Evaluating early warning indicators for real estate related risks

Stijn Ferrari
Mara Pirovano

Introduction

Adverse developments in the real estate sector can be an important source of systemic risk and financial instability. Addressing systemic concerns related to the real estate sector is one of the priorities on the macroprudential agenda of European authorities. A number of member states, including Belgium, are taking action to dampen systemic risk in real estate markets.

The European Systemic Risk Board (ESRB) strongly encourages countries to develop sound macroprudential policy strategies to frame such actions. Macroprudential policy strategies involve linking the ultimate objectives of macroprudential policy to indicators and instruments. Instruments targeting systemic risk stemming from real estate markets include risk weights for real estate exposures, and limits to loan to value and debt service to income ratios. The operationalisation of such instruments requires identifying sound leading indicators and associated thresholds, which could serve as a basis for guided discretion in the activation of macroprudential instruments.

Steps towards the identification of early warning indicators signalling excessive developments (e.g., in credit and leverage) and imbalances in the run-up to a banking crisis have been undertaken by policy makers as well as in the academic literature. Such early warning exercises assess the performance of indicators in predicting banking crises over a particular horizon. In addition, thresholds above which the indicators signal the potential occurrence of a banking crisis over a given horizon are computed.

A usual first step in such early warning exercises is a graphical analysis of the behaviour of a set of potential indicators in a relevant window around crisis events. Such graphical presentation provides a first assessment of the ability of variables to signal the occurrence of excessive developments or imbalances in the run-up to a crisis.

Applications of early warning models to banking crises related to developments in the real estate sector are relatively scarcer. Under the auspices of the ESRB Instruments Working Group (IWG), the early warning properties of a subset of indicators for European Union (EU) countries have been assessed. On the basis of a graphical analysis, variables related to the build-up of credit as well as volume- and price-based real estate related indicators have been identified as potential early warning indicators for real estate related banking crises.

This article builds on the IWG work and presents a novel graphical methodology to identify leading indicators of real estate related banking crises. Using information for 15 EU countries, the methodology compares the cross-country average behaviour of indicators in a relevant time window around crisis events for countries experiencing a real estate related banking crisis to countries that did not experience a crisis in these periods and to observations in tranquil times (outside periods around real estate related banking crises).

Accounting for the uncertainty surrounding the estimates of cross-country average levels of indicators, the methodology provides a graphical tool for assessing the power of indicators in predicting real estate related
banking crises. The framework also allows identification of thresholds that determine zones, which correspond to different intensities of the signal issued by each indicator for a given prediction horizon. As such, the framework can be applied as a monitoring tool for systemic risks stemming from the real estate sector.

The article highlights the relevance of the results for systemic risks stemming from the Belgian real estate sector. In particular, signals related to increasing levels of household indebtedness in combination with a potential overvaluation of housing prices suggest the need for close monitoring of developments in the Belgian real estate market and Belgian banks’ mortgage loan portfolios. As described in the article on recent developments and prudential measures in the Belgian mortgage market in this Financial Stability Review, such in-depth analysis of banks’ mortgage loan portfolios has resulted in recent actions undertaken to mitigate systemic risk stemming from the Belgian real estate sector.

The remainder of the article is organised as follows. Section 1 outlines the novel graphical early warning methodology. In Section 2, we apply the monitoring framework to Belgium. The final section concludes.

1. Methodology

1.1 Identification of real estate related crises

To construct an indicator of real estate related banking crises, we complement banking crisis data for the EU with data relating to real estate prices. The information on banking crises comes from a database compiled by Babecky et al. (2012), which provides quarterly data on the occurrence of banking crises in the EU from 1970 to 2012. The dataset is based on information on the timing of banking crises gathered from various sources: influential papers, the authors’ own survey and country experts’ opinions (mostly from national central banks). (1)

In order to isolate banking crises related to developments in the real estate sector, we complement this information with data on nominal house price growth. Specifically, we consider that banking crises are related to real estate only if they are accompanied by a decrease in nominal house price growth of at least 5% in at least one quarter in the period ranging from 4 quarters before to 8 quarters after their onset. (2)

---


(2) The choice of the interval is dictated by two considerations. First, we aim at capturing extreme developments in the real estate market occurring before the onset of a banking crisis, to consider the potential role of real estate related events in triggering the crisis. Second, we extend the time period up to two years after the start of the crisis to account for potential delays in the dynamics of house prices in reflecting problems originating in the real estate sector and resulting in banks’ distress.
For illustrative purposes, Chart 1 presents the results of this procedure for Belgium and Denmark. For Belgium, periods in which nominal house price growth is below −5% (the purple shaded areas) are never observed in the period from 4 quarters before to 8 quarters after the onset of a banking crisis (the orange shaded areas in the chart). Hence, we do not identify any real estate related banking crisis for this country. In contrast, in Denmark there are two cases in which the purple shaded area is situated in the period from 4 quarters before to 8 quarters after the start of an orange shaded area. Therefore, we consider these two intervals identified by Babecky et al. (2012) as real estate related banking crises.

This methodology leads us to identify 11 real estate related banking crisis episodes involving 9 countries out of the 15 EU countries of our sample. Annex 1 provides a detailed overview of the periods of real estate related banking crises identified for all 15 EU countries in the sample.

1.2 Potential early warning indicators

We consider a broad set of macrofinancial and real estate specific variables as potential leading indicators of real estate related banking crises, at a quarterly frequency and ranging from 1970Q1 to 2013Q1 for the series with the longest coverage. Data are collected from various sources, among which the ECB, OECD, BIS and Eurostat databases. For the purpose of this article we focus on four variables that have been identified as promising leading indicators for (real estate related) banking crises, both on conceptual grounds and on the basis of the existing literature on early warning indicators (see Box 1 for a brief overview of the literature). Annex 1 provides an overview of these variables’ time coverage for each country.

First, we consider measures of credit granted to the household sector. We rely on data provided by the BIS on credit to households (including non-profit institutions serving households), adjusted for structural breaks and denominated in euro. We consider both the level of household credit to GDP and the deviation of household credit to GDP from its long-term trend up to that point (i.e., the household credit to GDP gap).\(^1\) While the deviation of household credit to GDP from its long-term trend captures cyclical developments, the level of household credit to GDP represents a structural indicator, capturing the level of indebtedness of the household sector.

Second, we consider developments in real estate prices. We again consider both a cyclical and a structural indicator. Nominal house price growth is obtained on the basis

\[^1\] The trend is calculated by means of a recursive one-sided HP filter with a smoothing parameter \(\lambda = 400000\). See Ravn and Uhlig (2002) and Borio et al. (2010) for details.
et al., 2013; Drehmann and Juselius, 2013; Detken et al., 2014) and macroprudential instruments targeting real estate related risks (ESRB, 2014).

A number of variables have been identified as useful early warning indicators of banking crises. First of all, indicators related to the supply of credit such as the deviation of credit to GDP from its long-term trend (e.g., Drehmann et al., 2010, 2011; Babecky et al., 2012; Behn et al., 2013; Drehmann and Juselius, 2013; Detken et al., 2014), credit growth (e.g., Schularick and Taylor, 2012; Behn et al., 2013; Drehmann and Juselius, 2013; Detken et al., 2014) and the debt service ratio (Drehmann and Juselius, 2013; Detken et al., 2014). Developments in other macrofinancial variables such as GDP growth, money growth, equity price growth, interest rates, current account balance, and banking sector profitability and capitalisation have also been found to influence the probability of banking sector distress (e.g., Demirgüç-Kunt and Detragiache, 1998; Babecky et al., 2012; Behn et al., 2013; Detken et al., 2014). Furthermore, studies affirm the importance of global developments in association with the occurrence of banking crises (e.g., Babecky et al., 2012; Behn et al., 2013), and of variables related to developments in the real estate sector (e.g., Drehmann et al., 2010, 2011; Behn et al., 2013; Drehmann and Juselius, 2013; Detken et al., 2014).

Studies on crises related to the real estate market are relatively scarce and mainly focus on identifying the determinants of booms and busts in asset and/or real estate prices. A number of potential early warning indicators for boom/busts are identified, including interest rates and money and credit developments (e.g., Agnello and Schuknecht, 2011; Alessi and Detken, 2011; Borgy et al., 2011; Gerdesmeier et al., 2012). Agnello and Schuknecht (2011) and Alessi and Detken (2011) emphasise the role of global liquidity and credit. The importance of credit is confirmed by Claessens et al. (2011), who uncover a strong connection between credit and housing market cycles (also see Drehmann et al., 2012). Finally, 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).

of a dataset compiled by the BIS and provides insight into the cyclical developments on the real estate market. Price to income ratios, which are constructed on the basis of BIS and OECD data, are useful indicators of overvaluation of real estate prices.

1.3 A novel graphical early warning methodology

CONTEXT

The operationalisation of macroprudential instruments requires developing a decision framework in which quantitative signals are mapped into policy decisions. This requires identifying robust leading indicators and their associated threshold values, which could serve as a basis for guided discretion in the activation of macroprudential instruments.

The identification and operationalisation of such an indicator framework typically involves two steps. First, it is necessary to identify a set of indicators with good and timely predictive power for events related to the materialisation of the targeted systemic risks (e.g., real estate related banking crises). Second, one may identify thresholds above which the indicator issues a “warning” or a signal on the potential materialisation of the targeted risk over a pre-specified horizon.

This article presents a novel graphical methodology for the identification of early warning indicators. The framework also allows identification of thresholds that determine zones, which correspond to different intensities of the signal issued by each indicator for a given prediction horizon. As such, the framework can be applied as a monitoring tool for systemic risks stemming from the real estate sector.

GRAPHICAL EVALUATION OF PREDICTIVE POWER

Early warning tests provide a statistical evaluation of an indicator or model’s predictive power for events related to the materialisation of the targeted systemic risk (see Box 2). A usual first step in such exercises is a graphical analysis of the behaviour of a set of potential indicators around crisis events. Such graphical presentation of the evolution of an indicator for crisis countries in a window around crisis events gives a first indication on whether the indicator accurately signals the occurrence of excessive developments or imbalances in the run-up to a crisis.
For example, if an indicator, on average, shows a clear upsurge before relevant crisis events, it can be considered a potential useful indicator for predicting upcoming crises.

At the same time, a necessary condition for this indicator to be a useful early warning indicator is that the observed upward evolution before crisis events differs significantly from the level and behaviour of the indicator in “normal” situations. Such normal situations include times outside the relevant window around crisis events. For example, Kaminsky and Reinhart (1999) report the cross-country average behaviour of indicators around crisis events, expressed relative to “trquil times”. Drehmann and Juselius (2013) plot the cross-country median indicator value outside the relevant window around crisis events, in addition to the cross-country median evolution of the indicator in the window around crisis events.

A useful early warning indicator should not only signal crises in a consistent and timely manner, but it should also not issue too many false alarms. Suppose an indicator has good signalling properties when considered only for crisis countries around their crisis events, but its behaviour is not different from that observed for countries not experiencing crises around the crisis countries’ crisis events. Then the indicator is likely to issue many false alarms, as it would signal the potential occurrence of a crisis over a particular horizon both in crisis and non-crisis countries.

Our methodology extends the existing graphical analysis underpinning existing early warning exercises. Using information for 15 EU countries, the methodology makes two types of comparisons: (1) the average behaviour of indicators around crisis events for countries experiencing a real estate related banking crisis compared to the average behaviour of the indicator in the windows around these crisis events for countries that do not experience a real estate related banking crisis at those points in time; (2) the average behaviour of indicators around crisis events for countries experiencing a real estate related banking crisis compared to the average level of the indicator in tranquil periods (i.e., outside the relevant window around any real estate related banking crisis event in the sample).

In our graphical evaluation of predictive power we also explicitly account for the uncertainty surrounding the cross-country averages, stemming from the dispersion of the indicator values across countries. In particular, we compute bootstrapped 95% confidence bounds around the cross-country averages. An indicator is considered to have good signalling properties if, in a given period, its confidence interval for crisis countries lies above the confidence interval for non-crisis countries and above the overall average in tranquil periods.

Chart 2 illustrates our methodology for the household credit to GDP gap (see Annex 2 for the equivalent charts for the other indicators). For our three subsamples of observations (crisis countries, non-crisis countries during crisis periods in another country, all countries in tranquil periods) the average household credit to GDP gap is plotted for a window of 20 quarters before to 12 quarters after the start of real estate related banking crises (i.e., a horizon [T–20; T+12] with T denoting the start of the crisis). The solid lines correspond to cross-country averages, whereas dashed lines provide the corresponding bootstrapped 95% confidence bounds.

Specifically, the red solid line represents the average household credit to GDP gap in crisis countries around their own real estate related banking crises (denoted “crisis countries”). The light green solid line depicts the average behaviour of the indicator in the windows around these crisis events for countries that do not experience a real estate related banking crisis at those points in time (denoted “non-crisis countries”). Finally, the dark green line represents the overall average household credit to GDP gap outside the relevant window around any real estate related banking crisis event in the sample (denoted “tranquil periods”).

(1) See Annex 3 for an example of how observations of a given indicator for a given country are classified as relevant for “crisis countries”, “non-crisis countries” or “tranquil periods”.

(2) We could in principle compute the cross-country average household credit to GDP gap for each individual quarter in the relevant window [T–20; T+12]. Given the relatively small size of our dataset, we instead compute cross-country averages for the yearly windows [T–20; T–17], [T–16; T–13], …, [T+4; T+12].
Chart 2 reveals that for horizons [T–16;T–13], [T–12;T–9] and [T–8;T–5] the 95% confidence interval for the cross-country average level of the indicator in crisis countries is situated above the 95% confidence interval of both the average household credit to GDP gap observed in the same period in non-crisis countries and the average

Box 2 – Statistical evaluation of predictive power and threshold identification

Evaluation of predictive power

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. The so-called "Confusion Matrix" classifies the four possible outcomes. After a signal has been issued (i.e., the indicator breached the threshold), it is classified as correct if a crisis follows within the relevant horizon (A); if a crisis does not follow, then the signal resulted in a false alarm (B). A non-issued signal (i.e., the indicator has not breached the threshold) is correct when a crisis does not follow (D) and it is incorrect when a crisis occurs (C).

| 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 \( 1–\text{TPR} \) 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 can be assessed through different metrics, such as the noise to signal ratio \( \frac{\text{FPR}}{\text{TPR}} \) and a policy maker’s loss function \( L = \Theta \left( \frac{C}{A+C} \right) + (1–\Theta) \left( \frac{B}{B+D} \right) \), where parameter \( \Theta \) represents the policy maker’s relative importance attached to missing crises (Type I error) versus issuing false alarms (Type II error). Finally, the relative usefulness of an indicator expresses the policy maker’s gain from using the model for predicting crises compared to disregarding the model and always issuing a signal or never issuing a signal: \( \text{RU} = \frac{\min[\Theta, (1–\Theta)] – L}{\min[\Theta, (1–\Theta)]} \).

The above metrics are all calculated for a given threshold, above which the indicator issues a signal. Recent early warning applications have evaluated the predictive power of indicators on the basis of the indicators’ AUROC (Area Under the Receiver Operating Characteristic). The ROC (Receiver Operating Characteristic)-curve plots the indicator’s TPR against the FPR for every possible value of the threshold. The area under the ROC-curve or AUROC ranges from 0 to 1: a value larger than 0.5 indicates that an indicator issues informative signals, while for a fully informative indicator the AUROC is 1.
level observed in tranquil periods. This indicates that the household credit to GDP gap can be considered as a good leading indicator for real estate related banking crises for these prediction horizons.

**THRESHOLD IDENTIFICATION**

A threshold value provides a quantitative benchmark to assess whether the current value of an indicator constitutes a “warning” or a signal. When the value of an indicator exceeds the threshold, this can signal the potential materialisation of the targeted risk over a pre-specified horizon and may serve as a trigger for more in-depth assessment and monitoring of the risk or potential policy actions. Typical techniques for identifying indicator threshold values include using the statistical distribution of the indicator (e.g., a percentile of the variable’s distribution), or estimation of values that minimise a policy maker’s “loss function”, in which the loss arising from missing crises and issuing false alarms are traded off (see Box 2).

This article proposes an alternative approach, in which the confidence intervals in Chart 2 serve as the basis for determining zones which indicate the severity of the signal for a particular time horizon. We consider as the “normal zone” the area in Chart 2 situated below the maximum of the upper confidence bounds for “non-crisis countries” and “tranquil periods”. We consider as the “danger zone” the area in Chart 2 situated above the lower confidence bound for “crisis countries”. Depending on whether or not the “normal zone” and the “danger zone” overlap, 4 zones can be identified, as summarised in Table 1.

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

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

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

For illustrative purposes, Chart 3 maps the confidence bounds in Chart 2 into the colour coding of signalling zones. The chart shows that, in contrast to the existing methodologies described in Box 2, the methodology does...
not result in a single threshold for a given prediction horizon, but rather multiple thresholds that determine zones with increasing likelihood of a crisis to be expected over the relevant prediction horizon. A further advantage is that these thresholds are based on the statistical distribution of the indicator across countries and over time; no assumption on an objective function is needed to obtain them.

As an example, consider the prediction horizon \([T–12;T–9]\) in Chart 3. No signal is issued for values of the household credit to GDP gap below 3.30 %. Values of the household credit to GDP gap between 3.30 % and 4.47 % would result in an intermediate signal (yellow zone) for a real estate related banking crisis to occur within 2 to 3 years. Finally, values above 4.47 % would result in a strong signal (red zone) of expecting a real estate related banking crisis over the prediction horizon.

2. Application of the monitoring framework to Belgium

In this section the graphical early warning methodology is applied to four potential early warning indicators of real estate related banking crises: measures of credit granted to the household sector (the level of household credit to GDP and the household credit to GDP gap) and developments in real estate prices (nominal house price growth and the price to income ratio). The indicator thresholds are obtained for a prediction horizon \([T–12;T–5]\), i.e., indicators would signal the potential occurrence of a real estate related banking crisis 1 to 3 years in advance.

2.1 Results

Chart 4 plots the historical pattern of the four variables in Belgium (up to 2013Q3) against the background of the zones resulting from the graphical methodology. The presence of the yellow zone reveals that the “normal zone” and the “danger zone” do not overlap for any of the four indicators, implying that they have good predictive power for the given prediction horizon (see Box 3 for a statistical evaluation of the indicators’ predictive power).

In addition to the zones derived from our novel graphical methodology, Chart 4 also plots optimal statistical thresholds (see Box 2 for the underlying methodology) obtained from minimising the noise to signal ratio conditional on predicting at least two thirds of the crises (the dashed horizontal line) and a policy maker’s loss function with equal weight given to Type I and Type II errors (the full horizontal line).

For 3 out of 4 indicators, one or more statistical thresholds are situated in the yellow area between the “normal zone” and the “danger zone”. For the household credit to GDP gap, statistical methods would issue warnings starting from levels still in the “normal zone”. Overall, the graphical methodology results in thresholds that are rather similar in magnitude to the statistical thresholds (see Box 3 for a discussion).

The top panels of Chart 4 present the historical evolution of the measures of credit granted to the household sector in Belgium. Panel A shows that the household credit to GDP gap reached levels that were no longer consistent with the “safe” zone in 2007Q4. The gap between household credit and its long-term trend continued to increase and entered the “danger zone” in 2009Q1. The gap peaked two quarters later and returned to levels below the “danger zone” in 2010Q2, though it remained above the “normal zone” until 2013Q2. If the household credit to GDP gap is compared with the statistical thresholds, the indicator already started issuing warnings from 2005-2006 onwards.

Panel B of Chart 4 reveals that the strong expansion of household credit resulted in an increasing level of household indebtedness. In particular, the level of household credit to GDP approached the upper bound of the “normal” zone towards the end of 2009 and continued moving further into the yellow zone. While still below the “danger zone” and (slightly) below the statistical warning thresholds, this increase in household indebtedness is considered as worrisome.

The bottom panels of Chart 4 show the historical developments in real estate prices in Belgium. Panel C reveals that
nominal house price growth started accelerating from early 2002 onwards. This resulted in growth rates no longer consistent with the “normal zone” in the period from 2005Q1 to 2006Q2, during which statistical thresholds were breached as well. Since then, nominal house price growth has returned to “safe” territory.

While nominal house price growth never entered the “danger zone”, accumulated strong house price growth in combination with the absence of a major correction (nominal house price growth turned slightly negative in 2009Q2-2009Q3) resulted in a potential overvaluation of the Belgian housing market. Panel D of Chart 4 indeed shows that the price to income ratio is no longer consistent with the “normal zone” from 2006Q1 onwards and entered the “danger zone” in 2010Q2. Statistical thresholds started issuing signals one quarter earlier.
Box 3 – Predictive power of the indicators for identified thresholds

Table 2 provides an overview of the predictive power of the indicators for the thresholds presented in Section 2. A review of the concepts used in Table 2 is presented in Box 2.

<table>
<thead>
<tr>
<th></th>
<th>AUROC</th>
<th>Threshold</th>
<th>TPR</th>
<th>(1-TPR)</th>
<th>Type I error (1-TPR)</th>
<th>Type II error (FPR)</th>
<th>Noise to signal</th>
<th>Loss</th>
<th>Relative usefulness</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Not in green zone</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HH credit to GDP gap</td>
<td>0.80</td>
<td>3.22</td>
<td>0.61</td>
<td>0.39</td>
<td>0.24</td>
<td>0.39</td>
<td>0.32</td>
<td>0.37</td>
<td></td>
</tr>
<tr>
<td>HH credit to GDP level</td>
<td>0.77</td>
<td>0.52</td>
<td>0.67</td>
<td>0.33</td>
<td>0.33</td>
<td>0.50</td>
<td>0.33</td>
<td>0.33</td>
<td></td>
</tr>
<tr>
<td>Nominal house price growth</td>
<td>0.75</td>
<td>10.79</td>
<td>0.74</td>
<td>0.26</td>
<td>0.30</td>
<td>0.41</td>
<td>0.28</td>
<td>0.44</td>
<td></td>
</tr>
<tr>
<td>Price to income</td>
<td>0.79</td>
<td>88.90</td>
<td>0.77</td>
<td>0.23</td>
<td>0.36</td>
<td>0.47</td>
<td>0.29</td>
<td>0.41</td>
<td></td>
</tr>
<tr>
<td><strong>In red zone</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HH credit to GDP gap</td>
<td>0.80</td>
<td>4.75</td>
<td>0.49</td>
<td>0.51</td>
<td>0.18</td>
<td>0.38</td>
<td>0.35</td>
<td>0.31</td>
<td></td>
</tr>
<tr>
<td>HH credit to GDP level</td>
<td>0.77</td>
<td>0.67</td>
<td>0.54</td>
<td>0.46</td>
<td>0.17</td>
<td>0.33</td>
<td>0.31</td>
<td>0.38</td>
<td></td>
</tr>
<tr>
<td>Nominal house price growth</td>
<td>0.75</td>
<td>13.69</td>
<td>0.53</td>
<td>0.47</td>
<td>0.20</td>
<td>0.37</td>
<td>0.33</td>
<td>0.33</td>
<td></td>
</tr>
<tr>
<td>Price to income</td>
<td>0.79</td>
<td>99.25</td>
<td>0.63</td>
<td>0.38</td>
<td>0.20</td>
<td>0.32</td>
<td>0.29</td>
<td>0.42</td>
<td></td>
</tr>
<tr>
<td><strong>Conditional minimum noise to signal</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HH credit to GDP gap</td>
<td>0.80</td>
<td>2.17</td>
<td>0.80</td>
<td>0.20</td>
<td>0.31</td>
<td>0.38</td>
<td>0.25</td>
<td>0.49</td>
<td></td>
</tr>
<tr>
<td>HH credit to GDP level</td>
<td>0.77</td>
<td>0.56</td>
<td>0.67</td>
<td>0.33</td>
<td>0.26</td>
<td>0.40</td>
<td>0.30</td>
<td>0.40</td>
<td></td>
</tr>
<tr>
<td>Nominal house price growth</td>
<td>0.75</td>
<td>11.01</td>
<td>0.68</td>
<td>0.32</td>
<td>0.27</td>
<td>0.40</td>
<td>0.29</td>
<td>0.41</td>
<td></td>
</tr>
<tr>
<td>Price to income</td>
<td>0.79</td>
<td>97.23</td>
<td>0.68</td>
<td>0.32</td>
<td>0.22</td>
<td>0.32</td>
<td>0.27</td>
<td>0.46</td>
<td></td>
</tr>
<tr>
<td><strong>Minimum Loss</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HH credit to GDP gap</td>
<td>0.80</td>
<td>1.21</td>
<td>0.97</td>
<td>0.03</td>
<td>0.41</td>
<td>0.42</td>
<td>0.22</td>
<td>0.56</td>
<td></td>
</tr>
<tr>
<td>HH credit to GDP level</td>
<td>0.77</td>
<td>0.59</td>
<td>0.64</td>
<td>0.36</td>
<td>0.24</td>
<td>0.37</td>
<td>0.30</td>
<td>0.40</td>
<td></td>
</tr>
<tr>
<td>Nominal house price growth</td>
<td>0.75</td>
<td>10.01</td>
<td>0.74</td>
<td>0.26</td>
<td>0.30</td>
<td>0.41</td>
<td>0.28</td>
<td>0.44</td>
<td></td>
</tr>
<tr>
<td>Price to income</td>
<td>0.79</td>
<td>97.23</td>
<td>0.68</td>
<td>0.32</td>
<td>0.22</td>
<td>0.32</td>
<td>0.27</td>
<td>0.46</td>
<td></td>
</tr>
</tbody>
</table>

Source: NBB calculations.

(1) In %.

The first column of Table 2 presents the indicators’ AUROC values over the prediction horizon [T–12;T–5]. These values, which are the same across the four parts of the table, show that all four indicators have good predictive power, with AUROCs well (and significantly) above 0.5. (1) The other columns of Table 2 provide an evaluation of the indicators’ signalling power for each of the thresholds derived in the four parts of the table.

The upper part of Table 2 presents the results based on the thresholds for the zones obtained on the basis of our novel graphical methodology. Specifically, “not in green zone” refers to a situation in which an indicator lies

(1) See Annex 4 for the dynamic movement in indicators’ AUROCs around crisis events.
2.2 Policy conclusions

The signals related to increasing levels of household indebtedness in combination with a potential overvaluation of housing prices suggest the need for close monitoring of developments in the Belgian real estate market and Belgian banks' mortgage loan portfolios.

Indeed, the Bank has closely monitored developments in the Belgian housing and mortgage market over the last years. In addition, it started in 2011 with a periodical quantitative survey of 16 Belgian banks, in order to assess and monitor the overall risk profile and quality of their residential mortgage loan portfolios. The Bank's Financial Stability Review of 2012 concluded that increased vigilance was required from banks and authorities to ensure the continuous application of sufficiently conservative credit standards and adequate risk pricing in all new mortgage loans. It also called for a tightening of credit standards, where necessary, in order to maintain high asset quality of the Belgian mortgage loan portfolios.

Further analysis over 2012 and 2013 suggests that if conditions in the Belgian housing market were to become less buoyant than they have been over the past 15 years, the riskier mortgage loan segments (in terms of maturities, loan size and/or debt service ratios) in the outstanding stock of mortgage loans could be the source of higher than expected credit losses for banks. Against the background of a potential overvaluation of property prices in Belgium, as acknowledged by both the Bank and international institutions such as the ESRB, the OECD and the IMF, this is considered to be a potential systemic risk.

As described in detail in the article on recent developments and prudential measures in the Belgian mortgage market in this Financial Stability Review, the Bank has therefore undertaken actions to mitigate systemic risk stemming from the Belgian real estate sector. These actions comprise a flat-rate 5 percentage point add-on to the risk weights applied by banks, under Belgian law, that use the internal ratings based approach to mortgage loans covered by residential real estate located in Belgium. In view of the cyclical character of this measure, the Bank will keep a close eye on market developments for the purpose of continuous assessment of the appropriate level of that add-on.

The graphical methodology described in this article serves as input into the Bank's general monitoring framework for housing and mortgage market developments. Signals received from the proposed early warning methodology facilitate the detection of possible excessive developments. It should be noted, however, that such signals should not serve as automatic triggers for policy action.

In particular, uncertainty over both threshold levels and the validity of cross-country results for individual countries warrants caution in the policy application of such frameworks. Particular developments in housing and mortgage markets may be driven by country-specific factors such as the fiscal treatment of mortgage debt and demographic trends. Furthermore, there may be substantial heterogeneity in the risk profile of individual loans underlying aggregate mortgage market developments. These country specificities and heterogeneities should be taken into account in in-depth systemic risk assessments. The role of the early warning methodology developed in this article is
exactly to indicate the potential need for such further in-depth assessment and monitoring of possible risk sources and triggers.

Conclusions

This article presents a novel graphical methodology for identifying leading indicators of real estate related banking crises. The framework also allows identification of thresholds that determine zones, which correspond to different intensities of the signal issued by the indicator for a given prediction horizon. As such, the framework can be applied as a monitoring tool for systemic risks stemming from the real estate sector.

The analysis could be applied to early warning indicators for other types of crises as well. For example, applying the methodology to banking crises stemming from excessive leverage and credit growth would result in a monitoring framework for guiding decisions on macroprudential instruments such as the countercyclical capital buffer.

It should be noted, however, that signals obtained from early warning indicators and thresholds should not serve as automatic triggers for policy action. Uncertainty over both threshold levels and the validity of cross-country results for individual countries warrants caution in the policy application of such frameworks. Rather, they should be considered as input into the first stages of the systemic risk assessment process, indicating the potential need for further in-depth assessment and monitoring of possible risk sources and triggers.

The article highlights the relevance of the results for systemic risks stemming from the Belgian real estate sector. In particular, signals related to increasing levels of household indebtedness in combination with a potential overvaluation of housing prices suggest the need for close monitoring of developments in the Belgian real estate market and Belgian banks’ mortgage loan portfolios. Such in-depth analysis of Belgian banks’ mortgage loan portfolios has resulted in recent actions undertaken to mitigate systemic risk stemming from the Belgian real estate sector.
References


Annex 1: Identified crises and data coverage

<table>
<thead>
<tr>
<th>Country</th>
<th>Real estate related banking crisis</th>
<th>HH credit to GDP level</th>
<th>HH credit to GDP gap</th>
<th>Nominal house price growth</th>
<th>Price to income ratio</th>
</tr>
</thead>
</table>

Notes: The Babeyci et al. (2012) database reports crisis periods distinguishing whether “at least one source” or “at least two sources” confirmed the occurrence of a crisis. We combine this information and consider that all episodes confirmed by at least one source are potentially real estate related banking crises. However, whenever the crisis period was confirmed by at least two sources, we consider the latter information to mark the start of banking crises. For the purpose of our analysis, the length of the crisis period does not matter (see Annex 3). What is important is to identify the start of a real estate related banking crisis.
Annex 2: Pattern of selected early warning indicators around crises

**PATTERN OF SELECTED EARLY WARNING INDICATORS AROUND CRISSES**

A – HOUSEHOLD CREDIT TO GDP GAP

B – HOUSEHOLD CREDIT TO GDP LEVEL

C – NOMINAL HOUSE PRICE GROWTH

D – PRICE TO INCOME RATIO

Source: NBB Calculations.
Annex 3: Three-country example of data classification

We classify three subsets of observations and calculate cross-country averages across the relevant observations:

– observations in crisis countries around their own real estate related banking crises (denoted “crisis countries”),
– observations in the windows around these crisis events for countries that do not experience a real estate related banking crisis at those points in time (denoted “non-crisis countries”),
– observations outside the relevant window around any real estate related banking crisis event in the sample (denoted “tranquil periods”).

In a three-country sample consisting of Belgium, Denmark and the United Kingdom, observations for the different countries would be classified as follows.

– Observations for which none of the three countries is in the relevant window \([T-12;T+12]\) around a crisis are classified as “tranquil times”. These are indicated by the dark green areas in the chart below.
– Observations for which a given country is in the window \([T-12;T-5]\) around the onset of its own crises are classified as “crisis countries” and indicated by the red areas.
– Observations for which a given country is not in the window \([T-12;T+12]\) around its own crises and at the same time another country is in the window \([T-12;T-5]\) around its own crises, are classified as “non-crisis countries” and indicated by the light green areas.
– Finally, white areas indicate observations that are excluded from the evaluation. Excluded observations are those for crisis countries in the window \([T-4,T+12]\) around their own crises.\(^{(1)}\)

THREE-COUNTRY EXAMPLE OF DATA CLASSIFICATION

\(^{(1)}\) In addition, the last three years of the sample are also excluded, as it is impossible to know whether or not these observations count as pre-crisis observations.
Annex 4: AUROC curves for selected early warning indicators

AUROC CURVES FOR SELECTED EARLY WARNING INDICATORS

A – HOUSEHOLD CREDIT TO GDP GAP

B – HOUSEHOLD CREDIT TO GDP LEVEL

C – NOMINAL HOUSE PRICE GROWTH

D – PRICE TO INCOME RATIO

Source: NBB Calculations.