

Identifying excessive credit growth and leverage

Lucia Alessi and Carsten Detken*

Abstract

Unsustainable credit developments lead to the build-up of systemic risks to financial stability. While this is an accepted truth, how to assess whether risks are getting out of hand remains a challenge. To identify excessive credit growth and aggregate leverage we propose an early warning system, which aims at predicting banking crises and gives an indication on the nature of specific vulnerabilities. The key indicators are selected by applying the “Random Forest” method, based on decision trees, and include (global) credit as well as real estate variables. The benchmark early warning tree identifies the associated warning thresholds.

Keywords: Early Warning Systems, Banking Crises, Credit, Macroprudential Policy, Decision Trees, Random Forest.

JEL Classification C40 · G01 · E44 · E61 · G21.

*Both European Central Bank, Kaiserstrasse 29, D-60311 Frankfurt am Main, Germany. Emails: lucia.alessi@ecb.europa.eu; carsten.detken@ecb.europa.eu. We thank Nadya Jahn for excellent research assistantship in the construction of debt service ratios.

1 Introduction

Past financial crises and in particular the global financial crisis have shown that excessive credit growth often leads to the build-up of systemic risks to financial stability, which may materialize in the form of systemic banking crises. The key stylized fact is that asset price bubbles tend to be more costly in terms of output if they are credit-fueled. Looking back at the global financial crisis, it is indeed uncontroversial that unsustainable credit booms and asset price bubbles were at its root. It is however much less straightforward to assess in real time where the economy stands in the credit cycle, when it is the right moment to act in order to smooth the cycle, and which instrument should be used to do it. Ultimately, one would need a quantitative framework, useful for benchmarking and analysing credit developments in a rigorous manner. Had such a framework been in place in 2006, the fact that credit was growing in the US at more than 10 p.p. above trend would have probably been taken more seriously. Having said this, it would be too naive to believe that the next financial crisis will unfold exactly in the same way. However, it would be irresponsible to ignore what we have learnt, would the same thing happen again.¹

Against this background, we propose an early warning model which is useful in at least two respects. On the one hand, it can be used for identifying those periods in which the build-up of leverage can be defined as excessive

¹On the “this time is different” syndrome see Reinhart and Rogoff (2009).

and may warrant policy action. On the other hand, the model is able to provide policymakers with concrete advice on which macroprudential instrument would be best suited to address a specific credit-related vulnerability.

This paper places itself at the crossing of two literature streams. The first stream investigates the role of credit growth and leverage as a cause of financial crises.² Indeed, many authors have shown that a relation between credit growth and financial crises exists, and more and more efforts are being devoted to the study of the credit cycle. Among the most recent contributions, Jordà et al. (2001), Schularick and Taylor (2012) and Aikman et al. (2014) present evidence, based on more than a century's worth of data, that credit growth is a good predictor of financial crises, and banking crises in particular. The second stream is the extensive literature on early warning indicators. The model presented here belongs to the new generation of early warning systems for financial crises, which put the lesson on credit booms into practice.³ We find that global liquidity is a better early warning indicator for credit-related systemic banking crises than many domestic variables. The debt service ratio and bank credit developments are also among the best

²As it is common in the macro-financial literature, and in contrast to the micro-financial concept of leverage, this paper defines leverage as the ratio of a credit aggregate to GDP at the country level. The broader definition of leverage used in this paper covers non-financial-corporations and household debt, i.e. a country's total private sector leverage. We use this definition of leverage to indicate the stock of debt, as opposed to the concept of credit growth (and gap).

³These recent models, as in e.g. Alessi and Detken (2011), Behn et al. (2013) and Betz et al. (2014), improve on the early warning systems developed in the 90's in many respects. One of the key improvements is the use of more advanced performance metrics than the noise-to-signal ratio, see Alessi et al. (2015) for a discussion.

indicators, followed by house prices.

Finally, our modelling technique of choice is based on decision tree learning, a greatly underutilized technology in economics. Indeed, while Classification and Regression Trees (CARTs, see Breiman et al. (1984)) are extensively used in other disciplines, their economic applications are rare. The early warning literature, in particular, has so far almost uniquely relied on two approaches, namely the signalling approach, pioneered by Kaminsky and Reinhart (1999), and the categorical dependent variable regression (see e.g. Eichengreen and Rose (1998)). Decision trees retain the advantages of both approaches, as they are on the one hand very easy to explain and use, and on the other hand able to provide an early warning *system* where the relevant indicators are considered in a unitary framework. We are aware of only a handful of papers using binary recursive trees for assessing vulnerabilities in relation to financial crises: Gosh and Gosh (2002) and Frankel and Wei (2004) analyze the determinants of currency crises, Manasse and Roubini (2009) and Savona and Vezzoli (2014) deal with sovereign crises, while Duttagupta and Cashin (2011) and Manasse et al. (2013) study banking crises in emerging markets. Similarly to this latter paper and to Savona and Vezzoli (2014), the present study grows the benchmark early warning tree on the solid ground of a preliminary analysis based on bootstrapping and aggregating a multitude of trees. However, our focus is on the European Union. Moreover, we aim at a model that allows for timely decision making and therefore focus on identifying pre-crisis periods rather than crisis periods (see Section 2).

The paper is structured as follows. In Section 2 we define our target variable, i.e. broadly speaking banking crises in the European Union in the last 40 years. Section 3 describes our candidate early warning indicators. Section 4 outlines the Classification Tree approach and its extension to Random Forests. The results of the empirical analysis using the Random Forest approach are presented in Section 5 and compared to the results from logit models in Section 6, while Section 7 illustrates the benchmark Early Warning Tree. Section 8 describes the results of an out-of-sample exercise using only pre-2007 information. The policy implications of our findings are discussed in Section 9, while Section 10 summarizes the main conclusions.

2 The Banking Crises Dataset

The basis for the banking crises dataset used in this paper is provided by the dataset assembled by Babecky et al. (2012). This quarterly dataset covers, inter alia, banking crisis episodes in EU countries over 1970-2010. The authors do not provide a unique definition of banking crisis: rather, they derive banking crisis episodes by aggregating the information about crisis occurrence coming from other works and an ad-hoc survey among country experts mainly in national central banks. None of the considered definitions of banking crisis, however, is fully aligned with the objective and operation of the macroprudential tools targeting credit, as they aim to avoid a broader array of circumstances than simply a banking crisis as defined in those terms

alone. Therefore, we use an updated and slightly amended dataset, which has been built in the framework of a broader project by the European Systemic Risk Board on the basis of country experts' judgement and is described and used in Detken et al. (2014)). In this dataset, the target variable captures: (i) systemic banking crises associated with a domestic credit/financial cycle; (ii) periods in which in the absence of policy action or of an external event that dampened the credit cycle a crisis as in (i) would likely have occurred.

The data cover all 28 EU members from 1970Q1 till 2012Q4. However, we have extended the coverage to 2013Q4, while limiting our analysis to euro area countries together with the UK, Denmark and Sweden. We excluded Central and Eastern European transition economies as their data series are generally relatively short, implying that the overall results would be driven by the evidence linked mainly to the global financial crisis, and in some cases exhibit peculiar patterns which would warn against pooling these countries together with the ones under study. Over the considered period, 25 separate crisis episodes are recorded for euro area countries, the UK, Denmark and Sweden. They are marked in black in Chart 1. While the incidence of crises shows a marked increase for the current financial crisis, only slightly more than half of the 21 country experts thought that for their country the current crisis met one of the above criteria. Moreover, some countries (Austria, Belgium, Luxembourg, Malta and Slovakia) did not record any crisis consistent with the above criteria over the sample period. Of the remaining countries, 8 experienced one crisis, 7 experienced two crises while the UK experienced

three crises.

Finally, in constructing our binary target variable we take into account policy lags. For example, with respect to countercyclical capital buffers, which are one of the main tools envisaged by Basel III, banks should usually be given at least one year time to meet the additional capital requirements before any increases in the buffer take effect. An early warning signal leading the inception of the crisis by less than one year, or once the crisis is already in place, would be late. At the same time, we do not aim at building a model which predicts exactly when a banking crisis will materialize. Rather, we propose an early warning system signalling that financial imbalances are building up and the risk of a systemic crisis in the not-so-far future is increasing. Therefore, we define as correct any warning signals issued in the four years preceding the start of a crisis, excluding from the analysis the three quarters immediately preceding the crisis and the crisis period itself. The pre-crisis periods are marked in red in Chart 1, while the periods excluded from the analysis are marked in grey. We do not remove from the sample the quarters following the crisis because our model is not expected to suffer from any post-crisis bias.⁴ With the exception of the Spanish and Cypriot crises, the period after 2009Q1 is de-facto not taken into account while optimizing the early warning thresholds because the dataset ends in 2012Q4 and ignores

⁴See Bussière and Fratzscher (2006), who show that the econometric results of binomial logit early warning models are at least in part explained by the behavior of the independent variables during and directly after a crisis, i.e. periods often characterized by disorderly and volatile corrections towards longer-term equilibria.

whether a crisis happened in any of the countries in 2013.

3 Early Warning Indicators

We examine a battery of indicators which could contain valuable information to predict systemic banking crises. In particular, we consider financial and macroeconomic variables, as well as real-estate based indicators. The dataset goes from 1970:Q1 to 2013:Q4; however, the last 4 years of data are excluded from the analysis (see previous section). To proxy for publication lags and taking a conservative stand, we lag all the variables by one quarter. In other words, the model aims at classifying the current quarter as pre-crisis or tranquil on the basis of data referring to no later than the last quarter, although some information on conjunctural developments from higher-frequency indicators would already be available in real time.

3.1 Credit-related indicators

With respect to credit related indicators, the key aggregate is broad credit. In this respect, we use a broad credit aggregate compiled by the BIS (see Dembiermont et al. (2013)), which covers credit from all sources, including debt securities, to the non-financial private sector. We consider the following transformations: i) the y-o-y rate of growth, ii) the ratio to GDP, and iii) the deviations of such ratio from its trend (i.e. the ‘gap’), computed with a backward-looking slowly-adjusting ($\lambda = 400,000$) Hodrick-Prescott filter.

The value of 400,000 for the smoothing parameter corresponds to assuming that the financial cycle is four times as long as the business cycle and has been suggested by the Basel Committee on Banking Supervision (BCBS (2010)) - we'll therefore refer to the resulting gap as the "Basel gap". However, such an HP trend might be adjusting too slowly following a prolonged period of negative credit growth, therefore we also consider an alternative gap computed with $\lambda = 26,000$, corresponding to a financial cycle which is twice as long as the business cycle. Deviations of the credit-to-GDP ratio from a long term trend would have performed well in signalling the build-up of excessive leverage in the past; however, the literature has also shown that credit gap suffers from some shortcomings.⁵

We also look at the narrower bank credit aggregate, which we analogously consider as y-o-y rate of growth, ratio to GDP and gap.⁶ The level of bank

⁵Drehmann et al. (2010) and Drehmann et al. (2011) show that the credit gap outperforms other candidate early warning indicators such as GDP and credit growth, the credit-to-GDP ratio as such, as well as indicators based on asset prices or measures of banking sector performance. Detken et al. (2014) also provide evidence for the good performance of the credit-to-GDP gap for the EU as a whole. However, the credit-to-GDP gap may provide misleading signals in real-time as it is prone to large revisions (Edge and Meisenzahl (2011)). This is mainly due to the end-point bias affecting the one-sided HP filter, which is indeed the most widely used to extract the long-term trend. Moreover, positive deviations from trend could be due to either excessive credit growth or low or negative output growth, two scenarios which arguably require different policy responses (Repullo and Saurina (2011)).

⁶Rates of growth are deflated by subtracting the y-o-y CPI changes. Gaps have been constructed by taking a standard HP filter for the first 5 years of available data and then a recursive HP filter. Although it is advisable to only use gaps after 5-10 years of data due to the start point problem affecting HP trend estimates (see Borio and Lowe (2002)), such an approach would have yielded too short time series. As a result, the evaluation of the predictive performance of gap measures would have been driven mainly by the recent global financial crisis. Also based on the results by Drehmann and Tsatsaronis (2014), who analyze the potential practical consequences of the start point bias, we decided in

loans as a ratio to GDP is one of the indicators Schularick and Taylor (2012) take as evidence of a *story of decades of slowly encroaching risk on bank balance sheets*: by including it in our model we aim at exploiting the panel dimension in order to pin-down an ‘early warning’ level of aggregate leverage.⁷ With respect to the time dimension, it could be argued that such an ‘early warning level’ does not make sense for nonstationary series. However, we would argue that the ratio of credit to GDP is theoretically bounded, hence stationary in the long run. Furthermore, our statistical procedure is not affected by ‘spurious regression’ problems. For this reason, we do include credit to GDP levels in the analysis as they serve as conditioning variables for other indicators. Sectoral credit aggregates, namely credit to households and non-financial corporations, are transformed into y-o-y rates of growth, deflated by CPI inflation, and ratios to GDP. The real rate of growth of housing loans is also considered.⁸

Global liquidity is included in the form of global credit growth and gaps, computed as GDP (at PPP) weighted averages of the relevant domestic concepts. In particular, global credit growth is constructed by averaging the y-o-y broad credit growth rates across countries, deflated by subtracting the y-o-y changes of the national CPI. The global credit gap is also based on the broader credit concept.⁹

favor of keeping the longest possible time series.

⁷Other indicators studied by Schularick and Taylor (2012) are e.g. the ratios of bank assets to GDP and money, which we do not analyze owing to lack of long enough quarterly bank balance sheet observations.

⁸The source for loans to households for house purchase is the ECB.

⁹The countries considered for the construction of the global credit variables are the ones

Finally, we consider debt service costs. In particular, we use extended debt service ratio (DSR) series with respect to those in Drehmann and Juselius (2012), computed on high-quality (and sometimes confidential) data.¹⁰ We include the aggregate DSR as well as sectoral DSRs for non-financial corporations and households. Finally, we include public debt, as a ratio to GDP, in the pool of credit-related indicators.¹¹

3.2 Macroeconomic indicators

The macroeconomic variables we examine are real GDP y-o-y growth and the current account in percentage of GDP (on the properties of the current account as an early warning signal for banking crises, see Kauko (2012)). We also consider the M3 money aggregate, in terms of real y-o-y rate of growth and gap, and the real effective exchange rate.¹²

under study together with Brazil, Canada, China, Hong Kong, India, Indonesia, Japan, Korea, Mexico, Norway, Russia, Singapore, South Africa, Switzerland, Thailand and the US.

¹⁰The DSR at time t is calculated using the standard formula for the fixed debt service costs (DSC_t) of an instalment loan and dividing it by income (Y_t):

$$DSR_t = \frac{DSC_t}{Y_t} = \frac{i_t D_t}{(1 - (1 + i_t)^{-s_t}) Y_t}$$

where D_t denotes the aggregate stock, i_t denotes the average interest rate per quarter on the stock, s_t denotes the average remaining maturity on the stock and Y_t denotes quarterly aggregate income. The source for credit aggregates is the BIS, income data are sourced from Eurostat, while lending rates and the average loan maturity are sourced from the ECB (MFI Interest Rate statistics and MFI Balance Sheet Items statistics, respectively). The interest rate is the 3 month average money market interest rate from Eurostat.

¹¹Eurostat data.

¹²The main source for real and nominal GDP data is the OECD; Eurostat data have been used whenever OECD series were not available or shorter (i.e. for Cyprus, Estonia, Greece, Latvia, Malta, Slovakia and Slovenia). The source for the current account balance

3.3 Property prices

With respect to property prices, house price growth (y-o-y, consumer price deflated) is considered, as well as gap measures. Moreover, we include in the dataset two standard property valuation measures, namely the house price to income ratio and the house price to rent ratio.¹³

3.4 Market-based indicators

Finally, the market-based indicators included in our pool are the long (10 years) and short (3 months) interest rates, both deflated by subtracting the y-o-y CPI changes, as well as the deflated y-o-y growth rate of equity prices.¹⁴

4 Classification Trees and the Random Forest

A binary classification tree is a partitioning algorithm which recursively identifies the indicators and the respective thresholds which are able to best split the sample into the relevant classes, say pre-crisis and tranquil periods. The output of the predictive model is a tree structure like the one shown in Figure 4, with one root node, only two branches departing from each *parent node* (hence “binary” classification tree), each entering into a *child node*, and

is Eurostat. M3 is provided by the ECB. The real effective exchange rate is sourced from the IMF’s IFS and from Eurostat for Estonia, Latvia and Slovenia.

¹³These valuation measures are provided by the OECD in its house price database as indexes and are transformed by subtracting the long-term mean.

¹⁴Interest rates are sourced from Eurostat, while the source for the stock price indexes is the OECD Main Economic Indicators database.

multiple *terminal nodes* (or “leaves”). Starting by considering all available indicators and threshold levels, the procedure selects the single indicator and threshold yielding the two purest subsamples in terms of some impurity measure. A standard impurity measure, which we also employ, is the Gini index:

$$GINI(f) = \sum_{i=1}^n f_i(1 - f_i) = 1 - \sum_{i=1}^n f_i^2 = \sum_{i \neq j} f_i f_j$$

where f_i is the fraction of periods belonging to each category i in a given node, with $i = 1, 2$ in our case, i.e. pre-crisis and tranquil. The value of the Gini index will be 0 for a node which contains only observations belonging to the same class. The more mixed a sample is, the higher the Gini index will be, reaching a maximum of 0.25 in the case of two categories. It is possible to generalize the above expression for the Gini index in order to take into account different misclassification costs C_{ij} for the various classes. The Gini index can then be written as follows:

$$GINI(f) = \sum_{i,j} C_{ij} f_i f_j$$

with $C_{ii} = 0$ and C_{ij} reflecting the cost of assigning an observation belonging to category i to category j . In our case, for example, it could make sense to be conservative and assume that misclassifying a pre-crisis quarter as tranquil would yield more serious consequences than vice-versa, implying that the cost of a banking crisis is in general larger than the cost of prudential pre-emptive measures. In other words, this would amount to assuming unbalanced pol-

icymakers' preferences against missing crises. Asymmetric misclassification costs will also impact the classification of the tree leaves.¹⁵

Once the first best split is selected, the algorithm proceeds recursively by further partitioning the two subsamples, i.e. finding the best split for each of them. The whole logical structure of the tree is then constructed recursively and the algorithm stops when either some stopping rule becomes binding (e.g. a minimal terminal node size) or there is no further gain from splitting nodes. Notice that a decision tree is not sensitive to outliers, which will end up isolated in leaves, and can handle nonstationary time series, as the time dimension is not relevant in this framework.

The resulting tree can be used in real time to map the current value of a set of indicators into a single prediction, expressed as the probability of being in each of the classes. Indeed, rare leaves will contain only observations (i.e. country-quarters in our case) all belonging to the same class. On the contrary, several observations from different classes typically end up in the same leaf.¹⁶ The probability that an out-of-sample observation belongs to a particular class can therefore be computed as the frequency of in-sample observations actually belonging to that class, which ended up in that same leaf while growing the tree. For early warning purposes, it is therefore enough to go down the classification tree, according to the current values of the rele-

¹⁵See e.g. Tuffery (2011).

¹⁶Theoretically, one can always grow a tree which has enough branches to yield pure leaves, i.e. correctly classify all sample data, unless the data is contradictory in some dimension. However, to avoid overfitting, such a tree should be *pruned* by replacing some parent nodes with leaves.

vant indicators, to see whether the model foresees an incoming banking crisis. If the policymaker's preferences between missing a crisis (type 1 error) and issuing a false alarm (type 2 error) are balanced, an early warning will be issued if the relevant leaf is associated with a frequency of pre-crisis periods larger than 50%. However, policymakers' preferences after the global financial crisis are likely to have become biased against missing crises, implying a lower threshold.

The main drawback of the tree technology is that, while it can be very good in-sample, it is known not to be particularly robust when additional predictors or observations are included. We overcome this problem by using the Random Forest method proposed by Breiman (2001). This framework is a popular machine learning technique which involves *bagging*, i.e. bootstrapping and aggregating, a multitude of trees. Each of the trees in the forest is grown on a randomly selected set of indicators and country quarters.¹⁷ Analogously to the tree, the forest allows for interaction across the various indicators, is able to handle large datasets, is not influenced by outliers and does not require distributional or parametric assumptions. Once a new quarter of data is available, the prediction of the forest will be based on how many trees in the forest classify it as a pre-crisis or tranquil period, and it will also reflect policymakers' preferences. Each of the trees in the forest is in itself

¹⁷Following the Random Forest literature, the number of indicators selected for each tree is equal to \sqrt{N} , where N is the total number of indicators. At each repetition, 70% of the observations are sampled with replacement. However, the forest is not very sensitive to the value of these parameters.

an out-of-sample exercise, as the observations that are not used to grow the tree (so called *out-of-bag* observations) can be put down the tree to get a classification. It is therefore possible to compute the total misclassification error of the forest.

Together with being an extremely powerful predictor, the Random Forest allows to measure the importance of each of the input variables by evaluating the extent to which it contributes to improve the prediction. This is done in practice by randomly permuting the values of the n -th indicator in the out-of-bag cases, and comparing these tree predictions to those obtained by not permuting the values. If the error rate increases substantially by permuting the values of an indicator, that means that the indicator does convey relevant information for an accurate classification. If, on the contrary, there is no difference between the two error rates, the indicator is useless.

5 Results from the Random Forest

The Random Forest could be used as a regular tool for policy purposes. Indeed, based on the error rate of a 100,000-tree forest we have grown on all of the indicators, the chance of misclassifying an incoming quarter of data is 6%. A standard metrics for the evaluation of the performance of a classifier across a range of preferences is the Area Under the Receiver Operating Characteristic curve (AUROC), the ROC curve plotting the combinations of true positive rate (TPR) and false positive rate (FPR) attained by the

model. It is constructed by varying the forest ‘early warning’ threshold, i.e. the required fraction of trees classifying a particular observation as pre-crisis, beyond which that observation will be actually classified as pre-crisis. The ROC curve of a random classifier will tend to coincide with a 45 degree line, corresponding to an AUROC of 0.5, while the AUROC of a good classifier will be closer to 1 than to 0.5. Chart 2 shows the ROC curve of the Random Forest, corresponding to an AUROC above 0.9 (0.94). This result is derived assuming biased policymaker’s preferences against missing crises - in particular, we set misclassification costs such that the cost of misclassifying a pre-crisis quarter is twice as large as the cost of misclassifying a tranquil quarter - and is robust to assuming balanced preferences.

Notwithstanding the remarkably good performance of the Random Forest, we acknowledge that this is a black-box model and its predictions would be hard to defend, in particular if they would support the activation of a macroprudential instrument. Therefore, in this paper we rely on the Random Forest in order to identify the key indicators, on which we construct our benchmark tree. By doing so, we ensure that the variables selected to grow the tree are truly the most important ones in the pool and we rule out the possibility that the tree selects a relatively weak indicator which just happens to seem useful in-sample but would not survive an out-of-sample robustness check. Chart 3 shows the ranking of the indicators in the forest, with the bars representing a measure of the increase in the classification error associated with randomly permuting the values of the considered indicator across the

out-of-bag cases. This measure is computed for every tree, then averaged and divided by the standard deviation over all of the trees.¹⁸

Not surprisingly, since the model is designed to predict banking crises associated with a domestic credit boom, the most important indicator turns out to be bank credit in the form of its ratio to GDP, followed closely by the gap derived with a very slowly adjusting trend. The level of broad credit and the Basel gap rank lower than the narrow credit counterparts, though still in the top half of all the indicators. The Lucas critique however applies: economic agents' decisions are indeed not policy-invariant, therefore one could expect that with increasing bank lending regulation, activity will more and more shift to the non-banking sphere - supporting the use of the total credit aggregate as a more comprehensive indicator for the future. In general, credit to GDP ratios appear helpful in assessing how vulnerable a country is because of excessive structural leverage rather than conjunctural developments, and are therefore useful in conditioning the information provided by gaps and rates of growth.

Global liquidity - in the form of both the global credit gap and the growth rate - turns out to be another key concept, ranking among the five most important indicators. This finding is in line with the results by Caballero

¹⁸Given that the forest includes an element of randomness, multiple runs of the algorithm on the same dataset won't necessarily yield the same indicators' ranking, in particular if the error associated with different indicators is similar. A robustness check based on several 1000-tree forests indicates that there could be a difference of at most two positions with respect to the ranking illustrated here. The exact ranking is anyway not the focus here, as we are only interested in telling the good indicators from the bad ones.

(2014), who shows that surges in international capital inflows significantly increase the likelihood of systemic banking crises even in the absence of a domestic lending boom. Indeed, (excess) global liquidity is likely to be at the origin of those international capital inflows identified by Caballero as one of the main determinants of banking crises.

The remaining two indicators among the top five are the level of household credit and the aggregate debt service ratio. Immediately following the top six indicators there are some measures relating to house prices, namely the house price to income ratio, the house price gap and house price growth. Equity price growth ranks a little lower. Indeed, heated asset price growth might be associated with excessive credit growth fuelling a growing bubble. After considering the housing market, the Random Forest suggests that the real short term rate should be looked at next, most likely because a low rate may encourage risk-taking in a search-for-yield behavior. Also among the top half of all the indicators are the household debt service ratio, bank credit growth, the NFC credit to GDP ratio and M3 gaps.

6 Comparison with logit models

In this section we aim at testing the predictive performance of competing regression models, namely discrete choice models.¹⁹ In particular, we estimate

¹⁹For a comparison of logit models and decision trees in the context of credit risk assessment see Joos et al. (2001), while Savona and Vezzoli (2014) test the performance of logit models and a similar algorithm to the Random Forest in predicting sovereign debt crises.

logistic regressions, where a logit mapping function takes the explanatory variables into a continuous indicator variable between 0 and 1, which indicates the (crisis) probability. The pooled logit model specification is as follows:

$$Prob(y_{it} = 1|X_{it-1}) = \frac{e^{\alpha_i + X'_{it-1}\beta}}{1 + e^{\alpha_i + X'_{it-1}\beta}} \quad (1)$$

The experimental design is the same as the one adopted for the Random Forest: $Prob(y_{it} = 1|X_{it-1})$ denotes the probability that a given country i in a given quarter t is in a pre-crisis state, with pre-crisis states defined as described in Section , i.e. five to one year before the outbreak of a crisis; also in this case, the 3 quarters immediately preceding the crisis and the crisis quarters themselves are excluded from the sample. The crisis probability at time t depends on the information set at time $t - 1$, as all regressors are lagged by one quarter. The logit models we estimate may also include a set of country dummy variables, α_i . The selection of the regressors X_{it-1} is unfortunately heavily affected by data availability. Indeed, ideally one would like to compare competing models on the same sample, both in terms of time and cross-sectional dimension. In this respect, more than 30 variables for 21 countries are included in the Random Forest model, each of which for the whole time-span for which observations for that indicator are available. On the contrary, the estimation of a pooled logit regression requires a balanced panel. In the selection of the relevant sample, a trade-off emerges between

maximizing the time dimension and the cross-sectional dimension.

The first of the two models we estimate aims at maximizing the time dimension, namely keeping observations as of 1970. This requires dropping a number of countries (Cyprus, Estonia, Latvia, Luxembourg, Malta, Slovakia and Slovenia), and restricting the regressors to a handful of credit variables. In particular, we estimate model 3 in Behn et al. (2013), which includes domestic broad credit growth, the domestic Basel gap, a term representing the interaction of the two, global credit growth, the global credit gap, an interaction term for global liquidity variables (i.e. global credit growth*global credit gap), an interaction term for broad domestic and global credit growth, and an interaction term for the domestic and the global gap. Country dummies are also included.²⁰ Table 1 shows the estimation results: with respect to the predictive power of this model, the AUROC is 0.84, i.e. 10 percentage points lower than the Random Forest AUROC.

The second model we estimate aims at extending the types of regressors included, e.g. by considering also asset prices. This requires restricting even further the number of countries considered, limiting them to Finland, France, Italy, the Netherlands, Sweden, Spain and the UK, while keeping observations as of 1980. The model includes the domestic broad credit growth, the Basel gap, the DSR, equity price growth, global credit growth and gap, the house price to income ratio, and real GDP growth. The estimation results are also

²⁰This amounts to excluding countries which did not experience a crisis, i.e. Austria and Belgium. See Behn et al. (2013) for a discussion of the bias arising from including country dummies and from not including them.

shown in Table 1: this model does much better than the first one, yielding an AUROC of 0.93, which is comparable to the Random Forest AUROC. However, it should be noticed that restricting the sample to a handful of countries with similar economic and financial systems, and excluding from the analysis the banking crises that took place in the 70's (in Spain and the UK), when the financial system was arguably quite different, makes the task easier for the logit than for the Random Forest.

7 The early warning tree

Chart 4 shows the benchmark tree grown on the best indicators described in Section 5, assuming that the underlying preferences of the policymakers with respect to missing crises and issuing false alarms are biased against missing crises.²¹ The Random Forest and the associated early warning tree grown by assuming balanced preferences between type 1 and type 2 errors are described in the Appendix. The indicator appearing in the root node is the DSR, associated with a threshold of 18%. According to end-2012 data, this threshold splits the sample equally, with around half of the countries ending up in the right branch and the other half in the left branch. The next node along the right branch of the tree corresponds to the bank credit to GDP ratio with a threshold of 92%. If this threshold is breached, the next relevant

²¹To avoid overfitting, this tree has been grown by imposing a minimum parent node size of 8 country/periods and a minimum leaf size of 4 country/periods, while some of the terminal branches have been pruned.

indicator is household credit as a percentage of GDP with a threshold of 54.5%. At the end of 2012 a relatively large number of countries breached all of these thresholds, ending up in the ‘warning’ leaf associated with a 90% in-sample crisis frequency. As cyclical developments might be less relevant along this branch of the tree, one could consider employing macroprudential instruments like the leverage ratio or the systemic risk buffer to increase resilience in the system given the elevated leverage identified by the model. The former tool aims at addressing risks directly linked to excessive leverage, namely losses occurring in the wake of fire sales and adjustments in asset valuation. The latter tool is envisaged to increase resilience in the banking sector by addressing structural systemic risks like the size of the banking sector compared to the rest of the economy. However, this estimate of the probability of a crisis should be interpreted with caution for the following two reasons. The first is that the better the tree is at fitting in-sample data, the purer the leaves it will yield, with associated in-sample frequencies close to 1 or 0. However, in assessing a country’s situation one should consider whether the relevant indicators only marginally exceed (or not) the respective thresholds. The second caveat relates to country specificities, which cannot be captured by the model. With respect to this leaf, for example, the concept of the DSR could be misleading for specific countries that for reasons not harmful for financial stability have structurally high private sector debt. In such a case, a net debt concept taking into account accumulated private sector wealth would be more suitable.

If the bank credit to GDP threshold of 92% is not breached, the next relevant indicator is the bank credit gap with a threshold of 3.6 p.p.. If this threshold is breached, the crisis probability increases to above 60%. In this case, there would be a role for macroprudential tools such as the countercyclical capital buffer as the credit gap can be associated with cyclical systemic risk. Indeed, the countercyclical capital buffer is designed to increase the resilience of the banking sector and smooth the credit cycle, by ensuring that the flow of credit is not unnecessarily reduced due to pro-cyclical supply side constraints during a bust phase.

Looking at the left branches of the tree, the main messages are as follows. If the DSR is below 10.6% the crisis probability is negligible. A relatively large number of countries, however, are in the middle range, with a DSR between 10.6% and 18%. For these countries, essentially depending on the sign of the M3 gap, different variables become relevant. These indicators relate to the following: i) house prices, in the form of house price growth and gap and in relation to income; ii) equity prices; iii) the Basel gap; iv) the short term real interest rate; v) bank credit level and growth; and vi) household credit. As an example, a country falling in the ‘warning’ leaf associated with a house price to income ratio 27 points above its long term average might consider adopting measures such as caps to loan-to-value and loan-to-income ratios.

With respect to the in-sample predictive performance of this benchmark tree, the true positive rate and the false positive rate (or share of type 2

errors) are equal to 85% and 4%, respectively, while the share of type 1 errors is 15%. The noise to signal ratio is 5%. A more sophisticated measure of the usefulness of the model, taking into account the policymaker's greater aversion towards type 1 errors, indicates that a policymaker using this tree increases his/her utility by 65% compared with ignoring it.²²

8 Out-of-sample exercise

An out-of-sample exercise testing the predictive performance of the model with respect to the global financial crisis is a heroic task, as only slightly more than half of the crisis episodes are left in the sample and some data series become extremely short. Nevertheless, the credibility of any early warning model of this sort crucially depends on whether the model would have been of any help in detecting in real time the build-up of financial imbalances in the run-up to the crisis. Therefore, in this section we describe what the suggestions of the model would have been in mid-2006, based on data up to the second quarter of 2006 only and ignoring whether the period starting in mid-2001 would later be classified as a pre-crisis period.²³

A 100,000-tree Random Forest grown on this information set indicates that the global credit, the bank credit and the Basel gaps would have turned

²²See Sarlin (2013).

²³For this exercise, gaps have been constructed by taking a standard HP filter for the first year and a half of available data and then a recursive HP filter, while the long term average of house price to income and house price to rent ratios is computed on observations up to the first quarter of 2006.

out to be the key variables back in 2006, as well as the level of bank credit (see Figure 5). The M3 gaps would have ranked immediately lower, followed by house price valuation measures. Among the best performing indicators there would have been also other global liquidity indicators, as well as the DSR, the level of broad credit, household and NFC credit, bank and broad credit growth and the house price gap.

The tree built on the indicators listed above (excluding global liquidity) would have had the M3 gap at the root node (see Figure 6). Germany and Greece would have ended up in the same ‘tranquil’ leaf, as at that time the M3 gaps, the Basel gap and the house price gap were all rather low in these countries. No warning signal would have been issued for Portugal, notwithstanding its large Basel gap. Despite a relatively low M3 gap, a warning signal would have been issued for Denmark, while the Netherlands would have been assigned a zero crisis probability due to its bank credit gap not breaching the relevant threshold. Considering the countries characterized by a relatively large M3 gap, Belgium and Luxembourg would have been assigned a zero crisis probability owing to low bank credit gap and ratio to GDP. Despite a more elevated level of bank credit, Austria would have also been assigned a zero crisis probability due to its Basel gap being relatively small, i.e. not breaching the 2.4 p.p. threshold. The UK would have ended up in a leaf associated with a 100% crisis probability as both its bank credit level and Basel gap breached their respective thresholds in 2006. Finland, France, Ireland, Italy, Spain and Sweden would have all ended up in a leaf

characterized by a 79% crisis probability due to rather elevated M3 and bank credit gap, with the house price to income ratio breaching its threshold at the same time. Finally, due to lack of data for Estonia, Cyprus, Slovakia, Latvia, Malta and Slovenia, all of these countries would have remained associated with parent nodes characterized by a low crisis probability (up to 17%).

As summarized in the matrix below, six of the eight countries for which the model would have issued a warning actually experienced a crisis in the five subsequent years. Overall, the crisis would have been correctly predicted for all of the large EU economies that did indeed later undergo one. A prompt policy reaction, assuming the current macroprudential legislation were already in place, would have allowed, for example, to have counter-cyclical capital buffers in place in these countries already for one year before the Lehman collapse. Considering type 2 errors and taking the size of the financial system as a proxy for the costs incurred by the economy as a consequence of the misclassification, the only large country for which the indication would have been to implement pre-emptive macroprudential measures when no credit related systemic banking crisis actually followed is Italy. Though one could argue that the Italian banking sector and thus the Italian economy would also have benefited from higher capital buffers during the post-Lehman crisis years. No warning signal would have been issued for the majority of the countries (in some cases due to data availability issues). Notably, no warning signal would have been issued for Germany, which indeed did not experience a crisis afterwards. Considering type 1 errors, it should be noted

that for some of these countries later crises were not due only, or mainly, to credit and asset price developments, but also to e.g. developments in the sovereign debt sphere, making it relatively difficult for the model to make a correct prediction.

	Crisis	No crisis
Warning	FR, IE, ES, SE, DK, UK	FI, IT
No warning	GR, PT, LV, SI, NL	AU, BE, LU, DE, EE, SK, MT, CY*

*Crisis started beyond prediction horizon

Finally, following Drehmann and Juselius (2013), we check the stability of the signals from the early warning tree going forward. Indeed, policy decisions are generally based on persistent indications for action, and an early warning system which gives contradictory messages quarter after quarter would be unreliable. Therefore, keeping the tree fixed, we investigate whether warning signals would have continued to be issued for the countries flagged in mid-2006. As shown in Chart 7, the early warning tree would have been an extremely stable model, as it would have suggested to continue closely monitor all of the countries for which a warning would have been issued in mid-2006, in all of the subsequent quarters until the outbreak of the global financial crisis.

9 Policy implications

In response to the global financial crisis, macroprudential policy has been given the objective of mitigating systemic financial stability risks, and several macroprudential tools have been designed to curb excessive leverage and/or build-up buffers against likely future losses. The macroprudential policy strategy has been defined by the European Systemic Risk Board (ESRB) with reference to the *guided discretion* principle, whereby the exercise of judgement is complemented by quantitative information derived from a set of selected indicators and associated early warning thresholds. In particular, with respect to the countercyclical capital buffer, the Basel Committee on Banking Supervision identified the aggregate private sector credit-to-GDP gap as a useful buffer guide. However, policymakers should supplement the signal coming from credit-to-GDP trend deviations with judgement based on a broader information set, as implicitly suggested also in the current Capital Requirements Directive (CRD IV) by the European Commission. Our results support the view that taking into account other conditioning variables is necessary, because not all credit expansions are bad for financial stability. Indeed, the heroic task of identifying credit bubbles in real time ultimately requires assessing whether conjunctural credit developments might be disconnected from fundamentals or reflect excessive risk taking and overly optimistic expectations.

Looking at the overall macroprudential policy process, tools like our pro-

posed early warning tree and Random Forest can serve several purposes. First, the good out-of-sample performance of such analytical models should help to overcome the possible inaction bias on the part of policy makers. In case risks are emerging which have in the past led to systemic banking crises, the onus is on those who aim to use judgement alone to justify why macroprudential policy tools are not activated. Second, the intuitive nature of a decision tree model and its easy visualisation is likely to increase acceptance of an analytical approach as a starting point for policy discussions. As shown in Section 7, the approach can be used to also trigger discussions on country specificities affecting the risk assessment. Third, a further advantage of the tree model is that depending on the characteristics of the leaf associated with a certain crisis probability, the nature of the vulnerability can also be identified, which in many cases would then suggest the use of a specific policy instrument over another.

Finally, one should also not understate the role of quantitative analyses and policy guides in macroprudential policy-related communication.²⁴ Indeed, analogously to what happens in the field of monetary policy, anchoring policy decisions to transparent analytical tools enhances their effectiveness. In the macroprudential field, banks could start adjusting their business lines and balance sheets even before a policy enters into force, because the analytical framework helps them understand that risks are building up in the

²⁴See Born et al. (2014) for an empirical analysis of the effects of central bank communication about financial stability in general.

system, and in order to smooth the transition to an anticipated new policy regime. More generally, the benchmark model we derive is a transparent tool which would also enable the public at large to understand and possibly anticipate macroprudential decisions. Increased transparency on the side of national and supra-national authorities competent for macroprudential policy would also help increase acceptance policy decisions which appear unpopular at first sight. In this respect, by emphasizing the importance of global liquidity as an early warning indicator, our work provides support for policy actions even in jurisdictions where domestic developments still appear to be under control.

10 Conclusions

We build an early warning system aiming at identifying whether the financial system is particularly vulnerable owing to aggregate credit and asset price developments. In such a situation, the increased likelihood and importance of a subsequent banking crisis would suggest to consider the implementation of macroprudential measures. Together with total credit to GDP deviations from trend (the so-called ‘Basel gap’), we consider a battery of indicators as a policy guide, including credit ratios and real estate indicators. Global liquidity stands out as one of the best early warning indicators in this framework.

One of the main advantages of the presented approach is that it takes

into account the conditional relations between various indicators when setting early warning thresholds. By doing so, it sheds light on the (nonlinear) relationship between credit, asset prices and the occurrence of banking crises. At the same time, the model is able to give an indication on the nature of specific vulnerabilities. Therefore, the proposed early warning system can also be regarded as a useful common reference point for policy makers.

Appendix

The ranking of the indicators derived by assuming balanced preferences between missing crises and issuing false alarms is very similar to that described in 5 and is shown in Figure 8. The top two indicators remain the level of bank credit and the global credit gap, while the main differences relate to global credit growth and the Basel gap, which turn out to be relatively less important than in the biased preferences case.

The early warning tree derived on the best half indicators, excluding global liquidity and assuming balanced preferences between Type 1 and Type 2 errors is shown in Figure 9. By and large, the same key variables appear in both the trees derived with biased and balanced preferences. When preferences are balanced, the root node is associated with the bank credit to GDP gap and a threshold of 3.4 p.p.. Along the right branch, we find the DSR with an almost identical threshold compared to the one relevant for the benchmark tree presented in Section 7, i.e. 17%. The lower level nodes in this part of the tree are associated with house price growth and the ratio of household credit to GDP, the M3 gap and government debt. The warning threshold for this latter, which is absent in the benchmark tree, is 60% of GDP. Along the left-hand side branch of the tree we find again house price based measures, namely gaps and the house price-to-income ratio, the DSR, the ratio of bank credit to GDP in two different nodes, the short term rate and household credit growth.

With respect to the in-sample predictive performance, this tree yields a true positive rate of 88% and a false positive rate of 2%, while the share of missed crises is 12%. Notice that, although the benchmark tree described in Section 7 is constructed by placing a higher weight on Type 1 errors, it still yields a higher share of missed crises compared to the balanced-preferences tree due to the fact that some branches have been pruned and therefore both trees are in some sense ‘suboptimal’. Finally, the noise to signal ratio associated with this tree is 2% while the relative Usefulness measure, i.e. the gain by using this model compared to ignoring it, is equal to 86%.

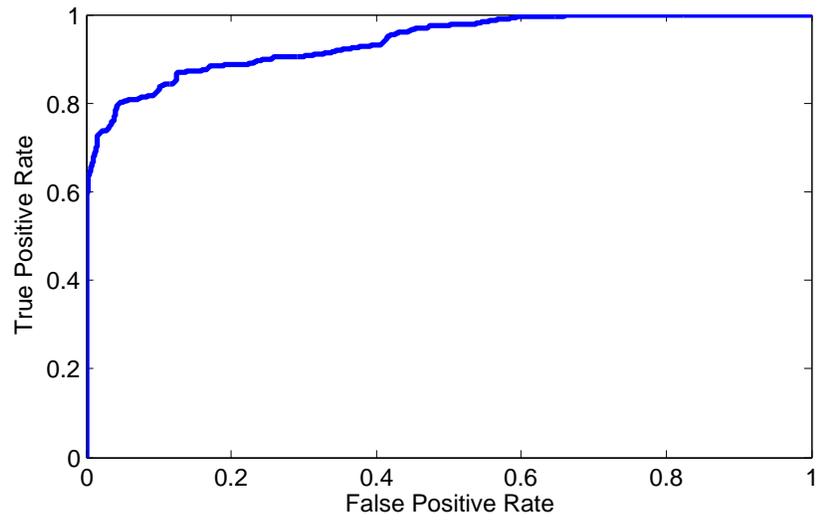


Figure 2: ROC curve associated with the Random Forest.

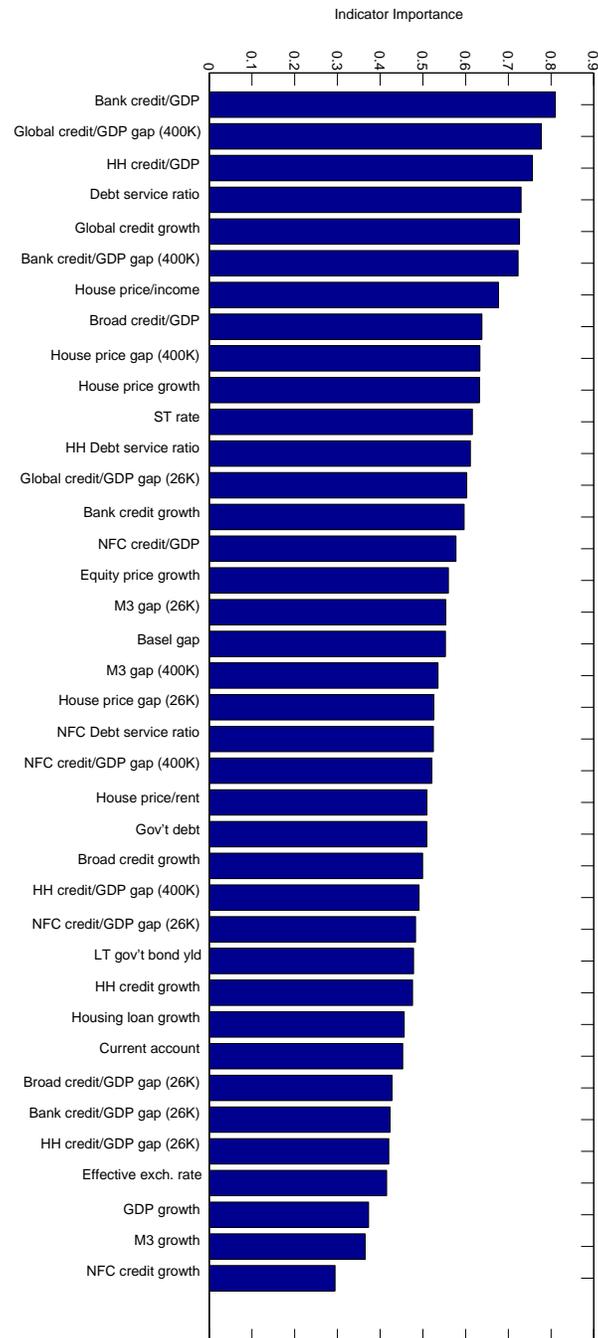


Figure 3: Ranking of the indicators according to the conveyed amount of useful information.

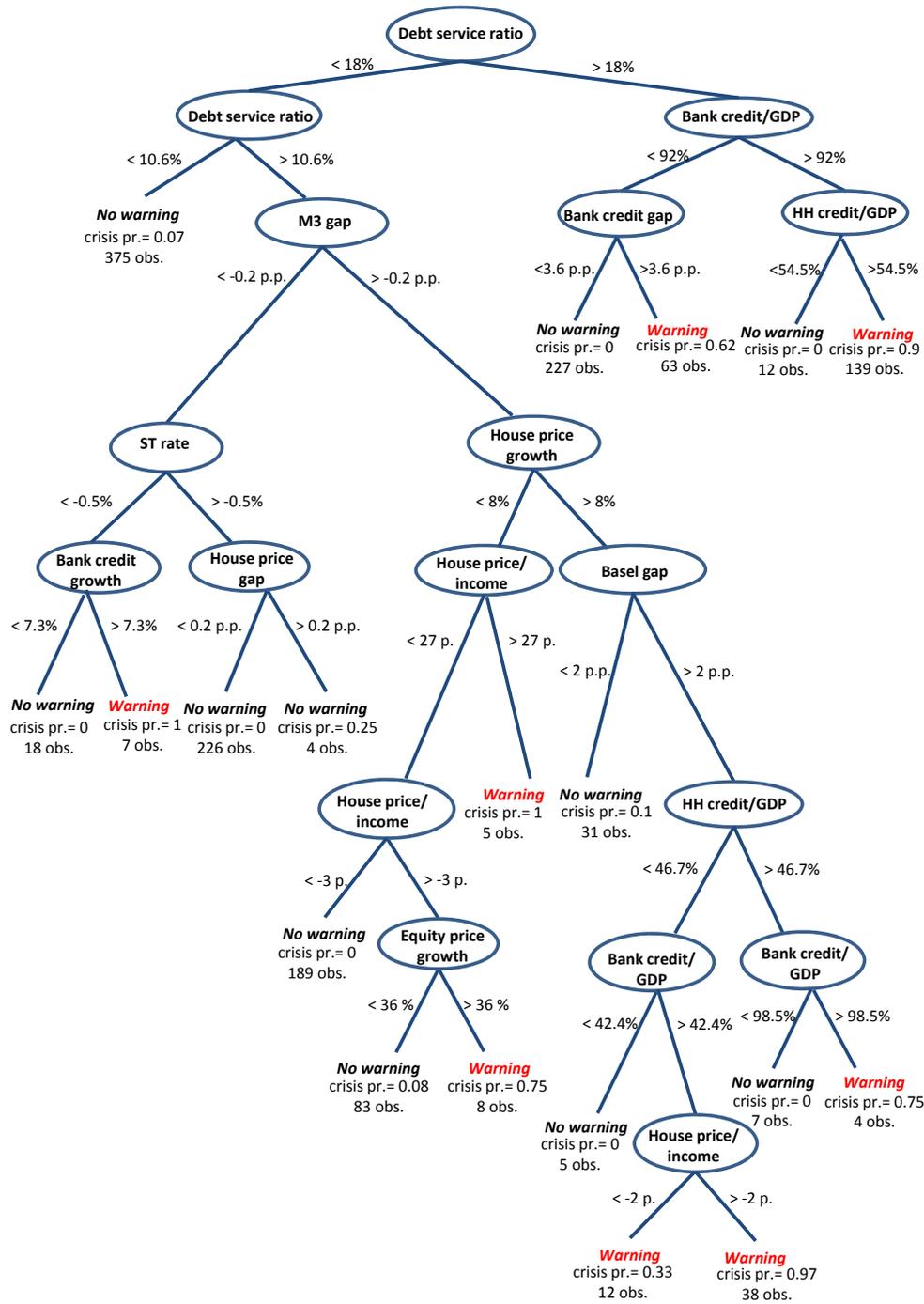


Figure 4: The benchmark early warning tree. The threshold for the house price to income ratio is in terms of index points above/below its long term average, while p.p. stands for percentage points. In each terminal node (leaf) of the tree the crisis probability is indicated, based on the frequency of pre-crisis quarters ending up in that particular leaf, considering the historical data on which the tree has been grown. The total number of country/quarters ending up in each leaf is also indicated. When the crisis probability associated with a leaf exceeds 30% the leaf is labelled as a ‘warning’ leaf.

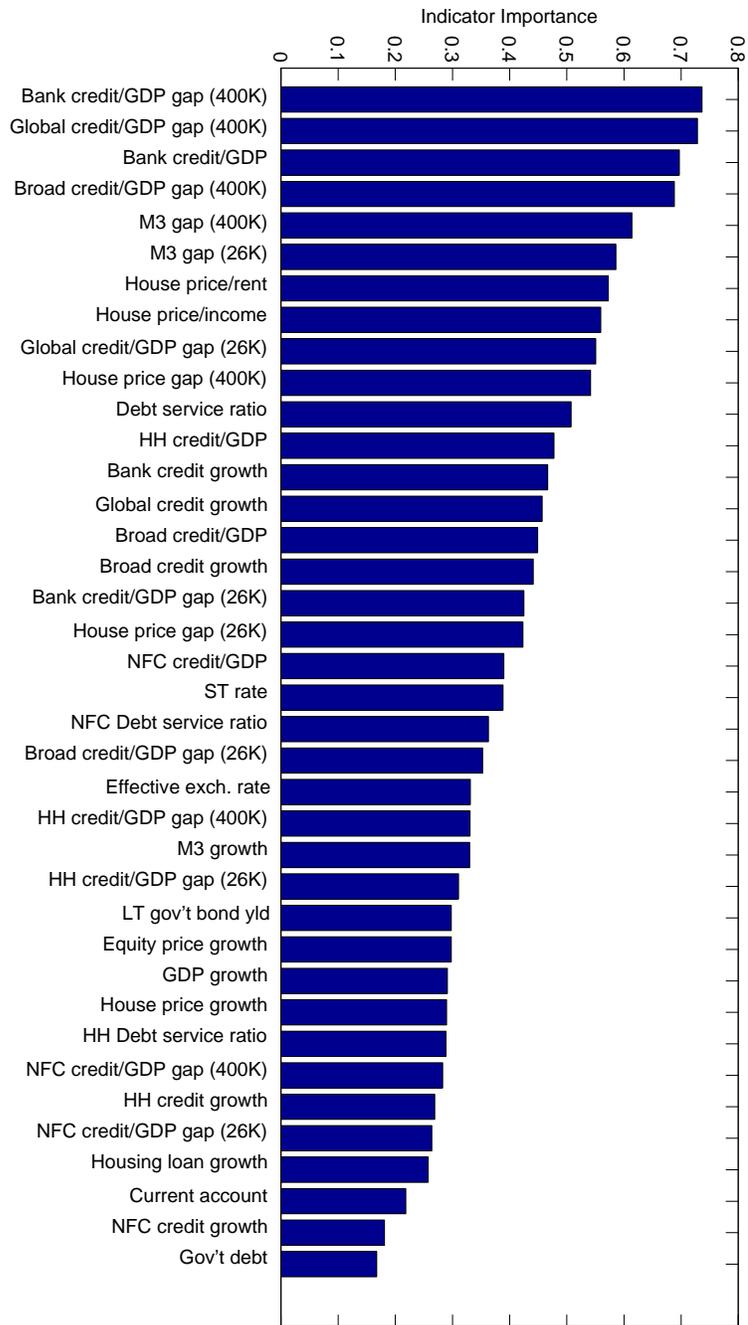


Figure 5: Ranking of the indicators according to the conveyed amount of useful information, using data available in mid-2006.

	AT	BE	CY	DK	EE	FI	FR	DE	GR	IE	IT	LV	LU	MT	NL	PT	SK	SI	ES	SE	GB
2006Q3				x		x	x			x	x								x	x	x
2006Q4				x		x	x			x	x								x	x	x
2007Q1				x		x	x			x	x								x	x	x
2007Q2				x		x	x			x	x								x	x	x
2007Q3				x		x	x		x	x	x								x	x	
2007Q4				x		x	x			x	x					x			x	x	
2008Q1				x		x	x			x	x		x			x			x	x	
2008Q2				x		x	x			x	x		x			x			x	x	
2008Q3						x				*	x		x				x		x		

Figure 7: Stability of the signals issued by the early warning tree in the period between mid-2006 and the outbreak of the global financial crisis. Crosses indicate issued warnings, while dark cells denote crisis periods.

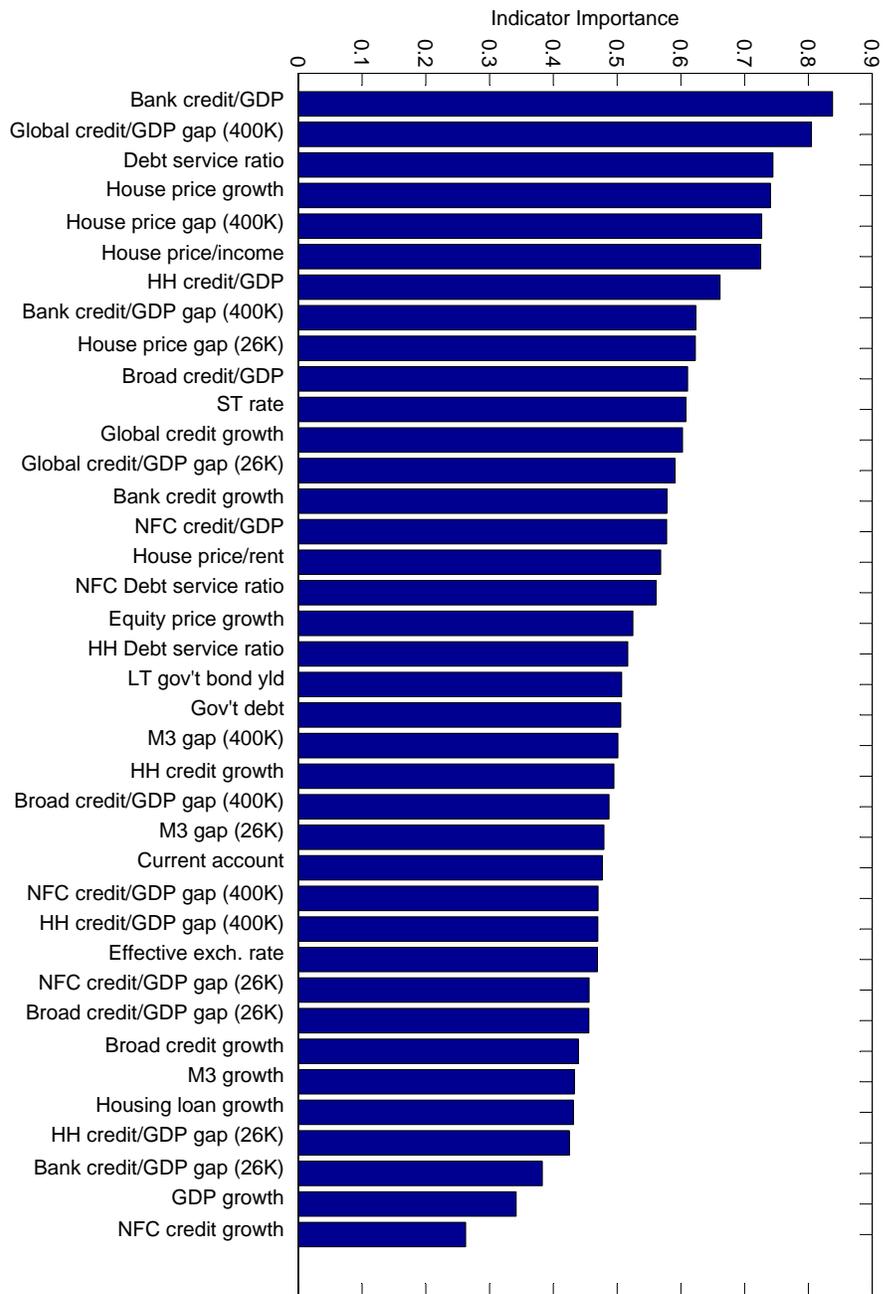


Figure 8: Ranking of the indicators according to the conveyed amount of useful information, assuming the policymaker has balanced preferences between Type 1 and Type 2 errors.

	Behn et al. model 3	Extended model
Dom. broad credit growth (DC1)	-5.72 (4.94)	5.35 (4.35)
Dom. Basel gap (DC2)	17.86*** (2.32)	12.32*** (3.12)
Interaction (DC1*DC2)	-0.65*** (0.18)	
Glo. credit growth (GC1)	-2.74 (6.34)	-20.41*** (7.78)
Glo. credit gap (GC2)	-21.28** (10.56)	61.76*** (8.77)
Interaction (GC1*GC2)	6.81*** (1.63)	
Interaction (DC1*GC1)	1.68** (0.79)	
Interaction (DC2*GC2)	-0.88** (0.39)	
DSR		273.40*** (60.05)
Equity price growth		1.81*** (0.53)
House price to income		11.11*** (1.24)
Real GDP growth		35.19*** (9.72)
Country dummies	YES	NO
Observations	1296	727
Pseudo R-Squared	0.28	0.52
AUROC	0.84	0.93

Table 1: Estimation results for multivariate logit models. Standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

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