for a preference parameter θ=0.7, the country-specific and state-dependent conditional moments result in lower noise to signal ratios for almost all country/indicator pairs, and a lower fraction (10% compared to 25%) of pairs for which the noise to signal is equal to or larger than one. For balanced preferences (θ=0.5), the conditional moments approach mainly limits the upper part of the noise to signal distribution; for the lower part of the distribution, the conditional moments approach results in slightly larger noise to signal ratios. As the former dominates the latter, the conditional moments approach on average results in a lower noise to signal ratio also for balanced preferences. The fraction of pairs for which the noise to signal ratio is equal to or larger than one amounts to 3% compared to 7% in the traditional approach.

The bottom panels of Figure 5 show the overall improvement in relative usefulness across country/indicator pairs. Irrespective of the policy maker's preferences, the country-specific and state-dependent conditional moments results in a larger relative usefulness for the large majority of country/indicator pairs. Furthermore, both figures show that the country-specific and state-dependent conditional moments result in a larger fraction of country/indicator pairs (80-90% compared to about 70%) having a strictly positive relative usefulness.

Finally, comparing the left-hand panels to the right-hand panels provides further evidence for the finding that the country-specific and state-dependent conditional moments result in a more stable statistical performance for different values of θ compared to the traditional common approach, especially in terms of the noise to signal ratio. That is, the upward (downward) shift in the distribution of noise to signal ratios (relative usefulness) when moving from balanced preferences to policy preferences with more weight on Type I errors is less pronounced for the conditional moments approach than for the traditional one.

5.2. Out-of-sample robustness

In practice, policymakers are interested in identifying the build-up of vulnerabilities that may lead to future crises. While this in part relies on information regarding the drivers of past crises, we perform as a sensitivity analysis an out-of-sample evaluation exercise, examining the ability of the model to predict crises not included in the estimation sample. Given the heterogeneity in historical crises and the relatively limited amount of crises in our data sample, we create 100 different samples based on random draws from the existing sample, where each observation has 50% probability of ending up in the estimation sample and 50% probability of ending up in the evaluation sample. This results in 100 estimation samples and 100 evaluation samples, each containing about half of the observations of the original sample. In a first step, the estimation samples are used to determine the thresholds, and in a second step the evaluation samples are used to assess the early-warning performance of the thresholds determined in the first step.

Table 7 presents the out-of-sample average signalling performance across the 100 samples for the pooled conditional moments and the country-specific and state-dependent conditional moments. The results confirm the in-sample finding that, on average, country specificities and state dependencies improve signalling performance, both in terms of relative usefulness and noise to signal ratios. Furthermore, while signalling performance is somewhat lower compared to the in-sample numbers, out-of-sample performance of the conditional moments approach is still satisfactory, especially when country specificities and state dependencies are accounted for. In fact, the latter on average performs more or less similar to or even better than the in-sample traditional common approach and the in-sample conditional moments with country dummies.

Table 7: Out-of-sample robustness conditional moments

			θ=0.5				θ=0.7			
	Observations		CM pooled		CM country dummies and state dependencies		CM pooled		CM country dummies and state dependencies	
Indicator	Pre-crisis	Normal	NTS	Relus	NTS	Relus	NTS	Relus	NTS	Relus
Bank credit to GDP gap	72	590	0.41	0.27	0.37	0.42	0.68	-0.22	0.56	0.13
Broad credit to GDP gap	72	590	0.54	0.24	0.48	0.33	0.67	-0.18	0.65	0.00
Broad HH credit to GDP gap	72	506	0.54	0.35	0.41	0.45	0.59	0.16	0.48	0.24
Nominal bank credit growth	72	589	0.57	0.22	0.31	0.38	0.69	-0.30	0.68	-0.02
Nominal broad credit growth	72	589	0.54	0.21	0.58	0.20	0.70	-0.53	0.83	-0.20
Nominal broad HH credit growth	70	493	0.60	0.30	0.44	0.31	0.60	0.01	0.71	-0.09
Debt service ratio	68	576	0.44	0.29	0.46	0.38	0.64	-0.24	0.60	0.27
Debt service ratio growth	68	572	0.45	0.39	0.48	0.38	0.60	0.19	0.63	0.21
HH debt service ratio	64	413	0.59	0.27	0.40	0.46	0.59	-0.14	0.51	0.30
HH debt service ratio growth	64	392	0.42	0.39	0.47	0.37	0.59	0.20	0.60	0.18
Nominal RRE price gap	72	560	0.24	0.40	0.33	0.46	0.59	-0.06	0.51	0.23
Nominal RRE price growth	72	557	0.47	0.29	0.45	0.32	0.66	-0.29	0.74	0.04
Price to income	68	512	0.37	0.34	0.23	0.57	0.58	0.07	0.34	0.31
Price to income growth	67	501	0.37	0.30	0.48	0.31	0.71	-0.18	0.76	0.05
Average	**69**	**488**	**0.47**	**0.30**	**0.42**	**0.38**	**0.63**	**-0.11**	**0.62**	**0.12**

Notes: "Observations" is the number of quarterly observations in the evaluation sample. "NTS" is the noise to signal ratio and "Relus" is relative usefulness

6. CONCLUSIONS

Frameworks for macroprudential policy are being developed and progressively coming into force. While a coherent implementation of policy instruments may be beneficial, structural differences across countries warrant the consideration of a country-specific dimension in the operationalisation of macroprudential policy instruments. In this context, and given their importance in the systemic risk assessment process, early-warning models should be adapted to better reflect country specificities. In fact, models relying on common thresholds based on cross-country data often result in poor signalling performance at the individual country level. Furthermore, the information content of particular indicator developments may differ across different states of the business or the financial cycle.

This paper presents a novel yet intuitive methodology to compute country-specific and state dependent thresholds for early-warning indicators of banking crises. Using panel data on a number of potential early-warning indicators for banking crises for 14 EU countries, our results show that the benefits of the conditional moments approach with country specificities and state dependencies can be substantial. In particular, compared to traditional common thresholds this methodology provides more robust signals and improves the early-warning performance at the country-specific level, by accounting for country idiosyncrasies and state dependencies, which play an important role in national authorities' macroprudential surveillance.

For the above reasons and due to its simplicity and flexibility, our methodology can be of great value to policymakers, in their periodic evaluation of vulnerabilities. Furthermore, the approach results in a multi-threshold early-warning monitoring framework that provides policymakers with more granular signals of different intensity. This granularity may be a useful input into both the decision on the timing of policy activation and the calibration of policy instruments.

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