Occasional Paper Series

No. 8 / August 2015

ESRB
European Systemic Risk Board
European System of Financial Supervision

Identifying early warning indicators for real estate-related banking crises

Stijn Ferrari[1]
Mara Pirovano[2]
Wanda Cornacchia[3]

1 National Bank of Belgium
2 National Bank of Belgium
3 Banca d'Italia

The authors would like to thank Saleem Bahaj, Frank Dierick, Sebastian Frontczak, Julia Giese, Christian Glebe, Mads Harmsen, Abdelaziz Rouabah and Luminita Tatarici for their useful comments and suggestions.

Contents

Executive summary

This Occasional Paper presents a formal statistical evaluation of potential early warning indicators for real estate-related banking crises. Relying on data on real estate-related banking crises for 25 EU countries, a signalling approach is applied in both a non-parametric and a parametric (discrete choice) setting. Such an analysis evaluates the predictive power of potential early warning indicators on the basis of the trade-off between correctly predicting upcoming crisis events and issuing false alarms.

The results in this paper provide an analytical underpinning for decision-making based on guided discretion with regard to the activation of macro-prudential instruments targeted to the real estate sector. After the publication of the ESRB Handbook and the Occasional Paper on the countercyclical capital buffer, it represents a next step in the ESRB's work on the operationalisation of macro-prudential policy in the banking sector.

This Occasional Paper highlights the important role of both real estate price variables and credit developments in predicting real estate-related banking crises. The results indicate that, in addition to cyclical developments in these variables, it is crucial to monitor the structural dimension of real estate prices and credit. In multivariate settings macroeconomic and market variables such as the inflation rate and short-term interest rates may add to the early warning performance of these variables. Overall, the findings indicate that combining multiple variables improves early warning signalling performance compared with assessing each indicator separately, both in the non-parametric and the parametric approach. Combinations of the abovementioned indicators lead to lower probabilities of missing crises while at the same time not issuing too many false alarms. In addition to EU level, they also perform relatively well at individual country level.

Even though the best performing indicators have relatively good signalling abilities at the individual country level, national authorities are encouraged to perform their own complementary analyses in a broader framework of systemic risk detection, which augments potential early warning indicators and methods with other relevant inputs and expert judgement.

Introduction

Systemic risks stemming from excessive developments in real estate markets have significantly contributed to financial instability in the past, as for example in Denmark, Sweden and the United Kingdom in the early 1990s, as well as in the recent financial crisis. Unfavourable developments in the real estate sector have played an important role in major financial crises. Financial and economic busts preceded by an excessive real estate boom are particularly harmful from a financial stability perspective since they are longer and costlier than the average downturn.[1] The rapid credit growth that accompanies such booms is associated with an increase in household and financial sector leverage which can lead to risks to financial stability and the real economy, weakening its ability to recover in the aftermath of a crisis. Furthermore, real estate is the asset in which the largest fraction of household wealth is invested, and the construction sector has key supply-side effects on growth. Against this backdrop, designing and operationalising macro-prudential instruments aimed at real estate markets is a key issue for European authorities.

Some practical country experience on addressing systemic concerns originating from the real estate sector is already available, including in EU Member States.[2] The ESRB strongly encourages countries to develop sound macro-prudential policy strategies to frame macro-prudential policy actions, and to seek further harmonisation in the application of such measures. Macro-prudential policy strategies involve linking the ultimate objectives of macro-prudential policy to instruments and indicators. Instruments such as risk weights for real estate exposures, limits to loan-to-value and debt service-to-income ratios are considered important macro-prudential tools to target real estate risks. The operationalisation of such instruments requires identifying sound leading indicators and associated thresholds signalling well in advance excessive developments in the real estate sector. Such indicators could then serve as a starting point for decision making based on guided discretion with regard to the activation of macro-prudential instruments.

First steps on the work in this area have been taken under the aegis of the ESRB Instruments Working Group for the preparation of the ESRB Handbook on the operationalisation of macro-prudential policy in the banking sector. Chapter 3 of the ESRB Handbook provides operational guidance on the implementation of real estate instruments for macro-prudential purposes, and presents a graphical analysis of potential indicators that could warn against the build-up of vulnerabilities in the real estate sector.

This Occasional Paper extends the graphical analysis presented in the Handbook to a formal statistical evaluation of potential early warning indicators for real estate-related banking crises, focusing on the activation phase of macro-prudential instruments targeted to the real estate sector. In particular, an extensive analysis of potential early warning indicators for real estate-related banking crises is provided using a wide range of variables capturing both structural and cyclical concepts related to credit and real estate price developments, as well as variables related to macroeconomic, sectorial (banking sector, construction sector) and market developments, covering 25 member states

[1] See Claessens et al. (2008).

[2] For a review of the macro-prudential measures recently introduced in Europe to contain risks emerging in the real estate sector, see Ciani et al. (2014) and the overview of macro-prudential policy actions notified to the ESRB (https://www.esrb.europa.eu/mppa/html/index.en.html).

of the European Union.[3] Building on a great body of literature on early warning models, a signalling approach – which evaluates the predictive power of potential early warning indicators on the basis of the trade-off between correctly predicting upcoming crisis events and issuing false alarms – is applied in both a non-parametric[4] and parametric[5] setting.

The analysis presented in this study highlights the important role of both real estate price variables and credit developments in predicting real estate-related banking crises. The results indicate that, in addition to cyclical developments in these variables, it is crucial to monitor the structural dimension of real estate prices and credit.[6] In multivariate settings macroeconomic and market variables such as the inflation rate and short-term interest rates may add to the early warning performance of these variables.[7] Overall, the findings indicate that combining multiple variables improves early warning signalling performance compared with assessing each indicator separately, both in the non-parametric and the parametric approach. Combinations of the abovementioned indicators lead to low probabilities of missing crises, while at the same time not issuing too many false alarms. In addition to EU level, they also perform relatively well at individual country level.

The remainder of the paper is organised as follows: Section 1 provides a description of the data and a graphical evaluation of potential early warning indicators. Section 2 outlines the signalling framework as well as the evaluation criteria adopted in this paper to evaluate early warning indicators for real estate-related banking crises. Section 3 presents the resulting ranking and evaluation of early warning indicators obtained by applying both a non-parametric and a parametric approach. In this section, a country level evaluation of the best indicators and logit model is also performed. In Section 4, a number of robustness checks related to the specification of the policymaker's loss function and out-of-sample evaluation are performed. Finally, Section 5 concludes with a policy discussion of the empirical findings.

Section 1 Data description

The statistical evaluation of potential early warning indicators for real estate banking crises requires two types of variables: a crisis dummy that identifies the banking crises stemming from excessive developments in real estate markets, and economic variables that signal the build-up of risks preceding the coming crises (early warning indicators).

---

[3] Due to lack of data for a large number of variables, Bulgaria, Croatia and Romania are not included in the evaluation.

[4] The non-parametric approach follows the seminal work by Kaminsky and Reinhart (1999) on leading indicators of banking and currency crises. For applications to banking crises, see for example Borio and Lowe (2002), Borio and Drehmann (2009), Drehmann et al. (2010, 2011), Alessi and Detken (2011), Drehmann and Juselius (2013) and Detken et al. (2014).

[5] See for example Demirguc-Kunt and Detragiache (1998), Babecky et al. (2012), Schularick and Taylor (2012), Behn et al. (2013) and Detken et al. (2014).

[6] Ferrari and Pirovano (2014) similarly find that both structural and cyclical developments in credit and real estate prices are important in signalling real estate-related banking crises. Claessens et al. (2011) uncover a strong connection between credit and housing market cycles (also see Drehmann et al., 2012).

[7] Other early warning indicators for boom/bust episodes in asset and/or real estate prices include interest rates and money developments (e.g. Agnello and Schuknecht, 2011 ; Alessi and Detken, 2011 ; Borgy et al., 2014 ; Gerdesmeier et al., 2012), as well as global liquidity and credit developments (Agnello and Schuknecht, 2011; Alessi and Detken, 2011). Real estate price developments are also found to be associated to credit conditions such as loan-to-value ratios (e.g. Crowe et al. 2011).

1.1. Real estate-related banking crises

In the context of the ATC's Instruments Working Group work stream on Real Estate Instruments, a database on real estate-related banking crises was compiled for the 28 EU Member States before and during the global financial crisis.[8] This database builds on the ESCB Heads of Research (HoR) Group's banking crises database, which defines a banking crisis as episodes characterised by significant signs of financial distress in the banking system, such as bank runs in relevant institutions, losses in the banking system (non-performing loans above 20% or bank closures of at least 20% of banking system assets) or significant public intervention in response to or with the aim of avoiding the realisation of losses in the banking system.[9] The HoR database has been narrowed down by the IWG Expert Group on Countercyclical Capital Buffers (CCB) by (1) excluding crises that were not systemic, (2) excluding systemic banking crises that were not associated with a domestic credit/financial cycle, and (3) adding periods where domestic developments related to the credit/financial cycle could well have caused a systemic banking crisis had it not been for policy action or an external event that dampened the financial cycle. The resulting CCB database has then been further adjusted on the basis of the IWG work stream on Real Estate Instruments members' judgement, in order to reflect only systemic banking crises stemming from real estate.[10]

According to this database, although 16 countries did not experience any real estate-related banking crisis since 1970, nine of the remaining 12 countries have experienced one crisis. In addition, three countries (Denmark, Sweden and the United Kingdom) experienced two crises, resulting in a total of 15 real estate-related banking crises in our sample (Figure 1). Real estate-related banking crises have mostly occurred at the beginning of the 1990s and during the global financial crisis (Figure 2). In particular, between Q2 2009 and Q3 2010 up to ten countries experienced simultaneously a real estate-related banking crisis. Real estate crises can vary according to the real estate segment they originate from: residential, commercial or both. In our dataset, two crises are classified as "only residential real estate-related", while the remaining ones are labelled as "both residential and commercial"[11].

[8] The work of this work stream resulted in Chapter 3 on real estate instruments of The ESRB Handbook on Operationalising Macro-prudential Policy in the Banking Sector.

[9] The underlying criteria closely follow the methodology applied by Laeven and Valencia (2012).

[10] Periods of banking distress resulting from the real estate sector could alternatively be analysed on the basis of a continuous financial stress index. The challenges in determining real estate-related stress in such analysis would, however, be similar to those arising in the context of a binary crisis variable used in our analysis. That is, financial stress emerging from other sources than real estate should be filtered out/accounted for. One option could be to analyse the behaviour of real estate prices during such periods of stress to determine whether or not the financial stress is related to the real estate sector. But overall, the construction of such a real estate-related financial stress index is expected to contain a degree of expert judgement as well.

[11] Table A1 in the Appendix provides details on the crisis episodes experienced by the 28 EU countries.

Figure 1: Number of real estate-related crises by country

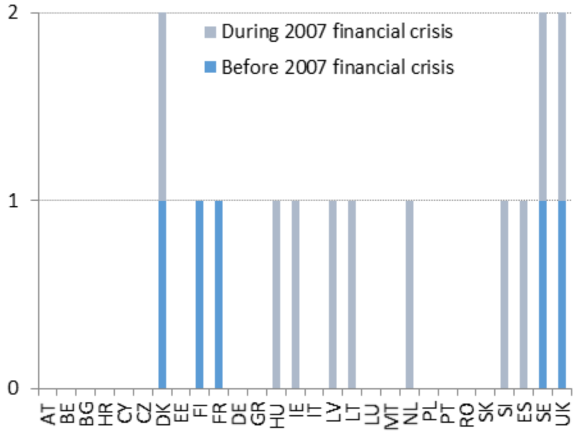
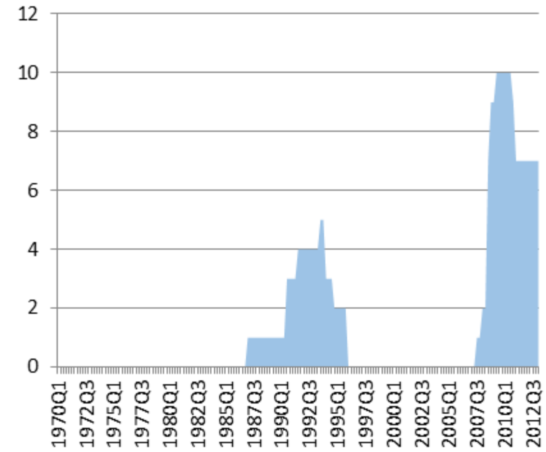


Figure 2: Number of countries in crisis per period



AT = Austria; BE = Belgium; BG = Bulgaria; CR = Croatia; CY = Cyprus; CZ = Czech Republic; DK = Denmark; EE = Estonia; FI = Finland; FR = France; DE = Germany; GR = Greece; HU = Hungary; IE = Ireland; IT = Italy; LV = Latvia; LT = Lithuania; LU = Luxembourg; MT = Malta; NL = Netherlands; PL = Poland; PT = Portugal; RO = Romania; SK = Slovak Republic; SI = Slovenia; ES = Spain; SE = Sweden; UK = United Kingdom.

1.2. Potential early warning indicators

Data on potential early warning indicators, i.e. economic variables able to inform on the build-up of risks in the run-up to a crisis, were collected for the 28 EU Member States. The data were obtained from public databases (ECB, Eurostat, BIS, Bloomberg, OECD) and, where necessary, corrected by national experts.[12] The longest available data series cover the period from 1970Q1 to 2013Q1 (cf. Table A2 in Annex A). Given the substantial lack of data for many variables, Bulgaria, Romania and Croatia were dropped from the sample.

Besides the variables' levels, transformations such as their annual growth rate and the deviation from their long-term trends ("gaps")[13] have also been considered for several variables (cf.

[12] National experts include members of the Instruments Working Group Expert Group on guidance on setting countercyclical buffer rates and the Instruments Working Group work stream on Real Estate Instruments.

[13] The long-term trends have been calculated with a one-sided (recursive) Hodrick-Prescott filter with lambda 400,000.

Table 1). This results in a dataset consisting of 5 categories of variables: structural credit variables, cyclical credit variables, real estate price variables, and other variables. Whereas structural credit variables relate to levels of credit (i.e. measures of credit to GDP), cyclical credit variables relate to their growth rates and gaps.

Table 1: Overview of variables in the four categories

Structural credit variables	***Other variables***
(Nominal) HH credit to GDP	*Macroeconomic variables:*
(Nominal) HH mortgage loans to GDP	Inflation
(Nominal) NFC credit to GDP	Real GDP growth
(Nominal) total credit to GDP	Unemployment rate
(Nominal) bank credit to GDP	Real effective exchange rate (level and growth)
Debt service ratio	Real M3 stock growth
Debt to income ratio	Current account deficit to GDP
	Government debt to GDP
	EC consumer survey
Cyclical credit variables	*Credit conditions variables:*
HH credit growth (nominal and real)	Average mortgage rate
NFC credit growth (nominal and real)	Rates mortgage fixed
Total credit growth (nominal and real)	Rate mortgage floating
Bank credit growth (nominal and real)	Spreads on HH mortgage rate
(Nominal) HH credit to GDP gap	Spread on NFC loan rate
(Nominal) HH mortgage loans to GDP gap	Share floating rate loans
(Nominal) NFC credit to GDP gap	
(Nominal) total credit to GDP gap	*Market variables:*
(Nominal) bank credit to GDP gap	Equity prices growth (nominal and real)
	Long term gov't bond yield (nominal and real)
	3-month money market rate (nominal and real)
Structural and cyclical real estate price variables	*Construction sector variables:*
(Nominal) RRE price to income gap	GFCF dwellings to GDP
(Nominal) RRE price to rent gap	GFCF other buildings to GDP
RRE price growth (nominal and real)	Value added construction to GDP
CRE price growth (nominal and real)	
RRE price gap (nominal and real)	*Banking sector variables:*
CRE price gap (nominal)	Leverage ratio
	Bank deposit liabilities to total assets
	Banks total assets to GDP
	Bank capital reserves to total assets

Notes: HH = “households”; NFC = “non-financial corporations”; RRE = “residential real estate”; CRE= “commercial real estate”; GFCF = “gross fixed capital formation”; gaps are deviations from long-term trend; RRE price to income and price to rent gaps are calculated as deviation from mean.

Similarly, the real estate variables include purely cyclical indicators (growth rates and gaps) as well as indicators that contain a structural dimension (price to income and price to rent gaps[14]).

The other variables category includes macroeconomic, banking sector, market, credit conditions and construction sector variables. Table 1 lists all the variables we consider by category; many of these have been found to be useful in predicting banking crises in previous studies. Summary statistics of the variables are included in Table A3 in Annex A. Since many variables represent similar concepts and/or are considered in different transformations, the dataset is by construction characterised by high correlation between variables. In particular as presented in Table A4 in Annex A, correlation is higher than 80% between a number of real estate price variables and within the cyclical credit variables category. These correlations will be accounted for in the variable selection procedures later in the paper.

1.3. Graphical evaluation of early warning indicators

Plotting the evolution of variables for crisis countries around crisis events, one can gauge whether the indicator signals the occurrence of excessive developments in the run-up to a crisis. A clearly upward or downward evolution of an indicator before a crisis can be considered as a preliminary indication of its ability to predict upcoming distress events.

Figure 3 depicts the evolution of representative indicators pertaining to the four categories considered in this study around crisis events. The green vertical line represents the onset of a real estate-related banking crisis; the solid lines show the simple average of indicators for countries experiencing real estate-related banking crises, in the window ranging from 20 quarters before to 20 quarters after the occurrence of a distress event.

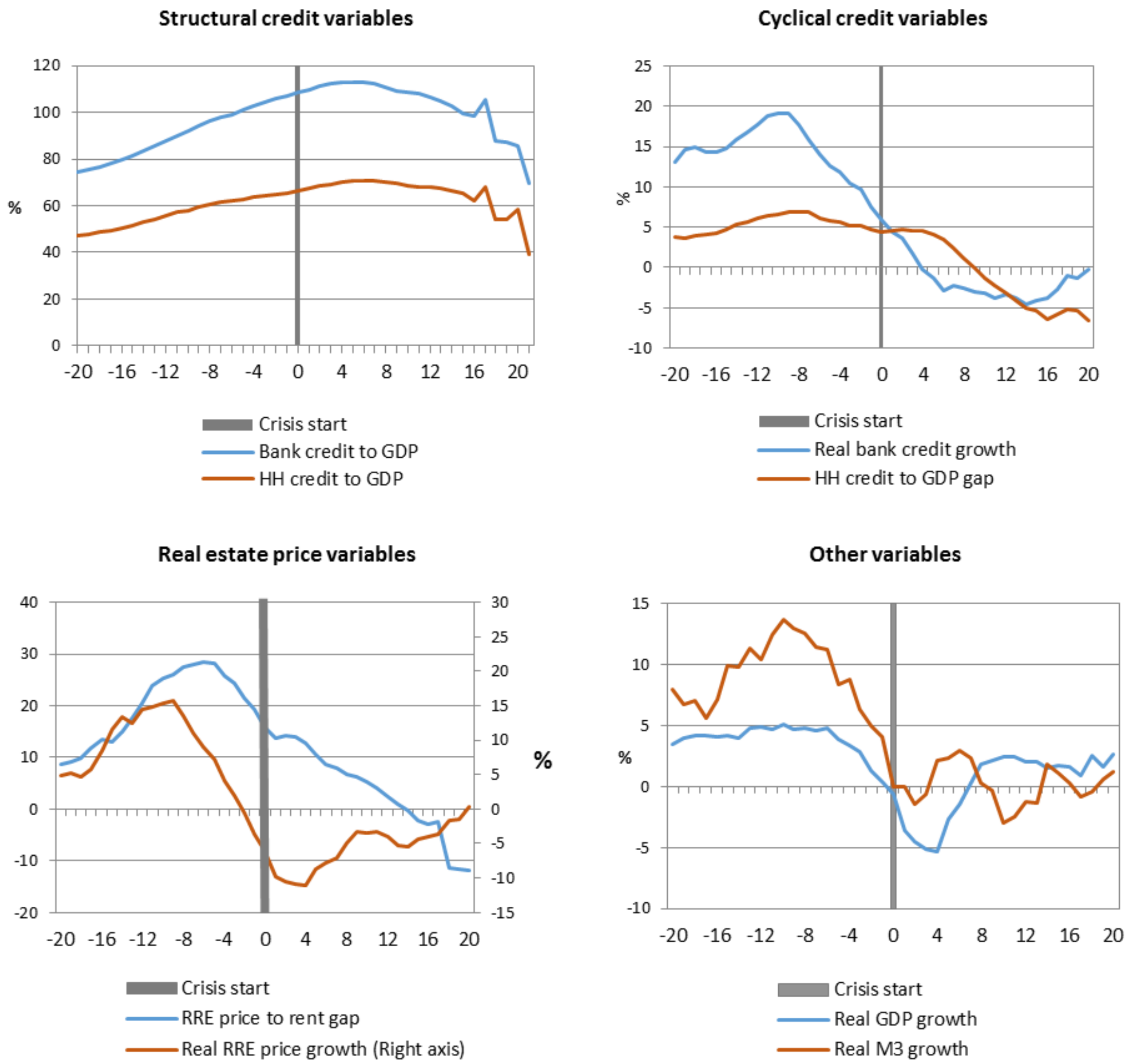
Whereas variables related to the structural dimension of credit exhibit a continuous increasing trend that starts relatively long before the onset of crisis events and continues until one year after the onset of these crises, cyclical indicators of credit show potential leading properties closer to, but nevertheless well ahead of crisis events. The two representative indicators depicted in the second panel of Figure 3, real bank credit growth and the household credit to GDP gap, start steadily increasing around the 15th quarter preceding crisis events, peaking two years later and then start decreasing, becoming even negative after the onset of the crisis. In contrast to real bank credit growth, the household credit to GDP gap remains rather stable up to six quarters after the onset of the crisis, before it drops sharply.

A similar pattern is followed by indicators related to real estate price developments, pictured in the third panel of Figure 3. Both the residential real estate price to rent gap and the real growth of residential real estate price increase in the run-up to a crisis, peak and start decreasing before the onset of the crisis, and continue this downward tendency in its aftermath. As expected, the purely cyclical indicator (real growth of residential real estate prices) reacts much more sharply than the indicator containing the structural component (residential real estate price to rent gap).

[14] Despite the fact that the price to income gap and price to rent gap ratios are expressed as normalised indices, they contain a structural component that results from cumulative changes in prices and is no longer present in the growth rates and gaps of the price variables. To remove any dependence on the base year used to calculate the index, we consider the residential real estate price to income gap and residential real estate price to rent gap ratios in the deviation from their mean.

The last panel of Figure 3 reveals that macroeconomic developments also seem to have early warning ability, since upswings in the economic cycle and rapid growth in the stock of broad money in the economy are precursors of banking distress events related to the real estate market.

Figure 3: Evolution of potential indicators around real estate-related crisis periods



Source: BIS, OECD, Eurostat and authors' calculations

Section 2 Evaluation methodology

While graphical analysis may provide a first indication on the early warning qualities of an indicator, a large body of literature exists on the statistical evaluation of potential early warning indicators. Following Kaminsky and Reinhart (1999), a methodology that is broadly applied in the early warning literature is the signalling approach. This section briefly outlines the signalling approach and presents the evaluation criteria adopted in the remainder of this paper. The results obtained from applying the signalling approach in both a non-parametric and a parametric setting are discussed in the next section.

2.1 Signalling approach

The predictive power of potential early warning indicators is evaluated on the basis of the likelihood that the indicator considered is able to correctly predict upcoming crisis events, while at the same time not issuing too many false alarms. Signals obtained from several both non-parametric and parametric combinations of indicators (see Section 3) can be evaluated using a similar set of statistical quantities.

The so-called "Confusion Matrix" (Table 2) classifies the four possible outcomes in a signalling framework. After a signal has been issued (i.e. an indicator or model output breaching a threshold), it 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 does occur (C).

Table 2: Confusion Matrix

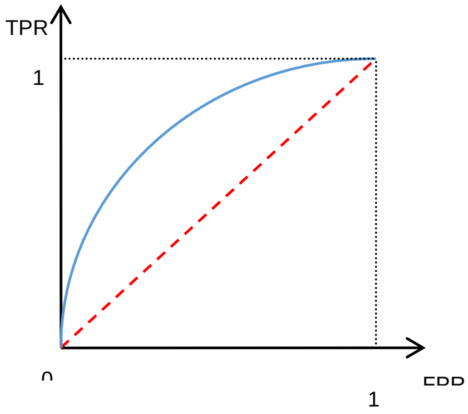
	Crisis	*No crisis*
Signal is issued	A	B
Signal is not issued	C	D

On the basis of the Confusion Matrix, a number of key ratios can be calculated. The true positive rate (TPR) is the fraction of correctly predicted crises $\left(\frac{A}{A+C}\right)$. 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.

From these quantities, the predictive power of an indicator or model can be assessed through different metrics, such as the noise to signal ratio $\left(\frac{TPR}{FPR}\right)$ and 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). Finally, the relative usefulness of an indicator or model expresses the policymaker's gain from using the indicator or model for predicting crises compared to disregarding the indicator or model and always issuing a signal or never issuing a signal: $RU = \frac{\min[\theta,(1-\theta)]-L}{\min[\theta,(1-\theta)]}$.

The above metrics are all calculated for a given threshold, above which the indicator or model issues a signal. As such, they permit calculation of the optimal threshold for an indicator. In particular, the threshold that minimises an objective function such as the noise-to-signal ratio (potentially conditional on the TPR being sufficiently large) or the policymaker's loss function (which for a given indicator or model is equivalent to maximising the relative usefulness) is selected. Optimal threshold identification involves a trade-off between missing crises (Type I error) and issuing false alarms (Type II error): a lower (higher) threshold decreases (increases) the probability of missing a crisis (Type I error rate) but at the same time increases (decreases) the probability of issuing a false alarm (Type II error rate).

Figure 4: The ROC curve



Recent early warning applications have evaluated the predictive power of indicators and models on the basis of their AUROC (Area Under the Receiver Operating Characteristic). The ROC (Receiver Operating Characteristic) curve plots the indicator or model's TPR against the FPR for every possible value of the threshold, as depicted by the solid blue line in Figure 4. The area under the ROC-curve or AUROC ranges from 0 to 1: a value larger than 0.5 (corresponding to a ROC curve situated to the left of the red dashed line in Figure 4) 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 predictive ability for all possible thresholds. Therefore, it does not rely on favourable values of the evaluation metrics for one specific, potentially very narrow, threshold range. On the other hand, policymakers may be interested in receiving guidance on when an indicator or combination of indicators is reaching excessive values, which requires the calculation of optimal thresholds. As both Type I and Type II errors entail a cost (either in terms of not enacting macro-prudential instruments due to the failure of foreseeing a crisis or erroneously activating instruments on the basis of a false alarm), evaluation of an indicator or model in combination with a given threshold is of relevance too for guiding policymakers' decisions.

2.2 Evaluation criteria adopted in this paper

A Confusion Matrix and the associated evaluation metrics require a predefined evaluation horizon. The prediction horizon needs to be chosen long enough before potential crises so that the policymaker still has time to take preventive action. On the other hand, the evaluation horizon should not be too long either, as this may blur the indicators' signalling power.

For our analysis we consider a prediction horizon of 12 to 5 quarters. Observations included in windows of 12 to 5 quarters before a real estate-related banking crisis determine the sample from which TPR and Type I errors are computed. Observations outside these windows serve as a basis for the calculation of Type II errors or false alarms.[15]

As a benchmark, optimal thresholds are calculated on the basis of maximising the relative usefulness for the policymaker with preference parameter θ = 0.5. For the reporting of our results, we provide robust rankings of the indicators or models based on their AUROC. For reasons of robustness, we only consider in-sample evaluation indicators and models with sufficient data and crisis coverage (including at least 13 real estate-related banking crises[16]). Robustness checks with respect to the preference parameter θ, out-of-sample evaluation, and data and crisis coverage are provided either in the main text (Section 4) or Annex.

Section 3 Statistical evaluation of early warning indicators

This section applies the signalling approach outlined above in both a non-parametric and parametric (discrete choice) setting. Two key characteristics distinguish the two approaches. First of all, the two methodologies differ in the assumptions related to the statistical distribution of the variables being assessed. Non-parametric models make no assumption regarding the probability distribution of the data, while parametric models are based on a parametrised probability distribution. Discrete choice models assume a probability distribution of the error term (be it the normal distribution in the case of probit or the logistic distribution in the case of logit), whose shape is defined by parameters such as the mean and variance.

A second element distinguishing the two approaches is the level of aggregation at which thresholds are defined in order to obtain the early warning signal. The non-parametric approach, as used in this study, considers indicators one (or a few) at a time and derives a separate threshold for each indicator. In a univariate setting, a signal is issued when a single indicator breaches its threshold; in a multivariate setting, a signal is issued when all indicators in the multivariate combination breach simultaneously their own thresholds or alternatively when one of the two or three indicators breaches its predefined threshold. On the other hand, the parametric approach aggregates information on a (potentially large) set of indicators in a single metric (i.e. the probability of a real estate-related banking crises occurring within the prediction horizon), for which a threshold is defined. In contrast to the non-parametric approach, no separate thresholds are obtained for the individual indicators in the model.

In what follows, we evaluate the potential early warning indicators and models according to their capacity to warn against the imminent occurrence of a real estate-related banking crisis.

[15] Observations in windows of 4 quarters before to 12 quarters after the start of a real estate-related banking crisis as well as any remaining observations during such crises were dropped from the sample. Furthermore, the last three years of the sample (i.e. from 2010 Q1 onwards) were dropped as it is impossible to determine for these observations whether or not they are followed by a crisis.

[16] This ensures crisis coverage beyond the recent financial crisis.

3.1 Non-parametric approach

In the non-parametric approach, signals are derived directly from the indicators' historical distribution both inside and outside the relevant pre-crisis windows.[17] Both univariate and multivariate approaches have been implemented.

3.1.1 Univariate non-parametric signalling

In the univariate non-parametric approach a signal is issued as soon as a single indicator breaches a predefined threshold. This threshold is optimised by trading off Type I and Type II errors by means of the relative usefulness criterion.[18] The signals issued by the indicator are then evaluated on the basis of the metrics presented in Section 3. The variables are considered one by one when checking how well each of them predicts the crisis.

Table 3 lists the top 10 indicators covering a sufficiently large data sample ranked according to their AUROC (the results for the full set of indicators with sufficient data coverage is presented in Table A5 in Annex A). The best early warning indicators, based on AUROC, belong to the categories related to real estate prices (both structural and cyclical) and cyclical credit. This confirms the initial insights provided by the earlier graphical evaluation. The confidence intervals around the AUROC[19] estimates indicate that difference in performance (in terms of AUROC) of the top ten indicators is not statistically significant. However, as indicated by the average result across all indicators in the sample, the top ten indicators do have AUROCs that are statistically larger than those of many of the lower ranked indicators (also see Table A5 in Annex A).

The two most reliable early warning indicators for real estate-related banking crises are real estate price variables that contain a structural dimension. The indicator with the highest AUROC (0.84) is the nominal RRE price to income gap. A signal is issued when the nominal RRE price to income gap (in deviation from its mean) exceeds 13.98, resulting in a relative usefulness of 0.53. These numbers reveal that the indicator has a high "informative content". The nominal RRE price to income gap exhibits a Type I error of 0.35, and a low Type II error equal to 0.12. Therefore, while incurring a 35% probability of missing a forthcoming crisis, when a signal is issued there is only a 12% probability that a crisis is wrongly predicted. The nominal RRE price to rent gap quite closely follows the nominal RRE price to income gap both in terms of AUROC (0.83) and relative usefulness (0.50). When issuing a signal above a value of 6.95, it performs well in correctly predicting crises (in 74% of the cases) while at the same time not issuing false alarms too often (24% of cases).

Indicators of cyclical residential real estate price dynamics (in nominal and real terms) immediately follow. Whereas the real RRE price gap trades off very precise signals (only 8% probability of issuing

---

[17] The observations on the 25 countries in our sample are equally weighted, so they are treated equally.

[18] To this end, a grid search is performed. The grid is bounded by the minimum and maximum indicator value in the sample, and possible thresholds are equally spaced between the minimum and the maximum. The search grid for the univariate case contained 10,000 thresholds. For each of these possible thresholds in the grid, the indicator's relative usefulness is calculated. The threshold that maximises relative usefulness is selected as the optimal threshold.

[19] The confidence interval around the AUROC are calculated as in Detken et al (2014), applying Hanley and McNeil (1982)'s formula for the calculation of AUROC's standard errors, which allows for the possibility that the number of crisis and no crisis events are not the same.

a false alarm) with a somewhat higher risk of missing a crisis (42%), the nominal RRE price gap show a more equal division of Type I and Type II error rates (28% and 23%, respectively).

While the top four indicators relate to real estate prices, the following six concern cyclical developments in credit, both total and sectorial. The real growth of credit to non-financial corporations, of total credit and of total credit granted by the banking sector have high informative content, while they exhibit different performances in terms of Type I and Type II errors: total credit growth has a very low probability of missing a crisis (14%) but risks of false alarms are slightly higher (42%). On the other hand, signals issued by real NFC credit growth are more precise in terms of false alarm rates (18%), albeit identifying crises less often (38% Type I error). Finally, deviations from the trend in various measures of credit to GDP are useful indicators, with the total credit to GDP gap and the household credit to GDP gap striking a relatively good compromise between Type I and Type II errors.

Table 3: Univariate non-parametric analysis: best 10 indicators

Indicator	*Threshold*	*Type I error*	*Type II error*	*Relative usefulness*	*AUROC*	*AUROC CI*
Nominal RRE price to income gap	13.98	0.35	0.12	0.53	0.84	[0.79, 0.88]
Nominal RRE price to rent gap	6.95	0.26	0.24	0.50	0.83	[0.79, 0.88]
Nominal RRE price gap	5.24	0.28	0.23	0.50	0.81	[0.76, 0.86]
Real RRE price gap	13.86	0.42	0.08	0.50	0.79	[0.74, 0.84]
Real NFC credit growth	11.02	0.38	0.18	0.44	0.78	[0.74, 0.83]
Nominal total credit to GDP gap	6.46	0.20	0.31	0.49	0.78	[0.73, 0.84]
Real total credit growth	6.76	0.14	0.42	0.44	0.78	[0.73,0.83]
Nominal HH credit to GDP gap	2.77	0.25	0.33	0.43	0.78	[0.73, 0.83]
Nominal bank credit to GDP gap	2.91	0.17	0.42	0.42	0.77	[0.72, 0.82]
Real bank credit growth	8.78	0.28	0.30	0.42	0.76	[0.71, 0.82]
Average for all indicators	**-**	**0.31**	**0.41**	**0.28**	**0.63**	**[0.58, 0.68]**

The categories of structural credit variables (e.g. household credit to GDP, the ratio of credit to non-financial corporations to GDP or the ratio of total credit to GDP) and other variables, including macroeconomic variables (e.g. real GDP growth, the growth of real M3 or the current account to GDP), market (e.g. the real three-month money market rate and the long term government bond yield) and credit condition (e.g. share of fixed or floating mortgage rates, spreads on loan rates to households and non-financial corporations) variables, are generally not among the top performers. Table A5 in Annex A shows that a number of these indicators nevertheless appears to have reasonable early warning capacities, with AUROCs well (and significantly) above 0.5 and still acceptable Type I and/or Type II errors.

Overall, although none of the top ten indicator errors are on the high side, there is substantial heterogeneity in performance in terms of Type I and Type II errors. Such heterogeneity suggests that gains in performance can be obtained combining multiple indicators, which will be the subject of the next section.

3.1.2 Multivariate non-parametric signalling

In the multivariate non-parametric approach several indicators are considered jointly and a signal is issued when one or more indicators breach their predefined threshold. These thresholds are again optimised by maximising relative usefulness. As the multivariate non-parametric signalling approach faces dimensionality problems, we only consider the bivariate and trivariate case.[20] The signals issued by the indicator combinations are then evaluated on the basis of the metrics presented in Section 3 and ranked according to their AUROC.

3.1.2.1 Simultaneous breach of thresholds

The first case we consider requires all two or three indicators to breach their predefined thresholds *at the same time* in order for a signal to be issued. Table 4a presents the top ten pairs of indicators ranked according to their AUROC. The best performing pair is the one including the nominal RRE price gap and the price to rent gap. A signal is issued when the former is higher than 1.98 and at the same time the latter exceeds -8.61. This pair results in a relative usefulness for the policymaker that is substantially higher than the one associated with the best performing univariate indicator (0.61 compared to 0.53). In terms of AUROC, the improvement is only small (from 0.84 to 0.85) and the confidence intervals indicate that the difference in performance is not statistically significant.

In general, the best performing pairs contain a combination of a structural real estate price variable (either the RRE price to income gap or the RRE price to rent gap) with a cyclical real estate price or credit variable. Compared to the univariate case in Table 3, there is less heterogeneity in Type I and Type II errors across the different pairs; for most top ten pairs, the proportion of missed crises is lower than the share of false alarms. Furthermore, the range of Type I and Type II error rates is generally lower than in the univariate case.

[20] The dimensionality problem stems from both the number of possible indicator combinations and the number of grid points to be searched when multiple indicators are combined. In the trivariate case, we limit the number of indicator combinations by selecting a subset of indicators based on correlations among indicators and economic intuition. The grid search is limited to an equally spaced grid of size 500 in the bivariate case and size 80 in the trivariate case.

Table 4a: Bivariate non-parametric analysis: best 10 indicator pairs (simultaneous breach)

Indicator 1	*Indicator 2*	*Threshold 1*	*Threshold 2*	*Type I error*	*Type II error*	*Relative usefulness*	*AUROC*	*AUROC CI*
Nominal RRE price gap	Nominal RRE price to rent gap	1.98	-8.61	0.05	0.34	0.61	0.85	[0.81 ,0.90]
Real RRE price gap	Nominal RRE price to rent gap	1.13	-2.67	0.09	0.31	0.60	0.85	[0.80, 0.90]
Real total credit growth	Nominal RRE price to rent gap	5.16	-3.39	0.13	0.25	0.63	0.85	[0.80, 0.89]
Real NFC credit growth	Nominal RRE price to rent gap	4.00	-5.53	0.11	0.30	0.60	0.85	[0.80, 0.89]
Real bank credit growth	Nominal RRE price to rent gap	5.52	-3.39	0.16	0.25	0.59	0.83	[0.78, 0.88]
Real total credit growth	Nominal RRE price to income gap	5.22	-2.44	0.18	0.24	0.59	0.83	[0.78, 0.87]
Nominal bank credit to GDP gap	Nominal RRE price to rent	2.66	-0.56	0.21	0.23	0.55	0.82	[0.78, 0.87]
Nominal bank credit to GDP gap	Nominal RRE price to income gap	2.40	-1.66	0.22	0.23	0.55	0.82	[0.78, 0.87]
Nominal HH credit to GDP gap	Nominal RRE price to rent gap	2.52	2.56	0.26	0.18	0.57	0.82	[0.77, 0.87]
Real NFC credit growth	Nominal RRE price to income gap	3.94	-2.44	0.20	0.25	0.55	0.82	[0.77, 0.87]
Average for all indicators pairs		**-**	**-**	**0.30**	**0.31**	**0.39**	**0.64**	**[0.58, 0.69]**

Table 5a similarly presents the ten best performing trivariate indicator combinations based on AUROC. The relative usefulness for the policymaker associated with the best performing combination (real total credit growth, real RRE price gap and price to rent gap) further increases to 0.68, while AUROC increases (again, not significantly) to 0.86.

The best triplets consist of combinations of a cyclical credit variable with both a cyclical and a structural real estate variable. The RRE price to rent gap is part of all top ten combinations. Overall, combining multiple indicators improves the performance of the signal at least in one dimension (Type I or Type II errors), if not in both. For example, supplementing the second best performing pair (real RRE price gap and nominal RRE price to rent gap) presented in Table 4a with real total credit growth results in a substantial decrease of the Type II error from 0.31 to 0.23, while the Type I error increases only slightly (from 9% to 10%). Similarly, adding nominal bank credit to GDP gap to this indicator pair reduces the Type I error from 9% to 4%, while keeping the Type 2 error virtually unchanged (32% instead of 31%).

Table 5a: Trivariate non-parametric analysis: best 10 combinations (simultaneous breach)

Indicator 1	*Indicator 2*	*Indicator 3*	*Threshold 1*	*Threshold 2*	*Threshold 3*	*Type I error*	*Type II error*	*Relative usefulness*	*AUROC*	*AUROC CI*
Real total credit growth	Real RRE price gap	Nominal RRE price to rent gap	5.21	-0.10	-6.07	0.10	0.23	0.68	0.86	[0.82, 0.91]
Real NFC credit growth	Real RRE price gap	Nominal RRE price to rent gap	3.70	-0.10	-6.68	0.11	0.25	0.64	0.86	[0.81, 0.90]
Real bank credit growth	Real RRE price gap	Nominal RRE price to rent gap	6.10	-0.10	-6.07	0.16	0.20	0.63	0.85	[0.80, 0.89]
Nominal bank credit to GDP gap	Real RRE price gap	Nominal RRE price to rent gap	-0.69	-0.10	-6.68	0.04	0.32	0.64	0.84	[0.79, 0.89]
Nominal total credit to GDP gap	Real RRE price gap	Nominal RRE price to rent gap	5.33	-0.10	-6.68	0.16	0.20	0.63	0.83	[0.79, 0.88]
Nominal HH credit to GDP gap	Real RRE price gap	Nominal RRE price to rent gap	0.35	0.75	-3.14	0.10	0.27	0.63	0.83	[0.78, 0.88]
Real HH credit growth	Real RRE price gap	Nominal RRE price to rent gap	3.05	0.75	-6.68	0.06	0.33	0.61	0.83	[0.78, 0.88]
Real total credit growth	Real RRE price growth	Nominal RRE price to rent gap	3.70	-1.87	-2.71	0.12	0.25	0.63	0.83	[0.78, 0.88]
Real NFC credit growth	Real RRE price growth	Nominal RRE price to rent gap	4.03	-1.62	-2.71	0.18	0.22	0.60	0.83	[0.78, 0.88]
Nominal bank credit to GDP gap	Real RRE price growth	Nominal RRE price to rent gap	0.95	-1.87	-2.67	0.15	0.24	0.61	0.82	[0.77, 0.87]
Average for all indicator triplets			**-**	**-**	**-**	**0.27**	**0.24**	**0.48**	**0.69**	**[0.63, 0.74]**

Comparing the results of the univariate and the multivariate analysis, it shows that combining multiple indicators can lead to different thresholds for the same indicator. For example, eight out of ten best bivariate combinations include the RRE price to rent gap, whose optimal threshold changes considerably according to the indicator it is paired with, ranging from -8.61 to 5.16. The same remark can be made when looking at trivariate combinations.

It can furthermore be noticed that adding more variables results, in general, in lower thresholds for a given variable. Such lower (and even slightly negative[21]) thresholds can be explained considering that milder developments exhibited by more than one indicator might be sufficient to create a vulnerability, whereas an indicator considered individually needs to assume high values before it becomes worrisome. As a consequence, when an indicator is considered in isolation, it triggers a signal only when it reaches relatively higher values than when combined with one (or two) other indicators that may be showing signs of overheating. Although the decrease in threshold values in this first case of simultaneous breach is therefore intuitive and not unexpected, it may nevertheless be difficult for policymakers to act on such low threshold values.

3.1.2.2 Single breach of thresholds

In the second case, a signal is issued when one of the two or three indicators breaches its predefined threshold.

Table 4b shows the ten best bivariate indicator combinations in terms of AUROC. While in general the type of indicators included in the best pairs is similar to those included in the best pairs in Table 4a and the top two pairs coincide, only three out of ten indicator pairs appear in both tables[22]. In addition to the indicator type combinations in Table 4a (a structural real estate price variable with a cyclical real estate price or credit variable), Table 4b also includes combinations of a cyclical real estate variable with both cyclical and structural (debt service ratio) credit indicators.

The most notable difference between Tables 4a and 4b is the larger magnitude of the thresholds in the latter. In contrast to the simultaneous breach condition, which requires lower thresholds for sufficient signals to be issued, single breach multivariate thresholds are similar to or even higher than the univariate thresholds. Compared to the latter, adding an indicator in the single breach case adds flexibility in capturing imminent crises, as either one of two indicators needs to cross its threshold. The fact that the signalling burden is shared by two indicators rather than one, allows increasing thresholds in order to achieve a reduction in false alarm rates.

Regarding statistical performance, the best indicator pair remains the combination of nominal RRE price gap and nominal RRE price to rent gap, however. In the single breach case, a signal is given when either the former exceeds 10.50 or the latter exceeds 31.50, or both. On average, the single breach case results – because of the higher thresholds – in higher Type I errors and lower Type II errors, but overall performance in terms of relative usefulness and AUROC is very similar to the simultaneous breach case.

[21] When placing these negative threshold levels in the context of the large variability in some of the indicators as summarised in Table A4 in Annex A, it could be argued that they are still broadly commensurate with the indicators' average levels.

[22] Namely, nominal RRE price gap and nominal RRE price to rent gap, real RRE price gap and nominal RRE price to rent gap, real total credit growth and nominal RRE price to rent gap.

Table 4b: Bivariate non-parametric analysis: best 10 indicator pairs (single breach)

Indicator 1	*Indicator 2*	*Threshold 1*	*Threshold 2*	*Type I error*	*Type II error*	*Relative usefulness*	*AUROC*	*AUROC CI*
Nominal RRE price gap	Nominal RRE price to rent gap	10.50	31.50	0.31	0.11	0.58	0.85	[0.80 ,0.89]
Real RRE price gap	Nominal RRE price to rent gap	13.84	31.50	0.28	0.10	0.62	0.84	[0.80, 0.89]
Real NFC credit growth	Nominal RRE price gap	11.92	11.81	0.25	0.17	0.58	0.83	[0.78, 0.88]
Real RRE price growth	Nominal RRE price to rent gap	8.38	27.53	0.17	0.23	0.60	0.83	[0.78, 0.88]
Real total credit growth	Nominal RRE price gap	11.19	10.36	0.23	0.21	0.56	0.82	[0.78, 0.87]
Real NFC credit growth	Nominal RRE price to rent gap	11.92	26.55	0.26	0.18	0.56	0.82	[0.77, 0.87]
Nominal total credit to GDP gap	Nominal RRE price to income	6.64	24.89	0.09	0.35	0.57	0.82	[0.77, 0.87]
Real NFC credit growth	Real RRE price gap	11.81	16.30	0.27	0.15	0.59	0.82	[0.77, 0.87]
Nominal NFC credit growth	Nominal RRE price gap	18.73	11.81	0.27	0.13	0.60	0.82	[0.77, 0.87]
Debt service ratio	Nominal RRE price gap	0.67	24.59	0.24	0.09	0.67	0.82	[0.77, 0.87]
Average for all indicators pairs		**-**	**-**	**0.27**	**0.34**	**0.38**	**0.64**	**[0.59, 0.70]**

Table 5b shows the ten best trivariate indicator combinations in terms of AUROC; five out of ten indicator combinations also appear in Table 5a[23]. While the predominant role of structural and cyclical real estate variables remains unchanged compared to the simultaneous breach case, there is now also a more important role for structural credit variables (debt service ratio and nominal bank credit to GDP).

On average, the trivariate approach results in both lower Type I and Type II errors than the bivariate approach. A trade-off between error types may exist at the level of the indicator combinations, however. For example, the best performing triplet adds real NFC credit growth to real RRE price gap and nominal RRE price to rent gap (the second best pair in Table 4b), thereby increasing the Type II error from 10% to 18% but decreasing the Type I error from 28% to 15%. Whereas AUROC remains unchanged, this increases the relative usefulness to the policymaker from 0.62 to 0.66.

[23] Namely, the combinations of indicators where indicator 1 is, respectively, real NFC credit growth, real total credit growth, real bank credit growth, nominal bank credit to GDP gap and nominal total credit to GDP gap.

Table 5b: Trivariate non-parametric analysis: best 10 combinations (single breach)

Indicator 1	*Indicator 2*	*Indicator 3*	*Threshold 1*	*Threshold 2*	*Threshold 3*	*Type I error*	*Type II error*	*Relative usefulness*	*AUROC*	*AUROC CI*
Real NFC credit growth	Real RRE price gap	Nominal RRE price to rent gap	12.33	14.42	30.08	0.15	0.18	0.66	0.85	[0.80, 0.89]
Real total credit growth	Real RRE price gap	Nominal RRE price to rent gap	11.41	14.42	27.97	0.16	0.20	0.63	0.84	[0.80, 0.89]
Real bank credit growth	Real RRE price gap	Nominal RRE price to rent gap	11.86	13.57	31.06	0.16	0.20	0.63	0.84	[0.79, 0.89]
Real NFC credit growth	Real RRE price gap	Nominal RRE price to income gap	12.70	14.42	31.86	0.19	0.17	0.65	0.83	[0.78, 0.88]
Debt service ratio	Nominal total credit to GDP gap	Nominal RRE price to income gap	0.67	40.73	23.55	0.24	0.10	0.66	0.83	[0.79, 0.88]
Nominal bank credit to GDP gap	Real RRE price gap	Nominal RRE price to rent gap	10.82	14.42	30.08	0.17	0.19	0.63	0.82	[0.78, 0.87]
Real total credit growth	Real RRE price gap	Nominal RRE price to income gap	11.51	13.57	31.86	0.19	0.21	0.61	0.82	[0.78, 0.87]
Nominal bank credit to GDP	Real RRE price gap	Nominal RRE price to rent gap	162.82	13.57	30.08	0.28	0.12	0.60	0.82	[0.77, 0.87]
Nominal total credit to GDP gap	Real RRE price gap	Nominal RRE price to rent gap	13.30	14.42	28.55	0.15	0.23	0.61	0.82	[0.77, 0.87]
Debt service ratio	Real RRE price gap	Nominal RRE price to income gap	0.68	27.24	23.72	0.24	0.10	0.66	0.82	[0.77, 0.87]
Average for all indicator triplets			**-**	**-**	**-**	**0.24**	**0.28**	**0.48**	**0.70**	**[0.65, 0.76]**

3.1.2.3 Summary

Overall, the multivariate non-parametric signalling analysis shows that combining more variables results in better signalling performance. Including more variables potentially results in a higher true positive rate (or lower Type I error), as it allows capturing more factors underlying pre-crisis developments. Besides, more indicators add an additional level of confirmation that the imbalances in the economy are building up and therefore the amount of false alarms may be reduced. More generally, when multiple thresholds can be chosen optimally, this adds flexibility to the framework in managing the trade-off between correctly predicting crises and limiting the amount of false alarms. Frameworks that give a signal when either one of two or three indicators breaches its threshold perform similar to frameworks that require all two or three indicators to breach their threshold at the same time, but have the advantage of resulting in politically more acceptable threshold levels.

3.2 Parametric approach

3.2.1 The discrete choice model

The discrete choice framework provides an alternative approach for considering potential early warning indicators in a multivariate, parametric setting. In particular, instead of obtaining thresholds for each individual indicator, the discrete choice approach maps a number of indicators into a single metric, i.e. the predicted probability of a real estate-related crisis occurring within the assumed prediction horizon. Imposing more structure on the aggregation process reduces the dimensionality problem faced in the multivariate non-parametric signalling approach; only one optimal threshold is obtained and a signal is issued when the predicted crisis probability exceeds this threshold.

In what follows, we consider the following discrete choice (logit) model:

$$\Pr\left(y_{it} = 1 | \alpha_i, X_{K,it}\right) = F\left(\alpha_i + X'_{K,it}\beta_K\right),$$

where y_{it} represents our response variable (taking the value 1 for observations 12 to 5 quarters before real estate-related banking crises and 0 otherwise), the matrix $X_{K,it} = (x_{1,it}, \dots, x_{k,it})$ collects the potential explanatory variables (including a constant term) and the vector $\beta_K = (\beta_1, \dots, \beta_k)$ their corresponding regression coefficients. $F(\cdot)$ represents a logistic function of the form $F(z) = (1 + e^{-z})^{-1}$, which maps the indicators into the predicted crisis probability. The logit models are estimated as population averaged regressions, so that $\alpha_i = \alpha$.[24] Since this model assumes independence over *i* and *t*, we use robust standard errors to take into account possible misspecifications.

We proceed in two steps. First, we estimate and statistically evaluate early warning performance of logit models for all possible uni, bi and trivariate indicator combinations.[25] This allows us to compare the ranking of (combinations of) indicators and their signalling properties across methodologies (non-parametric vs parametric) when considering the same number of indicators. Second, we estimate

[24] As an alternative we could have estimated the logit models with country fixed effects. However, this would have led to excluding from the estimations countries for which the binary dependent variable is zero for the entire sample period, thereby eliminating from the estimation countries which never experienced a crisis in the sample considered. To exploit the maximum amount of information at our disposal, we opted for population average regressions.

[25] Like for the non-parametric approach, we limit the number of indicator combinations in the trivariate case, by selecting a subset of indicators based on the indicators' correlations and economic intuition.

and statistically evaluate the early warning performance of logit models for all potential combinations of a subset of indicators in order to obtain the overall best logit model.[26]

3.2.2 Uni, bi and trivariate indicator combinations

In this section, we estimate and statistically evaluate early warning performance of logit models for all uni, bi- and trivariate indicator combinations. In particular, we compare the ranking of (combinations of) indicators and the predictive abilities of the discrete choice approach with those of the non-parametric approach in warning against the imminent occurrence of real estate-related banking crisis events when the two methodologies are applied on an equal number of variables.

[26] Some of the potential explanatory variables are characterised by a high degree of persistence. Panel unit root tests (not shown, but available upon request) indeed reveal the presence of non-stationarity for some explanatory variables. However, while non-stationarity affects the standard errors of the estimated coefficients, it does not affect their unbiasedness (see Cameron and Trivedi (2005), p.705, Greene (2012), p.946 and Berg and Coke (2004) in the context of panel probit early-warning systems). This implies that the logit model predictions are not influenced by the potential presence of non-stationary explanatory variables (since the estimated coefficients are still unbiased) and that our analysis based on the signals derived from these model predictions is robust to the non-stationarity of the explanatory variables.

Table 6: Univariate, bivariate and trivariate logit regressions (t-values in parentheses)

	Univariate 1	*Univariate 2*	*Univariate 3*	*Bivariate 1*	*Bivariate 2*	*Bivariate 3*	*Trivariate 1*	*Trivariate 2*	*Trivariate 3*
Nominal RRE price to income gap	0.086*** (4.097)			0.093*** (4.069)	0.080*** (2.923)				
Nominal RRE price to rent gap		0.049*** (4.312)				0.056*** (4.835)	0.067*** (4.960)	0.056*** (4.209)	0.038*** (3.066)
Nominal RRE price gap			0.137*** (5.157)						
Debt service ratio				4.455*** (4.724)					
Real NFC credit growth						0.140*** (4.172)	0.180*** (6.046)		0.158*** (3.852)
HH credit to GDP									0.040** (2.571)
Real 3-month money mkt rate					0.164* (1.787)				
Real total credit growth								0.097*** (3.176)	
Nominal 3-month money mkt rate							0.294*** (-3.424)	0.255*** (-3.568)	
Constant	-3.567*** (-5.734)	-2.737*** (-5.365)	-3.300*** (-6.168)	-4.691*** (-5.421)	-3.203*** (-3.522)	-3.203*** (-3.522)	-5.436*** (-6.471)	-4.430*** (-5.403)	-6.432*** (-6.087)
Type I error	0.35	0.26	0.28	0.24	0.13	0.17	0.06	0.06	0.21
Type II error	0.12	0.24	0.23	0.13	0.27	0.22	0.30	0.27	0.11
Relative usefulness	0.53	0.50	0.50	0.63	0.60	0.60	0.64	0.67	0.68
AUROC	0.84	0.83	0.81	0.89	0.88	0.87	0.91	0.90	0.90
AUROC CI	[0.79, 0.88]	[0.79, 0.88]	[0.76, 0.86]	[0.85, 0.93]	[0.84, 0.92]	[0.83, 0.92]	[0.87,0.95]	[0.86,0.90]	[0.86,0.94]

* significant at 0.1; ** significant at 0.05; *** significant at 0.01

Table 6 shows the estimation results of the three best performing uni, bi and trivariate logit models in terms of AUROC.[27] Whereas the three best performing univariate logits contain structural and cyclical indicators related to developments in real estate prices, the bivariate case either combines a structural real estate price indicator (either the RRE price to income gap or price to rent gap) with variables related to cyclical developments in credit to non-financial corporations, the real short-term money market rate or the debt service ratio. In the trivariate logits, a structural real estate price variable (the nominal RRE price to rent gap) is combined with indicators of credit growth, structural credit and with the real short-term money market rate. The coefficients on all explanatory variables carry the expected sign and are highly significant.[28] The statistics reported in the bottom rows of Table 6 reveal that trivariate models perform better in terms of relative usefulness and AUROC: more specifically, they combine a very low Type I error with a reasonably low Type II error.

Table 7 compares the ranking of indicators and their performance resulting from parametric logit estimation with the best performing non-parametric combinations of indicators reported in Section 3.1.[29] Not surprisingly, the results of the non-parametric and parametric approach are identical in the univariate setting. The two approaches agree in ranking the nominal RRE price to income gap, the nominal RRE price to rent gap and the nominal RRE price gap as the three best performing indicators. In addition, the evaluation metrics reported in the last four columns of Table 7 show that the performance of the two univariate approaches is identical.

The other parts of Table 7 present a comparison of multivariate models. In contrast to the univariate case, the two approaches lead to different results, both in terms of best indicators and of signalling performance. While, in general, the two methodologies in the bi and trivariate setting agree on the presence of a structural real estate price variable in each combination (RRE price to rent gap or price to income gap), the non-parametric approach privileges combinations with indicators related to cyclical credit and/or real estate price developments, whereas the parametric approach adds cyclical credit variables, structural credit variables (debt service ratio, household credit to GDP) and/or the short-term interest rate. It is noteworthy that cyclical real estate variables are not present in the best three bi and trivariate logit models.

[27] For each model, the optimal threshold on the implied predicted crisis probability is obtained by maximising the relative usefulness of the model. A grid search was performed over a grid of size 100, bounded by the model's minimum and maximum predicted crisis probability in the sample.

[28] For an interpretation of the estimated coefficients, see the description of the overall best logit models in Section 3.2.

[29] The best three non-parametric bi and trivariate combinations are selected across both the simultaneous and single breach cases. The overall best three cases happen to coincide with the best three combinations from the simultaneous breach case.

Table 7: Comparison of top 3 non-parametric and discrete choice models

			Type I error	*Type II error*	*Relative Usefulness*	*AUROC*	*AUROC CI*
	Univariate non-parametric						
Nominal RRE price to income gap			0.35	0.12	0.53	0.84	[0.79, 0.88]
Nominal RRE price to rent gap			0.26	0.24	0.50	0.83	[0.79, 0.88]
Nominal RRE price gap			0.28	0.23	0.50	0.81	[0.76, 0.86]
Average			**0.31**	**0.41**	**0.28**	**0.63**	**[0.58, 0.68]**
	Univariate parametric						
Nominal RRE price to income gap			0.35	0.12	0.53	0.84	[0.79, 0.88]
Nominal RRE price to rent gap			0.26	0.24	0.50	0.83	[0.79, 0.88]
Nominal RRE price gap			0.28	0.23	0.50	0.81	[0.76, 0.86]
Average			**0.30**	**0.40**	**0.30**	**0.65**	**[0.60, 0.71]**
	Bivariate non-parametric						
Nom RRE price gap	Nominal RRE price to rent gap ratio		0.05	0.34	0.61	0.85	[0.81, 0.90]
Real RRE price gap	Nominal RRE price to rent gap ratio		0.09	0.31	0.60	0.85	[0.80, 0.90]
Real total credit growth	Nominal RRE price to rent gap ratio		0.13	0.25	0.63	0.85	[0.80, 0.90]
Average			**0.30**	**0.31**	**0.39**	**0.64**	**[0.58, 0.69]**
	Bivariate parametric						
Debt service ratio	Nominal RRE price to income gap		0.24	0.13	0.63	0.89	[0.85, 0.93]
Real 3-month money mkt rate	Nominal RRE price to income gap		0.13	0.27	0.60	0.88	[0.84, 0.92]
Real NFC credit growth	Nominal RRE price to rent gap ratio		0.17	0.22	0.60	0.87	[0.83, 0.92]
Average			**0.30**	**0.31**	**0.39**	**0.73**	**[0.68, 0.78]**
	Trivariate non-parametric						
Real total credit growth	Real RRE price gap	Nominal RRE price to rent gap	0.10	0.23	0.68	0.86	[0.82, 0.91]
Real NFC credit growth	Real RRE price gap	Nominal RRE price to rent gap	0.11	0.25	0.64	0.86	[0.81, 0.90]
Real bank credit growth	Real RRE price gap	Nominal RRE price to rent gap	0.16	0.20	0.63	0.85	[0.80, 0.89]
Average			**0.27**	**0.24**	**0.48**	**0.63**	**[0.63, 0.74]**
	Trivariate parametric						
Real NFC credit growth	3-month money mkt rate	Nominal RRE price to rent gap	0.06	0.30	0.64	0.91	[0.87, 0.95]
Real total credit growth	3-month money mkt rate	Nominal RRE price to rent gap	0.06	0.27	0.67	0.90	[0.86, 0.90]
Real NFC credit growth	Household credit to GDP	Nominal RRE price to rent gap	0.21	0.11	0.68	0.90	[0.86, 0.94]
Average			**0.28**	**0.23**	**0.49**	**0.80**	**[0.75, 0.85]**

Concerning the signalling performance of the two methodologies, Table 7 reveals that both the non-parametric and parametric approach result in broadly similar performance when they are applied using the same number of indicators. Differences in relative usefulness are small overall, and the increase in AUROC values obtained using the parametric approach is not significant. In addition, no specific pattern can be found in terms of the differences in the percentage of missed crises and false alarms from a comparison of the two methodologies.

3.2.3 Overall best logit model

As mentioned, imposing more structure on the aggregation process, the discrete choice approach suffers less from the dimensionality problem faced in the multivariate non-parametric signalling approach. This means that a larger number of variables can easily be included. Nevertheless, one should be aware of the fact that one of the most difficult tasks in econometric estimation is the choice of explanatory variables to include in a model. If insufficient variables are considered, an omitted variable problem will arise resulting in biased estimates. But if redundant or highly correlated regressors are included, the outcome is inflated standard errors and erratic changes in coefficient signs for small perturbations of the model or the data.

To choose the relevant variables to include as regressors in the logit analysis, we could in principle try all possible combinations. However, doing so would result in a large number of possible models soon becoming computationally impracticable. To circumvent dimensionality problems given by the large number of potential combinations of variables, we use information concerning the correlation structure of regressors and economic intuition to consider only the combinations of variables with the highest informative content. In particular, other than excluding combinations of highly correlated variables, we favour either nominal or real specifications based on the results of the univariate analysis. Furthermore, we exclude the presence of combinations of variables pertaining to the same category (e.g. two structural credit variables in the same regression model). This procedure leads to the selection of 25 possible explanatory variables, listed in Table 8.

Table 8: Potential explanatory variables for logit regressions

Structural credit variables	***Real estate price variables***
(Nominal) HH credit to GDP	(Nominal) RRE price to income gap
(Nominal) NFC credit to GDP	(Nominal) RRE price to rent gap
(Nominal) total credit to GDP	RRE price growth (nominal and real)
(Nominal) bank credit to GDP	RRE price gap (real)
Debt service ratio	***Other variables***
Cyclical credit variables	Inflation
HH credit growth (real)	Real GDP growth
NFC credit growth (real)	Unemployment rate
Total credit growth (real)	Real effective exchange rate growth
Bank credit growth (real)	Current account deficit to GDP
(Nominal) HH credit to GDP gap	Long term gov't bond yield (nominal)
(Nominal) NFC credit to GDP gap	3-month money market rate (nominal)
(Nominal) total credit to GDP gap	Equity prices growth (real)
(Nominal) bank credit to GDP gap	

[a]: HH = "households"; NFC = "non-financial corporations"; RRE = "residential real estate"; GFCF = "gross fixed capital formation"

This procedure leads us to estimate more than 13,000 logit models (containing up to five explanatory variables), for which we obtain the corresponding predicted values. These predicted values represent the probability of a real estate-related banking crisis occurring within the assumed prediction horizon. For each model, the optimal threshold on the predicted crisis probability is obtained by maximising the relative usefulness of the model.[30] The regression results for the ten best models ranked according to their AUROC are presented in Table 9 below.[31]

[30] A grid search was performed over a grid of size 100, bounded by the model's minimum and maximum predicted crisis probability in the sample.

[31] Estimation results for the best ten models in Table 9 with country fixed effects included are qualitatively very similar, with most coefficient estimates somewhat larger and even more significant than in the population average model. Signalling performance (restricted to the subset of countries that experienced at least one crisis) is somewhat worse than for the population average model. See Table A9 in Annex A.

Table 9: Regression results panel logit models (t-values in parentheses)

	Model1	*Model2*	*Model3*	*Model4*	*Model5*	*Model6*	*Model7*	*Model8*	*Model9*	*Model10*
Real total credit growth	0.166***	0.242***			0.196***		0.122***			
	(4.849)	(4.616)			(3.644)		(4.479)			
Nominal bank credit to GDP	0.049***		0.048***			0.035***		0.056***		
	(6.078)		(5.824)			(4.518)		(5.513)		
RRE price to rent gap	0.037***	0.042***	0.031**	0.049***	0.034***	0.051***		0.044***	0.051***	
	(2.787)	(2.578)	(1.974)	(3.542)	(3.145)	(3.651)		(2.804)	(3.861)	
3-month money mkt rate	0.426***	0.544***	0.401***	0.409***	0.471***	0.390***	0.347***	0.455***	0.445***	0.327***
	(5.633)	(5.242)	(5.728)	(4.334)	(5.044)	(4.336)	(2.685)	(5.087)	(4.892)	(2.379)
Inflation	-0.302***	-0.378***	-0.284***	-0.264**	-0.257***	-0.296***	-0.333**	-0.324**	-0.287***	-0.336**
	(-2.760)	(-2.971)	(-2.597)	(-2.184)	(-2.148)	(-2.646)	(-2.434)	(-2.499)	(-2.294)	(-1.966)
Household credit to GDP		0.085***		0.060***						
		(4.211)		(3.497)						
Real bank credit growth			0.131***							
			(4.713)							
Real NFC credit growth				0.218***		0.200***			0.234***	0.159***
				(5.619)		(5.783)			(6.223)	(4.780)
Nominal total credit to GDP					0.038***				0.028***	
					(5.363)				(3.604)	
Debt service ratio							7.216***			6.805***
							(6.207)			(6.655)
RRE price to income gap							0.116***			0.116***
							(3.683)			(3.841)
Real HH credit growth								0.113***		
								(7.856)		
Constant	-10.224***	-12.115***	-9.543***	-9.746***	-11.977***	-9.100***	-8.021***	-10.583***	-10.683***	-7.968***
	(-14.079)	(-4.906)	(-11.367)	(-6.215)	(-6.626)	(-10.652)	(-5.378)	(-9.638)	(-6.924)	(-5.969)
Type I error	0.02	0.18	0.12	0.18	0.14	0.06	0.17	0.06	0.11	0.13
Type II error	0.20	0.07	0.15	0.11	0.12	0.21	0.08	0.20	0.19	0.12
Relative usefulness	0.78	0.74	0.74	0.71	0.74	0.73	0.75	0.74	0.71	0.75
AUROC	0.95	0.94	0.94	0.94	0.94	0.94	0.94	0.93	0.93	0.93
AUROC CI	[0.92, 0.98]	[0.91, 0.97]	[0.91, 0.97]	[0.91, 0.97]	[0.91, 0.97]	[0.90, 0.97]	[0.90, 0.97]	[0.90, 0.97]	[0.90, 0.97]	[0.90, 0.97]

* significant at 0.1; ** significant at 0.05; *** significant at 0.01

Among the 25 considered regressors, 12 appear in the best ten models, including structural (bank credit to GDP, household credit to GDP, total credit to GDP, debt service ratio) and cyclical credit indicators (real total credit growth, real bank credit growth, real NFC and real household credit growth), structural real estate price indicators (nominal RRE price to income gap and price to rent gap), a macroeconomic indicator (inflation) and a market indicator (three-month money market rate). Indicators of cyclical developments in real estate prices do not appear in the best ten regression models.[32]The results again point towards a high importance of structural real estate price variables in identifying periods of vulnerability in the run-up of a real estate crisis. In fact, all ten best models feature either the RRE price to rent gap or RRE price to income gap among the chosen explanatory variables. Such indicators of residential real estate price overvaluation are positively associated with the probability of occurrence of a real estate-related distress event.

Furthermore, vulnerable periods are characterised by both a structural and cyclical increase in credit. In fact, a combination of one structural and one cyclical credit indicator appears in every model in Table 9, with highly statistically significant coefficients. While a marked expansion of credit during the upturn of the cycle might signal overheating in the real estate sector and can be associated with a loosening of credit standards which can expose banks to credit risk, a structurally high level of credit in the economy is a symptom of excessive leverage, which can significantly exacerbate the impact of a downturn. The more households are burdened by loan repayments, the less their resilience to the negative wealth effect resulting from a steep fall in house prices. This results in higher credit risk for banks amid falling debt servicing capabilities of households.

The results presented in Table 9 also reveal that accounting for inflation and for the level of the short-term money market rate is important. In fact, these two variables appear in all the best ten regression models, with a highly statistically significant coefficient. While increasing levels of the three-month money market rate seem to increase the probability of a crisis, high inflation is found to dampen the probability of a distress event related to the real estate sector. A possible explanation for the former relates to the increased debt burden of variable rate mortgages when interest rates increase, whereas the latter can be explained by the debt deflation effect of increasing price level, which has positive effect on balance sheets of leveraged borrowers by reducing the real burden of debt. More generally, increasing interest and inflation rates are commensurate with periods of economic prosperity, during which underestimation of risks and herd behaviour may result in the creation of imbalances.

The performance of the best logit models can be evaluated looking at the statistics reported in the bottom lines of Table 9. AUROCs range from 0.93 to 0.95, indicating a very high informative power of these models. Also, Type I and Type II error rates are very small: the overall best model results in a probability of missing a crisis of only 2%, whereas it issues false alarms with a 20% probability.

[32] This may be due to the fact that only one real estate variable at a time is allowed in the regression specifications. On the other hand, the best three trivariate logit models (where no restriction was imposed on the number of real estate variables included in the regression) did not include a cyclical real estate price either. Hence, it turns out that real estate variables containing a structural component have a stronger contribution to predictive ability than purely cyclical real estate price variables.

Although the performance in terms of Type I and Type II errors varies across models, error rates of both types never exceed 21%.[33]

A comparison with the statistical performance of the non-parametric and parametric models in Table 6 reveals that the overall best logit models significantly improve performance: moving from values around 0.5 in the univariate case to values around 0.75 for relative usefulness, and a rise in AUROC from values slightly above 0.80 in the univariate case to levels larger than 0.93. The AUROCs of the best ten logit models are in fact significantly larger than those of many of the uni, bi and trivariate non-parametric and parametric indicator combinations.

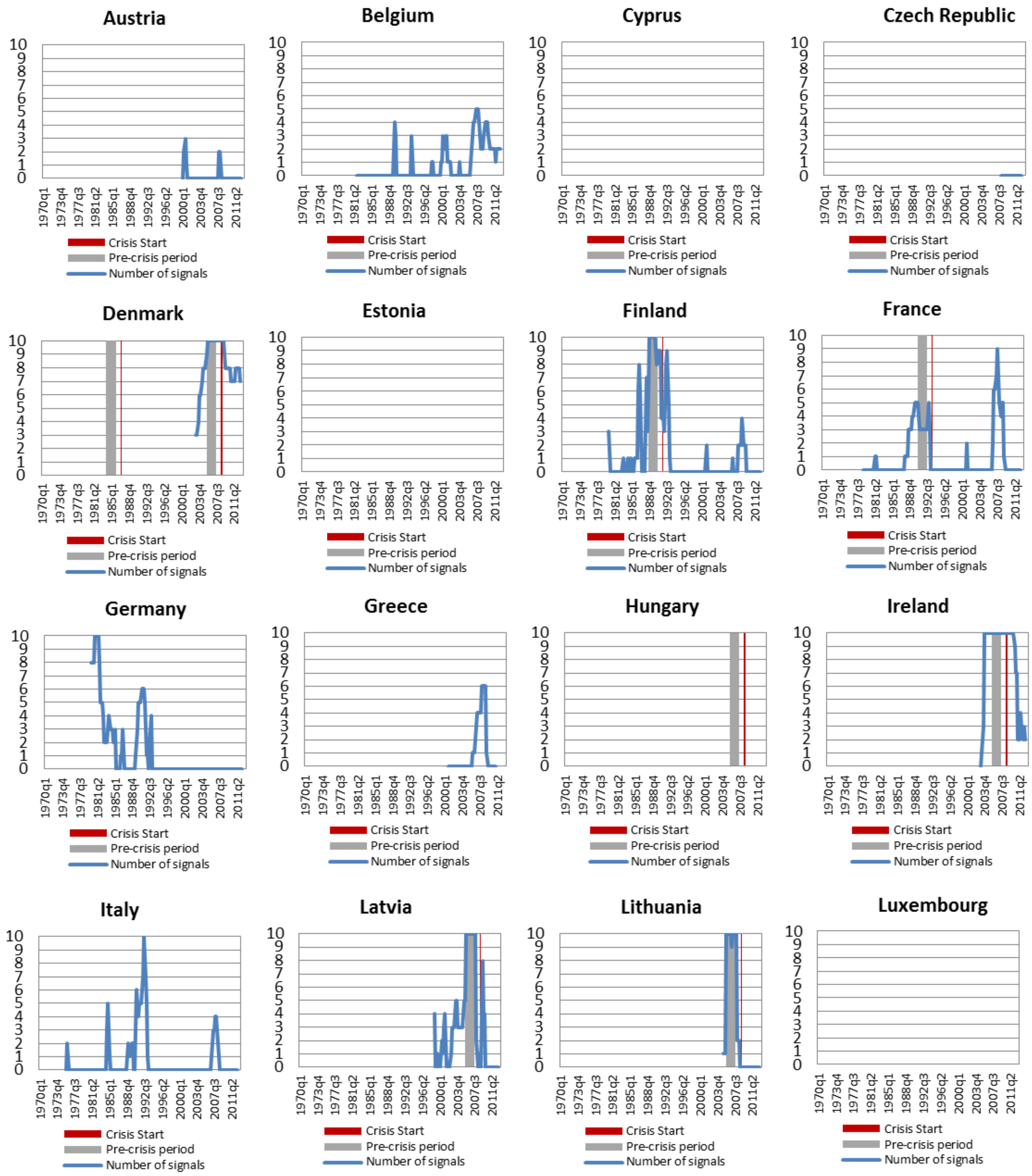
To gauge the consistency of the signals issued across the ten best logit models, Figure 5 depicts the number of models (ranging from 0 to 10) issuing a signal in each quarter, together with the start of real estate-crisis events and the correspondent pre-crisis period. For all crisis countries except France and Slovenia, all ten best logit models correctly signal the imminent occurrence of a real estate-related crisis during the pre-crisis horizon. In France's case, only five models issue a signal in the pre-crisis period.[34]

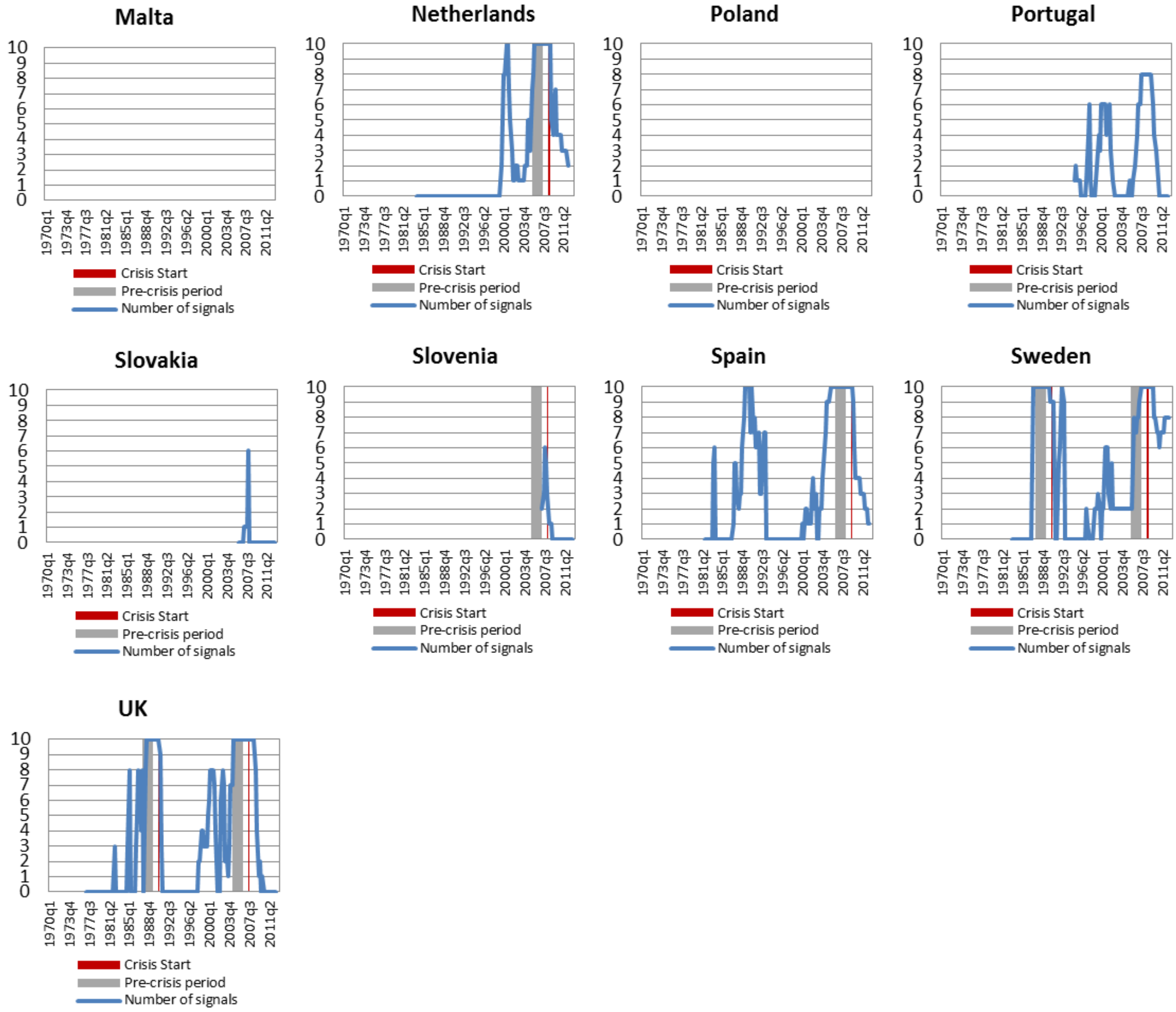
For the Netherlands and Spain the models agree in issuing a false alarm earlier in the sample, while in the case of France, nine models out of ten wrongly issue a warning in 2007 Q3. Some false alarms can also be observed in countries which do not experience a crisis, notably in Germany (in the beginning of the 1980s), Italy (around 1992) and Portugal (2008), and to a lesser extent in Austria, Belgium, Greece and Slovakia. However, signals issued by the best ten models are consistent, since a large fraction of models issue warnings at the same time.

[33] The sample on which the analysis has been performed is unbalanced; in fact, Table A2 in Annex A shows that the data availability of different variables is very heterogeneous. Therefore, though each cover at least 13 crises, the samples used for estimating the different models depend on the variables included. To test the robustness of our results, we consider only periods in which all variables are non-missing for a given country, thereby running each regression on the same sample. This restricted data sample, which covers ten crises (eight coinciding with the recent financial crisis, two with crises in the early nineties), results in similar estimates and performance to the models in Table 9. The results of the ten best models resulting from this robustness exercise are presented in Table A10 in Annex A.

[34] A possible explanation may be that in France the property bubble of the early 1990s was concentrated in the Paris area (see for example https://www.tresor.economie.gouv.fr/File/326927).

Figure 5: Signals from the best 10 models and actual crisis onset





3.3 Country-level evaluation of best models

The results presented so far refer to the pooled set of the 25 EU countries for which we have sufficient data coverage. However, financial cycles are likely to be heterogeneous across countries, and the application of macro-prudential policies occurs at national level. In this section, we assess how well the indicators and models estimated on pooled EU-wide data perform at individual country level. We furthermore show that estimating country-specific thresholds may improve signalling performance at the level of individual countries.

3.3.1 Country level evaluation of the best trivariate non-parametric combination of indicators

Table 10 provides information on the country-level true and false positive rates as well as the relative usefulness corresponding to the best trivariate non-parametric combination of indicators in Table 5, highlighting in bold countries which experienced at least one crisis episode.[35] The good ability of this

[35] For the best trivariate combination of indicators, a signal is issued when all three indicators breach their individual thresholds. On the other hand, no signal is issued when either one of the three indicators in the combination does not breach its threshold.

combination to identify vulnerability periods preceding a real estate-related crisis is evident from the high values attained by the true positive rate. For 7 out of 11 crisis countries, pre-crisis periods are perfectly identified, while lower, but still satisfactory true positive rates can be observed for Denmark and the Netherlands (81% and 75%, respectively). The only two countries for which the pre-crisis period is poorly identified are Hungary and France, where the true positive rate settles at 0 and 38%, respectively. In the case of Hungary this is driven by the very short availability of time series of the three variables concerned, while for France the low value of the true positive rate can be attributable to the peculiarity of the real estate crisis, concentrated in the Paris area.

At the same time, although the picture concerning false alarms is more heterogeneous across countries, the overall probability that this model wrongly issues a signal is quite low. For non-crisis countries, the best trivariate combination leads to a very small share of false alarms: only in Belgium's case does the probability of false alarms reach 32%, the highest value in the sample. The other 12 non-crisis countries settle on values between zero (seven countries) and 24% (Italy). The share of wrongly identified crises is slightly higher for crisis countries, ranging from 2% (Sweden) to 27% (Finland).

In terms of relative usefulness for the policymaker, the performance of the best trivariate non-parametric combination is quite heterogeneous, ranging from 0.15 (France) to 0.98 (Sweden). Since in Hungary both the true and the false positive rates are equal to zero, the relative usefulness of the signal is zero.

Table 10: Signalling performance of best trivariate non-parametric combination of indicators, by country

Country	*TPR*	*FPR*	*Relative usefulness*
Austria	.	0.08	.
Belgium	.	0.32	.
Cyprus	.	0	.
Czech Republic	.	0	.
Denmark	**0.81**	**0.13**	**0.69**
Estonia	.	0	.
Finland	**1**	**0.27**	**0.73**
France	**0.38**	**0.22**	**0.15**
Germany	.	0.06	.
Greece	.	0.10	.
Hungary	**0**	**0**	**0**
Ireland	**1**	**0.19**	**0.81**
Italy	.	0.24	.
Latvia	**1**	**0.12**	**0.88**
Lithuania	**1**	**0.11**	**0.90**
Luxembourg	.	0	.
Malta	.	0	.
Netherlands	**0.75**	**0.18**	**0.57**
Poland	.	0	.
Portugal	.	0.12	.
Slovakia	.	0	.
Slovenia	**.**	**0**	**.**
Spain	**1**	**0.26**	**0.75**
Sweden	**1**	**0.02**	**0.98**
United Kingdom	**1**	**0.16**	**0.84**

3.3.2 Country level evaluation of the best logit model

Figure 6 plots the predicted crisis probabilities of the best logit model by country (cf. Model 1 in Table 9), as well as the first quarter of real estate-related banking crises and the corresponding pre-crisis period. The model predictions clearly peak in the pre-crisis period, although the signal is somewhat weaker for France. In Slovenia, the model seems to warn against the occurrence of vulnerabilities too late, but data are not available throughout most of the pre-crisis period for Slovenia. Figure 6 also shows that false alarms are sporadic: unjustified signals can be observed in Denmark, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain and the UK.

Figure 6: Predictions of best logit model and actual crisis start, by country

A formal evaluation of the country-specific performance of the best logit model is presented in Table 11, where information on the true positive and false positive rates as well as the relative usefulness is provided. The model exhibits a true positive rate of 100% in 8 out of 10 crisis countries, while in Sweden and the UK the fraction of correctly identified crises amounts to 94%. This implies an overall very good ability of the model to identify the occurrence of a vulnerable, pre-crisis period.

In countries that did not experience a crisis, the false positive rate is below 30% (with the exception of the 44% registered in Portugal), with particularly low levels observed for Austria (2.5%), Belgium (2.4%), the Czech Republic (0%) and Slovakia (4.8%). Only in Cyprus does the model wrongly issue a signal in 100% of cases; this has, however, to be interpreted considering the very short time period in which predictions are available (cf. Figure 6). Among crisis countries, values of the false positive rates lower than 10% are observed for Finland and Sweden, whereas other countries settle between 13% (France) and 46% (Denmark).

In terms of relative usefulness for the policymaker, the best logit model performs very well, with values between 0.54 and 0.96.

Overall, both the non-parametric and discrete choice methodologies lead to models with relatively good signalling performance for most individual countries. In particular, the risk of missing a crisis is quite limited. While the parametric approach seems to be better in identifying periods of vulnerability, it issues wrong signals more often than the non-parametric trivariate approach. In terms of relative usefulness, the picture is mixed; while strong improvements are observed for some countries (especially France and the Netherlands), the opposite is observed for other countries (especially Latvia and Lithuania).

Table 11: Signalling performance of best logit model, by country

Country	*Optimal threshold*	*TPR*	*FPR*	*Relative usefulness*
Austria	0.0616	.	0.02	.
Belgium	0.0616	.	0.03	
Cyprus	0.0616	.	1	.
Czech Republic	0.0616	.	0	.
Denmark	0.0616	**1**	**0.46**	**0.54**
Estonia	0.0616	.	.	.
Finland	0.0616	**1**	**0.04**	**0.96**
France	0.0616	**1**	**0.13**	**0.87**
Germany	0.0616	.	0.12	.
Greece	0.0616	.	0.26	.
Hungary	0.0616	**.**	**.**	**.**
Ireland	0.0616	**1**	**0.29**	**0.71**
Italy	0.0616	.	0.15	.
Latvia	0.0616	**1**	**0.44**	**0.56**
Lithuania	0.0616	**1**	**0.33**	**0.67**
Luxembourg	0.0616	.	.	.
Malta	0.0616	.	.	.
Netherlands	0.0616	**1**	**0.15**	**0.86**
Poland	0.0616	.	.	.
Portugal	0.0616	.	0.44	.
Slovakia	0.0616	.	0.05	.
Slovenia	0.0616	**.**	**.**	**.**
Spain	0.0616	**1**	**0.37**	**0.63**
Sweden	0.0616	**0.94**	**0.08**	**0.86**
United Kingdom	0.0616	**0.94**	**0.23**	**0.71**

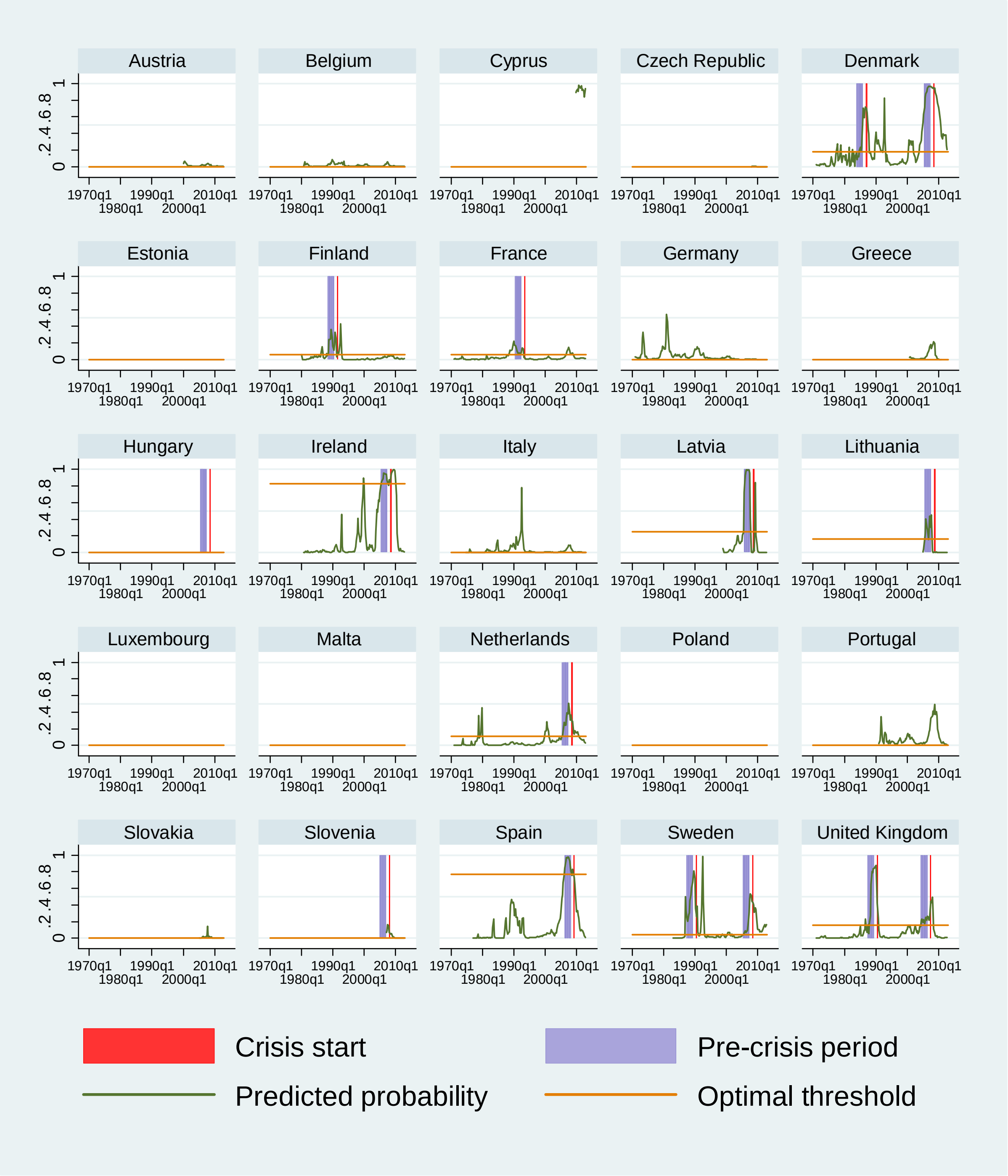
3.3.3 Country-specific thresholds of best logit model

The results presented in the previous section reveal a degree of cross-country heterogeneity in the country-level performance of the best logit model on the basis of a pooled threshold. In this section, we assess whether country-level early-warning precision can be increased by computing country-specific optimal thresholds based on the prediction of the best (pooled) logit model[36]. Again, the optimal threshold is chosen as the one yielding the highest relative usefulness for the policymaker.

Figure 7 depicts the country-specific thresholds together with the predictions of the best logit model (which remain unchanged in comparison to Figure 6), the pre-crisis periods and the onset of real estate-related crises related to this exercise.

[36] The optimal threshold for each country is calculated using the same methodology as for the pooled threshold. Cf. footnote 30.

Figure 7: Country-specific thresholds and predicted probabilities of best logit model



As it is readily noticeable, country-specific, optimal thresholds differ substantially from the pooled threshold for the best logit model (equal to 0.06), except for Finland and France. For most of the crisis countries, the optimal threshold is higher than the pooled one, most notably for Ireland and Spain. Only Sweden exhibits an optimal country-specific threshold lower than the pooled one.

While the true positive rate for crisis countries is still very high, a strong reduction in the false positives rate can be noticed, due to the negative relationship between the value of the threshold and the Type II error. In particular, the share of wrongly predicted crises now ranges from 1% (UK) to 17% (Denmark), well below that corresponding to signals obtained using the pooled threshold (from 2% to 46%). This is due to the much higher optimal threshold for some countries (e.g. Ireland, Spain, Latvia), which allows a better balancing of the true and the false positive rates, thereby making the signal more precise. For all countries, the relative usefulness is at high levels and at least as large as with the pooled threshold.

Table 12: Signalling performance of best logit model with country-specific thresholds

Country	*Optimal threshold*	*TPR*	*FPR*	*Relative usefulness*
Austria	.	.	.	.
Belgium	.	.	.	.
Cyprus	.	.	.	.
Czech Republic	.	.	.	.
Denmark	**0.18**	**0.81**	**0.17**	**0.64**
Estonia	.	.	.	.
Finland	**0.06**	**1**	**0.04**	**0.96**
France	**0.06**	**1**	**0.13**	**0.87**
Germany	.	.	.	.
Greece	.	.	.	.
Hungary	**.**	**.**	**.**	**.**
Ireland	**0.83**	**1**	**0.01**	**0.99**
Italy	.	.	.	.
Latvia	**0.25**	**1**	**0**	**1**
Lithuania	**0.16**	**0.88**	**0**	**0.88**
Luxembourg	.	.	.	.
Malta	.	.	.	.
Netherlands	**0.11**	**1**	**0.07**	**0.93**
Poland	.	.	.	.
Portugal	.	.	.	.
Slovakia	.	.	.	.
Slovenia	.	.	.	.
Spain	**0.77**	**1**	**0**	**1**
Sweden	**0.04**	**1**	**0.13**	**0.88**
United Kingdom	**0.16**	**0.94**	**0.01**	**0.93**

While this analysis of country-specific thresholds is based on only one or two crises per country and therefore is not necessarily robust, it shows that obtaining country-specific thresholds is an important area for future research on improving early warning signalling performance.

Section 4 Robustness analysis

This section provides an account of the sensitivity of the results to assumptions related to the policymaker's loss function as well as to the choice of countries in the sample.

4.1 Parameter of the policymaker's loss function

The results presented so far are based on optimal thresholds calculated by optimising a policymaker's loss function, for which the preference parameter (θ) representing the relative preference between missing crises and issuing false alarms was set at 0.5. This implies the policymaker is indifferent between incurring a Type I and a Type II error.[37] However, with the recent financial crisis still fresh in their memory, policymakers might be more adverse towards missing crises, since they might associate the cost of banking crises larger than the cost society would incur in case of macro-prudential policies unwarrantedly implemented. On the other hand, policymakers might be inclined towards inaction bias, since the cost of policy action arises in the short term, while its benefits can only been reaped after a time lag.[38]

Tables 13 and Table 14 show the signalling performance of the best trivariate non-parametric combination of indicators and the best logit model obtained for different values of θ, where θ>0.5 implies that the policymaker has a stronger preference towards minimising the Type I error. The tables reveal that, as expected, the choice of the preference parameter influences the optimal thresholds and, consequently, the signalling performance of the model in both the non-parametric and parametric framework. In general, setting θ above 0.5 leads to lower thresholds and, therefore, to lower Type I errors and higher Type II errors. Note that the ranking of the indicators and models based on AUROC in the previous sections is not influenced by the choice of the loss function's preference parameter as the AUROC is calculated for every possible threshold value and therefore independently of θ.

[37] It should be noted though that following an extension suggested by Sarlin (2013) and applied by for instance Behn et al. (2014), the loss function can account for the relative frequency of pre-crisis and tranquil periods, in addition to the policymaker's preference parameter. Given the lower relative frequency of pre-crisis periods, a higher weight on Type I errors does not necessarily result in a higher overall weight on Type I errors in the loss function in this framework. Our benchmark case of θ=0.5 could be considered a "reduced form" specification of the Sarlin (2013) extension.

[38] The reader is referred to Chapter 9 of the ESRB Handbook on "Operationalising Macro-Prudential Policy in the Banking Sector" for an extensive discussion of inaction bias, and how it can be overcome using a solid signalling framework.

Table 13: Signalling performance of best trivariate non-parametric combination for different values of theta

θ	var1	var2	var3	Thres1	thres2	thres3	Type I	Type II	Rel. usefulness	AUROC	AUROC CI
0.5	Real total credit growth	Real RRE price gap	Nominal RRE price to rent gap	5.21	-0.10	-6.07	0.10	0.23	0.68	0.86	[0.82,0.91]
0.7	Real total credit growth	Real RRE price gap	Nominal RRE price to rent gap	2.56	-0.96	-9.16	0	0.37	0.63	0.86	[0.82,0.91]
0.9	Real total credit growth	Real RRE price gap	Nominal RRE price to rent gap	2.55	-0.96	-9.16	0	0.37	0.63	0.86	[0.82,0.91]

Table 14: Signalling performance of best logit model (Model1) for different values of theta

θ	threshold	Type I	Type II	Relative usefulness	AUROC	AUROC CI
0.5	0.0615	0.02	0.20	0.78	0.95	[0.92,0.98]
0.7	0.0566	0.01	0.22	0.76	0.95	[0.92, 0.98]
0.9	0.0456	0	0.27	0.73	0.95	[0.92, 0.98]

4.2 Out-of-sample analysis

Due to the limited number of crisis observations it is not possible to do an out-of-sample exercise along the time dimension (out-of-sample predictive ability). Instead, an out-of-sample exercise along the cross-country dimension is performed in this section.

The sample of countries and crises considered in the analysis can have strong repercussions on the results, especially in a sample where crises are scarce. This section presents the results of the logit analysis performed excluding a set of countries from the estimation, and then comparing the model predictions with actual outcomes for the full sample of countries. In addition, we use the model estimated on the reduced set of countries to perform an out-of-sample evaluation of the model for the excluded countries.

To conduct this exercise we could exclude one country at a time from the sample, re-estimate the logit model and consider how it performs out of sample for the excluded country. However, in what follows we opt for a somewhat “stricter” approach in which we exclude from the sample the three countries that experienced two crisis periods (i.e. Denmark, Sweden and the UK) and re-run the estimations of the best ten logit models.

Table 15 illustrates the results of this exercise, confirming the robustness of the models to changes in the composition of the sample. All variables retain their sign and statistical significance, with the exception of inflation, which is no longer statistically significant in five out of ten models. The magnitudes of the regression coefficients change only negligibly. Furthermore, comparing the bottom lines of Table 15 with those in Table 9, one notices that the early warning performance of the models remains broadly unchanged.

Table 15: Regression results panel logit models (t-values in parentheses): DK, SE and UK excluded

	Model1	*Model2*	*Model3*	*Model4*	*Model5*	*Model6*	*Model7*	*Model8*	*Model9*	*Model10*
Real total credit growth	0.170***	0.274***			0.191***		0.140***			
	(4.093)	(3.841)			(3.283)		(3.103)			
Nominal bank credit to GDP	0.050***		0.050***			0.038***		0.062***		
	(4.894)		(4.634)			(4.242)		(3.926)		
RRE price to rent gap	0.034***	0.032*	0.026*	0.041***	0.036***	0.047***		0.038***	0.053***	
	(2.969)	(1.941)	(1.767)	(3.328)	(3.514)	(4.287)		(2.376)	(4.186)	
3-month money mkt rate	0.417***	0.646***	0.414***	0.458***	0.436***	0.404***	0.340**	0.471***	0.453***	0.301*
	(5.013)	(7.187)	(5.469)	(3.996)	(3.961)	(3.378)	(2.082)	(5.008)	(3.516)	(1.683)
Inflation	-0.269**	-0.467***	-0.234*	-0.267	-0.217	-0.286*	-0.321	-0.275	-0.288*	-0.304
	(-2.066)	(-4.005)	(-1.761)	(-1.569)	(-1.417)	(-1.901)	(-1.930)	(1.604)	(-1.679)	(-1.512)
Household credit to GDP		0.107***		0.075***						
		(3.381)		(3.091)						
Real bank credit growth			0.148***							
			(4.297)							
Real NFC credit growth				0.258***		0.227***			0.266***	0.160***
				(4.378)		(4.036)			(3.855)	(3.280)
Nominal total credit to GDP					0.035***				0.026***	
					(3.903)				(2.837)	
Debt service ratio							18.401***			14.749***
							(2.642)			(2.320)
RRE price to income gap							0.098***			0.095***
							(3.141)			(3.084)
Real HH credit growth								0.126***		
								(7.147)		
Constant	-10.819***	-13.970***	-10.802***	-11.359***	-12.015***	-10.149***	-10.104***	-12.151***	-11.477***	-9.044***
	(-9.102)	(-3.954)	(-7.425)	(-4.796)	(-4.947)	(-6.745)	(-3.995)	(-6.661)	(-4.260)	(-4.248)
Type I error	0.01	0.16	0.11	0.16	0.14	0.06	0.17	0.04	0.12	0.15
Type II error	0.22	0.10	0.17	0.13	0.12	0.22	0.09	0.23	0.19	0.11
Relative usefulness	0.77	0.74	0.72	0.71	0.73	0.72	0.75	0.73	0.70	0.74
AUROC	0.95	0.94	0.94	0.94	0.94	0.94	0.91	0.93	0.93	0.91
AUROC CI	[0.90, 0.99]	[0.90, 0.98]	[0.89, 0.98]	[0.89, 0.98]	[0.89, 0.98]	[0.89, 0.98]	[0.86, 0.95]	[0.89, 0.98]	[0.89, 0.98]	[0.86, 0.95]

To gauge the ability of the model to identify pre-crisis periods in the countries excluded from the estimation sample, Figure 8 depicts the predicted probabilities corresponding to the best logit model in Table 15, together with the pre-crisis period and the optimal threshold of the model. The model is able to correctly identify all pre-crisis periods, even in Denmark, Sweden and the UK, with predicted probabilities peaking and breaching the optimal threshold. Only in the case of the second Swedish crisis, predicted probabilities peak somewhat late, but still breaching the threshold within the chosen pre-crisis period. Overall, this confirms the out-of-sample performance of the best logit model, and the validity of the results for countries not included in the estimation sample.

A more formal evaluation of the country-specific properties of the model estimated on the sample of 22 countries is presented in Table 16. The ability of the model to identify upcoming crisis events is very similar to that of the best logit model estimated over the full sample (cf. Table 11), also for the out-of-sample countries. The performance of the model in terms of false positive rates and relative usefulness is comparable to the baseline results, once again confirming their robustness.

Figure 8: Predictions of best logit model and actual crisis start, by country – out of sample

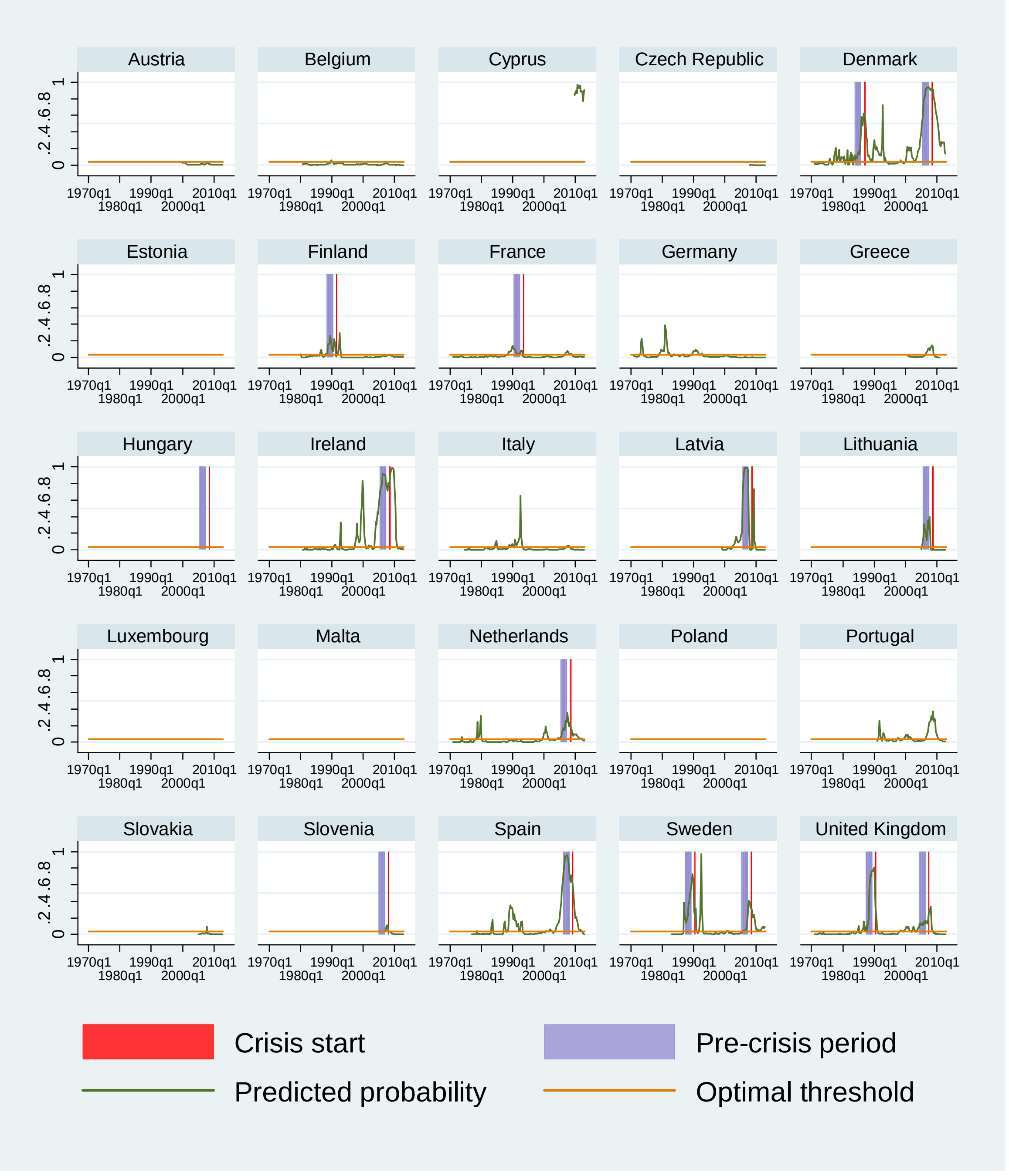


Table 16: Signalling performance of best logit model – "out-of-sample"

Country	*Optimal threshold*	*TPR*	*FPR*	*Relative usefulness*
Austria	0.0393	.	0.03	.
Belgium	0.0393	.	0.03	.
Cyprus	0.0393	.	1	.
Czech Republic	0.0393	.	0	.
Denmark	0.0393	**1**	**0.48**	**0.52**
Estonia	0.0393	.	.	.
Finland	0.0393	**1**	**0.06**	**0.94**
France	0.0393	**1**	**0.13**	**0.87**
Germany	0.0393	.	0.19	.
Greece	0.0393	.	0.27	.
Hungary	0.0393	**.**	**.**	**.**
Ireland	0.0393	**1**	**0.29**	**0.71**
Italy	0.0393	.	0.15	.
Latvia	0.0393	**1**	**0.48**	**0.52**
Lithuania	0.0393	**1**	**0.33**	**0.67**
Luxembourg	0.0393	.	.	.
Malta	0.0393	.	.	.
Netherlands	0.0393	**1**	**0.13**	**0.87**
Poland	0.0393	.	.	.
Portugal	0.0393	.	0.43	.
Slovakia	0.0393	.	0.05	.
Slovenia	0.0393	**.**	**.**	**.**
Spain	0.0393	**1**	**0.35**	**0.65**
Sweden	0.0393	**0.88**	**0.08**	**0.80**
United Kingdom	0.0393	**0.94**	**0.24**	**0.70**

Section 5 Policy discussion and conclusions

The operationalisation of macro-prudential instruments requires the identification of sound leading indicators capable of signalling the build-up of vulnerabilities and systemic risk in a timely manner, including excessive developments in the real estate market which could potentially lead to bank distress. This paper presents a comprehensive statistical evaluation of early warning indicators for real estate-related systemic banking crises. Relying on data on real estate-related banking crises for 25 EU countries, both non-parametric and discrete choice analyses are applied in a signalling framework aimed at evaluating the early warning performance of a set of indicators.

Our analysis shows that, although monitoring single indicators may provide valuable information on real estate-related vulnerabilities, multivariate models that combine the information of several indicators exhibit a better signalling performance. Combining more variables results in lower Type I errors, as it allows for capturing more factors underlying pre-crisis developments. Furthermore, more indicators give an additional level of confirmation that imbalances in the economy are building up and hence the amount of false alarms may be reduced.

In addition, the results in the paper indicate that multivariate logit models may be more suitable for combining the information of several indicators than the non-parametric signalling method. First, multivariate logit models generally tend to present better signalling performance than non-parametric models. Second, multivariate non-parametric indicator combinations are also characterised by low threshold values in case of a simultaneous breach of thresholds. It may be difficult for policymakers to decide and communicate on the activation of macro-prudential instruments based on such low threshold values.

The overall best logit models point towards the high importance of structural real estate price variables (price to rent gap; price to income gap) in identifying periods of vulnerability in the run-up to a real estate-related banking crisis. Vulnerable periods are also characterised by both a structural and cyclical increase in credit. Finally, accounting for inflation and the level of short-term money market rates is found to be important.

The aforementioned best performing indicators and models provide an analytical underpinning for decision-making based on guided discretion concerning the activation of macro-prudential instruments targeted to the real estate sector. National authorities are encouraged to perform their own complementary analyses in a broader framework of systemic risk detection which augments potential early warning indicators and methods with other relevant inputs and expert judgement. Indeed, country-specific optimal thresholds result in a strong reduction of false alarms, improving early warning signalling performance. Therefore, the development of methodologies for obtaining country-specific thresholds is an important area for future research aimed at improving early warning signalling performance. More specifically, methods that account for country specificities as well as interactions between structural and cyclical elements should be further explored. Furthermore, methods that exploit information on the depth of crises may provide additional insights into the development of early warning frameworks.

Finally, regardless the indicators and methods used, early warning signals always imply a trade-off for policymakers between missing crisis events (Type I errors) and issuing false alarms (Type II errors). In our robustness analysis we departed from the initial assumption of policymaker indifference between Type I and II errors by increasing the weight given to Type I errors in the policymaker's loss function. If policymakers consider the cost of banking crises to be larger than the output loss society would incur if macro-prudential policies were to be implemented based on a false alarm, their aversion towards missing crises will be greater. This results in lower thresholds which correctly identify a large share of crisis events, but which, on the other hand, result in many false alarms being issued, with a lower relative usefulness overall for the policymaker. Whatever their relative aversion towards missing crises, national authorities are encouraged to integrate and interpret early warning signals within a broader risk assessment framework, where both quantitative and qualitative information is met with expert judgement. More generally, the macro-prudential decision process should incorporate both the potential costs and benefits of policy (in)action, where possible accounting for the uncertainties on signals received at the risk assessment stage.

List of tables

List of figures

Annex A: Tables and Figures

Table A1: Real estate-related banking crisis periods in EU member states

Country	Crisis periods					
	Before the global financial crisis			During the global financial crisis		
	Start	End	Real Estate	Start	End	Real Estate
AT	no crisis according to definition					
BE	no crisis according to definition					
BG	no crisis according to definition					
CR	no crisis according to definition					
CY	no crisis according to definition					
CZ	no crisis according to definition					
DK	1987q1	1993q4	3	2008q3	ongoing	3
EE	no crisis according to definition					
FI	1991q3	1995q4	3			
FR	1993q3	1995q4	3			
DE	no crisis according to definition					
GR	no crisis according to definition					
HU				2008q3	ongoing	3
IE				2008q3	ongoing	3
IT	no crisis according to definition					
LV				2008q4	2010q3	3
LT				2008q4	2010q4	3
LU	no crisis according to definition					
MT	no crisis according to definition					
NL				2008q3	ongoing	3
PL	no crisis according to definition					
PT	no crisis according to definition					
RO	no crisis according to definition					
SK	no crisis according to definition					
SI				2008q1	ongoing	1
ES				2009q2	2013q2	3
SE	1990q3	1993q4	3	2008q3	2010q4	1
UK	1990q3	1994q2	3	2007q3	ongoing	3

1: Residential real estate crisis
2: Commercial real estate crisis
3: Residential and commercial real estate crisis

Crisis periods include:
(a) systemic banking crisis associated with the credit cycle, and
(b) periods where domestic developments related to the credit/financial cycle could well have caused a systemic banking crisis had it not been for policy action/an external event that dampened the credit cycle.
Up to two crisis periods have been identified per country; the table provides the starting date (year, quarter) and end date (year, quarter) of each crisis period
Country names:

AT = Austria; BE = Belgium; BG=Bulgaria; CR = Croatia; CY = Cyprus; CZ = Czech Republic; DK = Denmark; EE = Estonia; FI = Finland; FR = France; DE = Germany; GR = Greece; HU = Hungary; IE = Ireland; IT = Italy; LV = Latvia; LT = Lithuania; LU = Luxembourg; MT = Malta; NL = Netherlands; PL = Poland; PT = Portugal; RO = Romania; SK = Slovak Republic; SI = Slovenia; ES = Spain; SE = Sweden; UK = United Kingdom.

Table A2: Data availability by country

More than 80 observations | Between 80 and 30 observations | Less than 30 observations

		AT	BE	BG	CY	CZ	DE	DK	EE	ES	FI	FR	GR	HR	HU	IE	IT	LT	LU	LV	MT	NL	PL	PT	RO	SE	SI	SK	UK
Structural credit	Total credit to GDP	169	130	61	77	69	169	169	37	169	169	169	42	53	69	129	169	69	40	69	161	169	69	141	49	169	45	36	169
	Bank credit to GDP	169	130	0	77	69	169	169	64	169	156	169	42	65	69	129	153	69	129	69	161	169	69	141	49	169	69	36	169
	HH credit to GDP	69	130	61	35	69	169	169	37	129	169	141	42	65	69	44	169	69	32	63	37	119	69	133	49	129	69	37	169
	NFC credit to GDP	69	129	61	35	69	169	169	37	129	169	141	42	65	69	44	169	69	32	63	37	118	69	133	49	129	69	37	148
	Debt service ratio	171	132	64	79	70	170	39	65	171	171	171	45	7	71	131	171	72	130	72	164	170	31	143	24	171	36	28	171
Cyclical credit	Total credit growth	168	166	60	76	76	168	168	33	168	168	168	168	49	89	163	168	73	36	64	160	168	80	168	49	168	41	32	168
	Bank credit growth	168	166	0	76	76	168	168	60	168	152	168	168	72	89	163	149	73	128	64	160	168	80	168	68	168	73	32	168
	HH credit growth	65	126	60	31	65	165	168	33	125	168	137	69	72	89	40	168	73	28	59	33	115	65	129	49	125	73	33	168
	NFC credit growth	65	125	60	31	65	165	168	33	125	168	137	69	72	89	40	168	73	28	59	33	114	65	129	49	125	73	33	144
	Total credit to GDP gap	149	110	41	57	49	149	149	17	149	149	149	22	33	49	109	149	49	20	49	141	149	49	121	29	149	25	16	149
	Bank credit to GDP gap	149	110	0	57	49	149	149	44	149	136	149	22	45	49	109	133	49	109	49	141	149	49	121	29	149	49	16	149
	HH credit to GDP gap	49	110	41	15	49	149	149	17	109	149	121	22	45	49	24	149	49	12	43	17	99	49	113	29	109	49	17	149
	NFC credit to GDP gap	49	109	41	15	49	149	149	17	109	149	121	22	45	49	24	149	49	12	43	17	98	49	113	29	109	49	17	128

Structural RE price	Residential RE price to income gap	52	173	0	0	20	132	128	0	168	152	140	64	0	60	144	172	57	72	56	52	172	41	72	0	172	24	32	152
	Residential price to rent gap	52	148	0	13	20	172	172	0	168	172	172	64	0	0	172	172	32	24	56	0	172	0	88	0	132	24	32	172
Cyclical RE price	Residential RE price growth	48	169	0	21	16	168	168	0	164	168	168	60	0	56	168	168	53	20	52	28	168	32	96	0	168	20	28	168
	Commercial RE price growth	59	60	0	0	59	59	59	0	59	59	59	54	9	59	69	59	32	59	0	0	59	59	40	0	59	16	41	101
	Residential RE price gap	32	153	0	0	0	152	152	0	148	152	152	44	0	40	152	152	37	0	36	0	152	0	80	0	152	0	0	152
	Commercial RE price gap	43	44	0	0	43	43	43	0	43	43	43	38	0	43	53	43	16	43	0	0	43	43	24	0	43	0	25	85
	Residential RE price to income gap growth	48	169	0	0	16	128	124	0	164	148	136	60	0	56	140	168	53	68	52	48	168	37	68	0	168	20	28	148
	Residential price to rent gap growth	48	144	0	9	16	168	168	0	164	168	168	60	0	0	168	168	28	20	52	0	168	0	84	0	128	20	28	168
	Residential RE price to income gap gap	50	171	0	0	18	130	126	0	166	150	138	62	0	58	142	170	55	70	54	50	170	39	70	0	170	22	30	150
	Residential price to rent gap gap	50	146	0	11	18	170	170	0	166	170	170	62	0	0	170	170	30	22	54	0	170	0	86	0	130	22	30	170
Other variables	Inflation	168	169	60	128	84	168	168	68	168	168	168	168	80	128	168	168	76	168	64	168	168	88	168	68	168	89	84	168
	Real GDP growth	168	129	60	68	64	168	168	68	68	168	168	41	64	68	128	168	68	68	68	147	168	68	136	48	76	68	76	168
	Unemployment rate	172	173	64	52	80	172	172	52	172	172	172	74	60	84	92	172	60	112	60	52	172	83	172	64	172	68	79	172
	Real effective exchange rate	14	14	80	12	88	16	14	72	12	16	12	12	80	12	14	12	72	14	72	14	14	12	14	85	14	72	88	14

growth	8	9		8		0	8		8	8	9	6		9	6	6		8		8	8	3	8		8			8
Real M3 stock growth	168	169	32	25	40	168	46	16	168	168	168	128	1	36	168	168	32	168	36	28	168	32	168	29	41	32	24	52
Current account to GDP	124	73	64	56	72	168	100	72	92	172	76	45	52	72	128	172	72	72	72	164	172	56	80	52	124	72	76	168
Government debt to GDP	172	133	52	52	52	52	52	52	52	172	69	52	49	52	62	172	52	52	52	52	169	52	132	57	52	52	52	52
EC consumer survey	70	93	47	47	47	93	93	66	93	69	93	93	0	53	93	93	47	45	73	41	93	47	93	47	70	68	56	93
Long term gov' t bond yield	112	133	40	60	51	132	168	55	132	101	132	82	56	48	98	168	48	112	48	56	168	48	108	31	104	44	48	116
Real 3-month money market rate	168	169	55	56	80	168	168	68	144	132	168	131	48	65	168	168	56	0	63	71	168	72	168	68	120	59	68	168
Real equity price growth	168	108	0	30	72	168	168	63	108	168	166	108	48	84	168	168	49	52	53	65	168	83	96	59	168	71	74	168
HH mortgage loans	63	63	37	30	45	63	41	49	63	63	63	42	0	41	62	63	37	63	41	33	63	37	63	34	46	37	29	57
Leverage ratio	62	63	36	29	44	62	50	20	62	62	62	60	0	40	62	62	36	62	10	32	62	36	62	33	45	36	28	0
Bank deposit liabilities to total assets	62	63	36	29	44	62	50	20	62	62	62	60	0	40	62	62	36	62	10	32	62	36	62	33	45	36	28	56
Banks total assets to GDP	62	63	36	29	44	62	50	20	62	62	62	42	0	40	62	62	36	62	10	32	62	36	62	33	45	36	28	56
Bank capital reserves to total assets	62	63	36	29	44	62	50	20	62	62	62	60	0	40	62	62	36	62	10	32	62	36	62	33	45	36	28	56
Average mortgage rate	41	41	25	21	37	41	41	33	41	41	41	41	0	41	41	41	34	37	37	21	41	33	41	25	31	41	21	0
Rates mortgage fixed	41	41	10	0	37	41	41	23	41	41	41	35	0	41	41	41	0	0	32	0	41	18	22	18	31	37	17	37
Rate mortgage floating	41	41	25	21	37	41	0	33	41	41	41	41	0	41	41	41	34	0	37	21	41	33	41	25	31	41	21	37
Spreads on HH mortgage rate	41	41	0	22	37	41	0	33	41	41	41	41	0	33	41	41	0	41	0	25	41	25	41	0	0	41	18	41
Spread on NFC loan rate	41	41	0	22	37	41	0	33	41	41	41	41	0	0	41	41	0	41	0	25	41	25	41	0	0	41	21	0

Share floating rate loans	41	41	25	18	0	41	0	26	41	41	41	31	0	31	41	41	34	14	37	21	41	33	41	25	0	39	21	23
GFCF dwellings	101	73	0	73	73	89	93	73	133	152	141	45	0	73	65	93	73	73	73	53	101	0	73	0	0	73	73	153
GFCF other buildings	101	66	0	0	0	89	93	0	133	133	133	0	0	61	65	93	73	0	0	53	101	0	73	0	0	0	0	109
Value added construction	94	126	65	66	66	81	86	65	126	144	134	45	0	73	69	0	73	69	65	53	97	66	66	47	0	44	64	126

Table A3 : Summary statistics of potential early warning indicators

Variable		Mean	Std. dev.	Min	Max	Observations
HH credit to GDP	overall	43.12815	27.74612	.6037281	146.2452	N = 2541
	between		25.37491	12.51735	110.47	n = 28
	within		16.54274	2.585732	102.0384	T = 90.75
HH mtg loans to GDP	overall	32.49554	22.76677	.486366	119.39	N = 1328
	between		21.96064	3.75523	102.9006	n = 27
	within		9.477572	2.287758	53.81182	T-bar = 49.18
NFC credit to GDP	overall	76.31093	45.45746	6.51548	396.2482	N = 2518
	between		57.97076	25.28902	319.8876	n = 28
	within		22.43105	-30.02535	163.206	T = 89.92
Total credit to GDP	overall	115.984	62.47207	6.19005	451.1346	N = 3035
	between		63.25003	39.52787	349.8533	n = 28
	within		41.2461	-3.85096	313.8757	T = 108.3
Bank credit to GDP	overall	74.24321	37.38941	5.767303	271.0969	N = 3097
	between		31.43628	25.84671	179.6844	n = 27
	within		25.90375	6.428261	173.4493	T = 114.70
Debt service ratio	overall	.1842224	.1591004	.010396	1.078463	N = 2939
	between		.1265514	.0597599	.7416968	n = 28
	within		.0586913	-.0297812	.520989	T = 104.96
Debt to income	overall	111.8698	84.44542	6.08143	490.214	N = 948
	between		88.75504	37.79404	410.7409	n = 20
	within		24.88182	-18.57806	191.3429	T-bar = 47.4
Real HH credit growth	overall	13.09114	88.99523	-47.86692	3800.081	N = 2530
	between		26.13465	2.994067	136.891	n = 28
	within		86.33916	-128.6548	3676.281	T = 90.35
Real NFC credit growth	overall	5.826398	10.01403	-62.92272	83.71224	N = 2504
	between		4.31839	.140224	18.19008	n = 28
	within		9.291177	-72.7205	71.34856	T = 89.42
Real total credit growth	overall	6.492954	9.801358	-57.02301	84.75587	N = 3262
	between		5.259598	2.439529	25.45739	n = 28
	within		8.898247	-68.83466	65.79143	T = 116.5
Real bank credit growth	overall	6.202945	10.94122	-46.31242	88.79761	N = 3360
	between		5.381802	2.363843	25.43596	n = 27
	within		10.11599	-52.44998	77.60994	T = 124.44
HH credit to GDP gap	overall	1.406335	5.099762	-24.90099	18.51716	N = 1981
	between		2.897092	-8.380877	3.955668	n = 28
	within		4.652635	-18.55177	16.73463	T = 70.75
HH mtg loans to GDP gap	overall	-.7607562	3.961151	-23.2891	16.3371	N = 734
	between		2.352361	-7.975663	1.655942	n = 27
	within		3.359656	-21.65987	14.6974	T-bar = 27.18
NFC credit to GDP gap	overall	2.545526	9.523089	-72.14731	40.94208	N = 1958
	between		11.77693	-55.60063	17.48551	n = 28
	within		7.603816	-29.79315	39.66094	T = 69.92
Total credit to GDP gap	overall	4.671483	13.14984	-75.20264	86.23048	N = 2475
	between		8.836191	-31.73815	20.40258	n = 28
	within		11.71697	-38.79301	70.49939	T = 88.39
Bank credit to GDP gap	overall	3.3441	9.174623	-43.004	44.89464	N = 2557
	between		3.119564	-2.316767	10.17021	n = 27
	within		8.645531	-49.8301	38.06853	T = 94.70
RRE price to income gap	overall	1.01e-07	17.47275	-64.035	75.31788	N = 2306
	between		2.21e-06	-3.70e-06	3.79e-06	n = 23
	within		17.47275	-64.03501	75.31788	T = 100.26
RRE price to rent gap	overall	-1.03e-08	21.43587	-67.55511	85.21371	N = 2228
	between		2.59e-06	-3.81e-06	7.27e-06	n = 21
	within		21.43587	-67.55511	85.21372	T = 106.09
RRE price growth	overall	2.429645	10.3027	-44.8645	120.0831	N = 2374
	between		3.704313	-3.570922	13.86303	n = 24
	within		10.004	-56.29789	108.6497	T = 98.91
CRE price growth	overall	1.463983	12.37494	-42.82963	63.43689	N = 1188
	between		4.487418	-11.40656	7.276694	n = 22
	within		11.8758	-43.99307	62.27345	T = 54
RRE price gap	overall	-.0827958	13.35375	-85.14675	47.74496	N = 1937
	between		8.493592	-23.70418	3.809456	n = 17
	within		12.26572	-61.52537	71.36635	T = 113.94
CRE price gap	overall	-3.942076	19.84856	-65.02522	51.83569	N = 843
	between		11.45999	-39.91648	7.487113	n = 20
	within		17.38448	-47.43143	42.18769	T = 42.15
Inflation	overall	8.963612	52.25124	-6.004602	1789.692	N = 3705
	between		16.54631	2.882688	89.59165	n = 28

	within		50.61733	-83.55173	1709.064	T = 132.32
Real GDP growth	overall	2.950696	3.702674	-18.5615	30.20264	N = 2924
	between		1.170491	1.857776	6.608546	n = 28
	within		3.505502	-20.24859	26.54479	T = 104.42
Unemployment rate	overall	7.666439	4.155852	.5	26.14567	N = 3200
	between		3.140236	2.963482	14.43797	n = 28
	within		3.022065	-2.732713	22.93887	T = 114.28
Real eff ER growth	overall	.950401	8.146668	-92.49329	92.04205	N = 3404
	between		1.948892	-.5171253	6.796118	n = 28
	within		7.973976	-91.674	89.6149	T = 121.57
Real M3 stock growth	overall	4.188724	6.569492	-52.38623	31.66305	N = 2478
	between		2.657936	-.9639205	10.58585	n = 28
	within		6.351528	-50.14489	33.5771	T = 88.5
Current account to GDP	overall	-1.3531	6.473704	-53.45812	37.17002	N = 2717
	between		4.403796	-9.386968	9.468045	n = 28
	within		5.139065	-48.23651	42.39163	T = 97.03
Government debt to GDP	overall	53.70984	31.21583	1.913674	170.3	N = 2122
	between		26.43425	5.451923	117.0865	n = 28
	within		16.29074	-1.091949	116.9308	T = 75.7857
EC consumer survey	overall	-82.25151	10.76353	-98.2	11	N = 1916
	between		6.180093	-91.91277	-61.05303	n = 27
	within		9.112382	-115.2985	-10.19848	T-bar = 70.96
LT gov't bond yield	overall	3.2169	2.890457	-12.88741	26.23744	N = 2498
	between		1.159978	.0081793	4.882	n = 28
	within		2.726184	-12.04916	24.57234	T = 89.21
Nom. 3m money mkt rate	overall	7.666538	7.83564	0	184.37	N = 3095
	between		4.122366	3.603991	24.08802	n = 27
	within		6.975277	-14.62148	167.9485	T = 114.63
Real 3m money mkt rate	overall	1.53219	6.760146	-126.5976	56.92493	N = 3036
	between		1.458363	-2.044615	4.081628	n = 27
	within		6.601075	-123.0208	56.68946	T = 112.444
Average mortgage rate	overall	-5.169093	2.430441	-17.77	-1.76	N = 929
	between		2.273223	-12.89366	-3.25439	n = 26
	within		1.036019	-10.04544	-2.005434	T-bar = 35.73
Rates mortgage fixed	overall	-5.801764	2.794205	-20.32	-2.58	N = 768
	between		2.45493	-14.20073	-3.894146	n = 23
	within		1.373392	-14.04899	1.148968	T-bar = 33.39
Spreads on HH mtg rate	overall	2.730829	2.348699	.16	15.2279	N = 767
	between		2.324939	.9553659	11.93027	n = 21
	within		.9101971	-2.237556	6.028464	T-bar = 36.52
Spread on NFC loan rate	overall	1.775857	1.201276	.05	6.67	N = 696
	between		.9924801	.7804878	4.371364	n = 19
	within		.7772288	-1.705507	4.885857	T-bar = 36.63
Equity pr. growth Nom.	overall	13.05688	49.23628	-82.08386	1430.952	N = 2900
	between		10.46288	.2255795	55.28458	n = 27
	within		48.41393	-109.1017	1388.725	T = 107.407
Equity pr. growth Real	overall	7.155162	41.52715	-82.57285	1054.658	N = 2900
	between		7.218716	-2.000311	34.54838	n = 27
	within		41.0682	-102.4226	1027.265	T = 107.407
GFCF dwellings to GDP	overall	4.979866	1.960291	1.05459	12.7418	N = 2022
	between		1.60276	2.063794	7.838155	n = 23
	within		1.251652	-.4677589	10.89902	T-bar = 87.91
GFCF other build./GDP	overall	6.31699	1.747162	2.21	15.0279	N = 1375
	between		1.630836	4.558769	10.26863	n = 15
	within		.937962	2.253187	11.07626	T-bar = 91.66
Value added constr/GDP	overall	6.362567	1.522439	1.52	12.5955	N = 2009
	between		1.03899	4.15549	8.511115	n = 25
	within		1.120861	1.327785	10.84133	T-bar = 80.36
Bank leverage ratio	overall	14.94026	5.916869	4.87043	49.66368	N = 1217
	between		5.132346	7.481619	25.35936	n = 26
	within		2.913935	6.253131	39.24457	T = 46.80
Bank dep. liab./assets	overall	.1221897	.1054614	.0002034	.494619	N = 1273
	between		.1066581	.004114	.4499175	n = 27
	within		.0234375	.0575339	.2038921	T = 47.14
Banks tot. assets/GDP	overall	406.6165	654.4768	19.85213	3619.755	N = 1255
	between		586.9694	26.8352	3140.006	n = 27
	within		103.8409	-567.391	886.3659	T = 46.48
Bank K res/tot. assets	overall	7.687431	2.919708	2.007915	20.8718	N = 1273
	between		2.763232	4.275157	13.54612	n = 27
	within		1.387227	1.876353	15.01311	T = 47.14

Table A4: Correlation between variables

Cyclical credit variables

	Real bank credit growth	Real NFC credit growth	Real HH credit growth	Real total credit growth	Bank credit to GDP gap	HH credit to GDP gap	Total credit to GDP gap	NFC credit to GDP gap
Real bank credit growth	1							
Real NFC credit growth	0.7372	1						
Real HH credit growth	0.8281	0.5873	1					
Real total credit growth	0.8329	0.8348	0.7641	1				
Bank credit to GDP gap	0.4052	0.3842	0.2045	0.3238	1			
HH credit to GDP gap	0.4032	0.3265	0.3237	0.3364	0.7316	1		
Total credit to GDP gap	0.2423	0.4595	0.1102	0.2851	0.8354	0.6552	1	
NFC credit to GDP gap	0.1612	0.4405	0.0364	0.238	0.6807	0.4876	0.902	1

Structural credit variables

	Bank credit to GDP	HH credit to GDP	NFC credit to GDP	total credit to GDP	Debt service ratio
Bank credit to GDP	1				
HH credit to GDP	0.9063	1			
NFC credit to GDP	0.4789	0.4335	1		
Total credit to GDP	0.7533	0.7661	0.905	1	
Debt service ratio	0.4521	0.4177	0.3763	0.4502	1

Cyclical real estate price variables

	RRE PTI gap	RRE price growth	RRE price gap	RRE PTR gap	RRE PTR growth	RRE PTI growth
RRE PTI gap	1					
RRE price growth	0.6829	1				
RRE price gap	0.9281	0.7161	1			
RRE PTR gap	0.807	0.5953	0.796	1		
RRE PTR growth	0.5205	0.8249	0.5017	0.6234	1	
RRE PTI growth	0.6999	0.939	0.6684	0.6111	0.8188	1

Structural real estate price variables

	RRE price to income gap	RRE price to rent gap
RRE price to income gap	1	
RRE price to rent gap	0.8592	1

Table A5: Univariate non-parametric analysis: all indicators

Indicator	*Threshold*	*Type I*	*Type II*	*Rel. Usefulness*	*AUROC LB*	*AUROC*	*AUROC UB*
Nominal RRE price to income gap	13.975	0.34821	0.12028	0.53151	0.78963	0.83634	0.88306
Nominal RRE price to rent gap	6.9502	0.25962	0.2399	0.50048	0.78588	0.83453	0.88317
Nominal RRE price gap	5.236	0.27679	0.22746	0.49576	0.76286	0.81196	0.86105
Real RRE price gap	13.862	0.41964	0.078267	0.50209	0.74278	0.79341	0.84405
Real NFC credit growth	11.016	0.38333	0.1798	0.43687	0.73546	0.7849	0.83435
Nominal total credit to GDP gap	6.4639	0.20354	0.30999	0.48647	0.73324	0.78419	0.83513
Real total credit growth	6.7567	0.14167	0.41583	0.4425	0.72907	0.77871	0.82835
Nominal HH credit to GDP gap	2.7664	0.24561	0.32518	0.42921	0.72713	0.77851	0.82989
Nominal bank credit to GDP gap	2.9077	0.16667	0.41547	0.41787	0.72283	0.773	0.82317
Real bank credit growth	8.7806	0.28333	0.29789	0.41878	0.71436	0.76482	0.81529
Total credit to GDP gap	3.6019	0.13761	0.45635	0.40604	0.68975	0.74428	0.79881
NFC credit growth	13.145	0.3	0.33567	0.36433	0.67712	0.72965	0.78218
Real RRE price growth	8.0531	0.4375	0.20605	0.35645	0.66601	0.72067	0.77534
HH credit to GDP	55.578	0.40833	0.21635	0.37531	0.64919	0.70273	0.75626
Bank credit to GDP	90.281	0.475	0.19368	0.33132	0.64563	0.69902	0.75242
Real HH credit growth	7.5383	0.175	0.46517	0.35983	0.64455	0.69824	0.75193
Real bank credit growth	17.045	0.46667	0.26102	0.27231	0.62365	0.67754	0.73143
Total credit to GDP	170.69	0.6	0.090106	0.30989	0.6218	0.67585	0.72989
Real total credit to GDP	16.806	0.46667	0.25953	0.27381	0.6211	0.67508	0.72906
Nom. RRE price growth	10.277	0.39286	0.34611	0.26103	0.60667	0.66299	0.71931
Nom. HH credit growth	9.875	0.125	0.59125	0.28375	0.60225	0.65693	0.7116
NFC credit to GDP gap	2.4774	0.26316	0.39968	0.33716	0.5949	0.65148	0.70806
Debt service ratio	0.20579	0.46429	0.17058	0.36513	0.58761	0.64402	0.70043
Real GDP growth	2.6678	0.16071	0.58433	0.25495	0.5791	0.63565	0.6922
Current account to GDP (neg)	1.8001	0.33654	0.37443	0.28903	0.56387	0.62267	0.68147
Nom. LT gov't bond yield	-4.3893	0.51667	0.192	0.29133	0.55391	0.60897	0.66403
Inflation (neg)	-7.3358	0.041667	0.67939	0.27894	0.53712	0.59161	0.6461
NFC credit to GDP	69.029	0.34167	0.43621	0.22213	0.53124	0.58626	0.64129
Real LT gov't bond yield (neg)	-2.6515	0.41667	0.36678	0.21655	0.52539	0.58036	0.63533
Nom. 3m money mkt rate (neg)	-4.9985	0.42373	0.39366	0.18261	0.51885	0.57386	0.62887
Unemployment rate (neg)	-8.75	0.041667	0.70755	0.25078	0.5152	0.56967	0.62415
Equity pr. growth Real	0.87809	0.24167	0.55693	0.2014	0.51444	0.56902	0.6236
Equity pr. growth Nom.	5.3408	0.225	0.56979	0.20521	0.50097	0.55536	0.60974
Real eff ER growth	-0.64358	0.2437	0.63772	0.11858	0.4848	0.53891	0.59303
Nom. GDP growth	4.8935	0.091667	0.73402	0.17431	0.48024	0.53409	0.58794
Real. 3m money mkt rate	-1.1762	0.050847	0.85494	0.094214	0.4691	0.5232	0.57731
Real. 3m money mkt rate (neg)	-1.9109	0.48305	0.48898	0.027972	0.42333	0.47591	0.5285
Real eff ER growth (neg)	-7.6163	0.02521	0.91238	0.062413	0.40872	0.4603	0.51188
Unemployment rate	3.6236	0.075	0.81769	0.10731	0.37949	0.42949	0.4795
Nom. 3m money mkt rate	2.1716	0.033898	0.92491	0.041189	0.37503	0.42527	0.47551
Real LT gov't bond yield	5.5257	0.73333	0.19671	0.069955	0.36856	0.4185	0.46845

Inflation	1.575	0.083333	0.85461	0.062052	0.35912	0.40769	0.45627
Nom.l LT gov't bond yield	8.6214	0.66667	0.2759	0.057432	0.34108	0.38934	0.4376
Current account to GDP	5.722	0.83654	0.085743	0.077718	0.32584	0.37632	0.42679

Table A6 – Univariate panel logit models (t-values in parentheses)

	Model1	*Model2*	*Model3*	*Model4*	*Model5*	*Model6*	*Model7*	*Model8*	*Model9*	*Model10*
RRE price to income gap	0.086***									
	(4.097)									
RRE price to rent gap		0.049***								
		(4.312)								
Nominal RRE price gap			0.137***							
			(5.157)							
Real RRE price gap				0.123***						
				(3.754)						
Real NFC credit growth					0.072***					
					(4.392)					
Total credit to GDP gap						0.089***				
						(4.800)				
Household credit to GDP gap							0.220***			
							(4.799)			
Real total credit growth								0.074***		
								(5.870)		
Bank credit to GDP gap									0.111***	
									(5.044)	
Real bank credit growth										0.056***
										(4.891)
Constant	-3.567***	-2.737***	-3.300***	-3.307***	-3.005***	-3.058***	-2.867***	-3.332***	-3.001***	-3.346***
	(-5.734)	(-5.365)	(-6.618)	(-4.987)	(-9.540)	(-8.096)	(-7.389)	(-9.933)	(-6.751)	(-10.944)
Type I error	0.35	0.26	0.28	0.42	0.39	0.19	0.24	0.14	0.17	0.28
Type II error	0.12	0.24	0.23	0.08	0.17	0.32	0.33	0.42	0.42	0.30
Relative usefulness	0.53	0.50	0.50	0.50	0.43	0.48	0.43	0.43	0.41	0.42
AUROC	0.84	0.83	0.81	0.79	0.78	0.78	0.78	0.78	0.77	0.76
AUROC CI	[0.79, 0.88]	[0.79, 0.88]	[0.76, 0.86]	[0.74, 0.84]	[0.73, 0.83]	[0.73, 0.83]	[0.72, 0.83]	[0.73, 0.82]	[0.72, 0.82]	[0.71, 0.82]

Table A7 – Bivariate logit models (t-values in parentheses)

	Model1	*Model2*	*Model3*	*Model4*	*Model5*	*Model6*	*Model7*	*Model8*	*Model9*	*Model10*
Debt service ratio	4.455***									
	(4.724)									
RRE price to income gap	0.093***	0.080***							0.091***	0.079***
	(4.069)	(2.923)							(4.885)	(3.063)
3-month money mkt rate		0.164*								
		(1.787)								
Real NFC credit growth			0.140***							
			(4.172)							
RRE price to rent gap			0.056***	0.033***	0.015		0.026*	0.048***		
			(4.835)	(2.833)	(0.780)		(1.854)	(3.789)		
RRE price to income gap gap				0.067**						
				(2.052)						
Nominal RRE price gap					0.118**	0.150***				
					(2.288)	(7.234)				
RRE price to rent gap growth						0.0002				
						(0.114)				
Real RRE price gap							0.099**			
							(2.275)			
Real total credit growth								0.085***		
								(3.514)		
Real GDP growth									0.123***	
									(4.745)	
Real long term gov't bond yield										0.170
										(1.322)
Constant	-4.691***	-3.203***	-4.245***	-3.094***	-3.437***	-3.563***	-3.566***	-3.750***	-4.415***	-3.383***
	(-5.421)	(3.522)	(-6.853)	(-6.425)	(-7.124)	(-8.873)	(-6.220)	(-6.209)	(-5.397)	(-3.541)
Type I error	0.24	0.13	0.17	0.26	0.28	0.17	0.23	0.13	0.12	0.16
Type II error	0.13	0.27	0.22	0.14	0.15	0.28	0.20	0.29	0.12	0.29
Relative usefulness	0.63	0.60	0.60	0.60	0.57	0.55	0.57	0.57	0.59	0.54
AUROC	0.89	0.88	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87
AUROC CI	[0.85, 0.93]	[0.84, 0.92]	[0.83, 0.92]	[0.82, 0.92]	[0.83, 0.92]	[0.82, 0.91]	[0.82, 0.91]	[0.82, 0.91]	[0.82, 0.91]	[0.82, 0.91]

Table A8: trivariate logit models (t-values in parentheses)

	Model1	*Model2*	*Model3*	*Model4*	*Model5*	*Model6*	*Model7*	*Model8*	*Model9*	*Model10*
Real NFC credit growth	0.180***		0.158***					0.145***		0.127***
	(6.046)		(3.852)					(3.914)		(4.170)
Real 3-month money mkt rate	-0.294***	-0.255***		-0.229***	-0.223***				-0.204***	
	(-3.424)	(-3.568)		(-3.548)	(-2.987)				(-3.008)	
RRE price to rent gap	0.067***	0.056***	0.038***	0.050***	0.037***	0.031**	0.030**	0.041***	0.056***	
	(4.960)	(4.209)	(3.066)	(3.733)	(2.679)	(2.106)	(2.324)	(3.135)	(4.705)	
Real total credit growth		0.097***				0.155***	0.115***			
		(3.176)				(4.523)	(5.237)			
Household credit to GDP			0.040**			0.055***				0.047**
			(2.571)			(3.197)				(2.543)
Real bank credit growth				0.069***						
				(2.936)						
Real RRE price gap					0.085**					
					(2.203)					
Nominal bank credit to GDP							0.031***	0.021**		
							(3.503)	(2.469)		
Real RRE price growth									0.036***	
									(3.314)	
RRE price to income gap gap										0.102***
										(2.581)
Constant	-5.436***	-4.430***	-6.432***	-3.905***	-3.924***	-7.417***	-6.615***	-5.931***	-3.515***	-6.932***
	(-6.471)	(-5.403)	(-6.087)	(-5.207)	(-5.958)	(-5.959)	(-8.228)	(-7.442)	(-6.273)	(-5.522)
Type I error	0.06	0.06	0.21	0.04	0.08	0.16	0.22	0.18	0.05	0.16
Type II error	0.30	0.27	0.11	0.32	0.26	0.16	0.14	0.18	0.29	0.16
Relative usefulness	0.64	0.67	0.68	0.64	0.66	0.68	0.64	0.64	0.66	0.68
AUROC	0.91	0.90	0.90	0.90	0.90	0.90	0.89	0.89	0.89	0.89
AUROC CI	[0.87, 0.95]	[0.87, 0.94]	[0.86, 0.94]	[0.86, 0.94]	[0.86, 0.94]	[0.85, 0.93]	[0.85, 0.93]	[0.85, 0.93]	[0.85, 0.93]	[0.85, 0.93]

Table A9: Regression results panel fixed effects logit models (t-values in parentheses)

	Model1	*Model2*	*Model3*	*Model4*	*Model5*	*Model6*	*Model7*	*Model8*	*Model9*	*Model10*
Real total credit growth	0.230***	0.315***			0.248***		0.129***			
	(4.679)	(5.529)			(5.795)		(3.385)			
Nominal bank credit to GDP	0.108***		0.119***			0.082***		0.120***		
	(6.519)		(6.774)			(4.973)		(6.675)		
RRE price to rent gap	0.106***	0.079***	0.093**	0.101***	0.098***	0.130***		0.103***	0.124***	
	(5.965)	(3.806)	(5.311)	(4.976)	(5.796)	(6.794)		(5.682)	(6.555)	
3-month money mkt rate	0.911***	0.919***	0.932***	0.892***	0.950***	0.968***	0.597***	0.605***	1.002***	0.917***
	(7.001)	(6.753)	(7.273)	(6.738)	(7.222)	(6.782)	(5.781)	(5.785)	(7.300)	(6.657)
Inflation	-0.550***	-0.521***	-0.608***	-0.587**	-0.566***	-0.692***	-0.536**	-0.393**	-0.631***	-0.635**
	(-3.415)	(-3.154)	(-3.979)	(-3.660)	(-3.767)	(-4.021)	(-3.076)	(-3.314)	(-4.017)	(-3.990)
Household credit to GDP		0.145***		0119***						
		(5.504)		(4.798)						
Real bank credit growth			0.158***							
			(3.690)							
Real NFC credit growth				0.203***		0.173***			0.147***	0.207***
				(5.325)		(4.632)			(4.433)	(5.806)
Nominal total credit to GDP					0.068***				0.044***	
					(5.849)				(3.639)	
Debt service ratio							4.620			4.097
							(6.207)			(0.793)
RRE price to income gap							0.199***			0.197***
							(8.517)			(8.139)
Real HH credit growth								0.176***		
								(3.725)		
Type I error	0.28	0.24	0.32	0.25	0.38	0.28	0.06	0.12	0.33	0.24
Type II error	0.10	0.10	0.09	0.17	0.06	0.18	0.19	0.17	0.09	0.21
Relative usefulness	0.62	0.66	0.59	0.58	0.56	0.55	0.75	0.72	0.58	0.55
AUROC	0.84	0.87	0.83	0.85	0.83	0.81	0.92	0.92	0.82	0.83
AUROC CI	[0.79, 0.84]	[0.82, 0.91]	[0.78, 0.88]	[0.80, 0.90]	[0.78, 0.88]	[0.76, 0.87]	[0.90, 0.97]	[0.88, 0.95]	[0.77, 0.87]	[0.78, 0.88]

* significant at 0.1; ** significant at 0.05; *** significant at 0.01

ESRB
European Systemic Risk Board
European System of Financial Supervision

Table A10: Robustness exercise: regression results panel logit on "balanced" sample (t-values in parentheses)

	Model1	*Model2*	*Model3*	*Model4*	*Model5*	*Model6*	*Model7*	*Model8*	*Model9*	*Model10*
Household credit to GDP gap	0.38***	0.36***								
	(2.68)	(2.37)								
Debt service ratio	7.22***	6.95***						7.84***		6.60***
	(8.20)	(7.35)						(7.42)		(7.29)
Nominal RRE price to income gap	0.14***	0.14***	0.09***	0.11***	0.10***		0.07***	0.16***		0.17***
	(3.41)	(3.58)	(3.48)	(4.80)	(4.54)		(3.24)	(4.44)		(5.27)
3-month money mkt rate	0.32***		0.48***		0.28*	0.66***	0.53***		0.59***	
	(2.87)		(2.63)		(1.88)	(4.47)	(3.29)		(3.93)	
Real GDP growth	0.62***	0.60***						0.33***		
	(5.99)	(5.72)						(3.00)		
Long term gov't bond yield		0.34***		0.36**						
		(2.54)		(2.06)						
Real total credit growth			0.33***						0.31***	
			(4.24)						(3.42)	
Household credit to GDP			0.11***	0.08**	0.07***	0.14***	0.12**		0.13***	
			(2.70)	(2.29)	(2.65)	(2.84)	(2.98)		(2.73)	
Current account deficit			-0.21**	-0.19**	-0.19**	-0.20	-0.16		-0.21*	-0.20*
			(-2.04)	(-2.01)	(-2.07)	(-1.65)	(-1.51)		(-1.78)	(-1.73)
Real NFC credit growth				0.34***	0.33***			0.20***		0.36***
				(6.46)	(7.12)			(2.63)		(6.08)
Real bank credit growth						0.29***	0.28***			
						(3.32)	(4.85)			
Real RRE price gap						0.14**			0.14**	
						(2.41)			(2.27)	
Real effective exchange rate growth								0.22**		0.30***
								(2.29)		(3.95)
Constant	-12.89***	-12.94***	-16.06***	-13.59***	-12.49***	-18.84***	-16.19***	-10.10***	-17.69***	-10.33***
	(-7.35)	(-6.39)	(-3.87)	(-4.58)	(-5.66)	(-4.19)	(-4.21)	(-6.99)	(-4.08)	(-7.00)
Type I error	0.04	0.01	0.05	0.04	0.04	0.01	0.04	0.01	0.01	0.05
Type II error	0.05	0.08	0.08	0.09	0.09	0.10	0.09	0.12	0.10	0.09
Relative usefulness	0.91	0.90	0.87	0.87	0.87	0.89	0.87	0.87	0.89	0.85
AUROC	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98
AUROC CI	[0.96, 1.00]	[0.96, 1.00]	[0.96, 1.00]	[0.96, 1.00]	[0.96, 1.00]	[0.96, 1.00]	[0.96, 1.00]	[0.96, 1.00]	[0.96, 1.00]	[0.96, 1.00]

* significant at 0.1, ** significant at 0.05, *** significant at 0.01

References

Agnello, L. and Schuknecht, L. (2011), "Booms and busts in housing markets: Determinants and implications", *Journal of Housing Economics*, 20(3): 171-190.

Alessi, L. and Detken, C. (2011), "Real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity", *European Journal of Political Economy,* 27(3): 520–533.

Babecky, J., Havranek, T., Mateju, J., Rusnak, M., Smidkova, K. and Vasicek, B. (2012), "Banking, debt and currency crises. Early warning indicators for developed countries", *ECB Working Paper* Series No. 1485.

Behn, M., Detken, C., Peltonen, T. and Schudel, W. (2013), "Setting countercyclical capital buffers based on early warning models: Would it work?", *ECB Working Paper* Series No. 1604.

Berg, A. and Coke, R.N. (2004), "Autocorrelation-corrected standard errors in panel probits: an application to currency crisis predictions", *IMF Working Paper* WP/04/39

Borgy, V., Clerc, L. and Renne, J. (2014), "Measuring aggregate risk: can we robustly identify asset price boom bust cycles?", *Journal of Banking and Finance*, 46: 132–150.

Borio, C. and Drehmann, M. (2009), "Assessing the risk of banking crises – revisited", *BIS Quarterly Review*, March: 29–46.

Borio, C. and Lowe, P. (2002), "Assessing the risk of banking crises", *BIS Quarterly Review*, December: 43–54.

Cameron, A.C., Trivedi, P.K. (2005), *Microeconometrics methods and applications*, Cambridge University Press, New York.

Ciani D., Cornacchia, W. and Garofalo, P. (2014), "The macroprudential measures adopted in Europe for the real estate sector", *Bank of Italy Occasional Paper* n.227.

Claessens S., Kose, M. and Terrones, M. (2008), "What happens during recessions, crunches and busts?", *IMF Working Paper* No /08/274.

Claessens, S., Kose, M. and Terrones, M. (2011), "How do business and financial cycles interact?", *IMF Working Paper* No 11/88.

Crowe, C., Dell'Ariccia, G., Igna, D., Rabanal, P. (2011), "How to deal with real estate booms: lessons from country experiences", IMF Working Paper No 2011/91

Demirgüç-Kunt, A. and Detragiache, E. (1998), "The determinants of banking crises: Evidence from industrial and developing countries", *IMF Staff Papers*, 45 (1): 81–109.

Detken C., Weeken, O., Alessi, L., Bonfim, D., Boucinha, M., Castro, C., Frontczak, S., Giordana, G., Giese, J., Jahn, N., Kakes, J., Klaus, B., Lang, J., Puzanova, N., Welz, P. (2014), "Operationalising the countercyclical capital buffer: indicator selection, threshold identification and calibration options", *ESRB Occasional Paper* Series No. 5/June 2014.

Drehmann, M., Borio, C., Gambacorta, L., Jiminez, G. and Trucharte, C. (2010), "Countercyclical capital buffers: exploring options", *BIS Working Papers* No 317.

Drehmann, M., Borio, C. and Tsatsaronis, K. (2011), "Anchoring countercyclical capital buffers: the role of credit aggregates", *International Journal of Central Banking*, 7(4): 189-240.

Drehmann, M., Borio, C. and Tsatsaronis, K. (2012), "Characterising the financial cycle: don't lose sight of the medium term!", *BIS Working Papers* No 380.

Drehmann, M. and Juselius, M. (2013), "Evaluating early warning indicators of banking crises: Satisfying policy requirements", *BIS Working Papers* No. 421.

Ferrari, S. and Pirovano, M. (2014), "Evaluating early warning indicators for real estate-related crises", *Financial Stability Review*, National Bank of Belgium, 123-134.

Gerdesmeier, D., Lenarcic, A. and Roffia, B. (2012), "An alternative method for identifying booms and busts in the euro area housing market", *ECB Working Paper* Series No. 1493.

Greene, W.H. (2012), *Econometric Analysis*, Pearson, England

Hanley, J.A. and McNeil, B. (1982), "The meaning and use of the Area under a Receiver Operating Characteristic (ROC) Curve", *Radiology*, 143 (1), pp. 29-36.

Kaminsky, G. and Reinhart, C. (1999), "The twin crises: the causes of banking and balance-of-payments problems", *American Economic Review*, 89 (3): 473–500.

Sarlin, P. (2013), "On policymakers' loss functions and the evaluation of early warning systems", *Economics Letters*, 119(1): 1-7.

Schularick, M., and Taylor, A. (2012), "Credit booms gone bust: monetary policy, leverage cycles and financial crises, 1870–2008", *American Economic Review*, 102 (2): 1029–1061.