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IDENTIFYING EXCESSIVE CREDIT GROWTH AND LEVERAGE

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In 2014 all ECB publications feature a motif taken from the €20 banknote.

MACROPRUDENTIAL RESEARCH NETWORK

Macroprudential Research Network
This paper presents research conducted within the Macroprudential Research Network (MaRs). The network is composed of economists from the European System of Central Banks (ESCB), i.e. the national central banks of the 27 European Union (EU) Member States and the European Central Bank. The objective of MaRs is to develop core conceptual frameworks, models and/or tools supporting macro-prudential supervision in the EU.

The research is carried out in three work streams: 1) Macro-financial models linking financial stability and the performance of the economy; 2) Early warning systems and systemic risk indicators; 3) Assessing contagion risks.

MaRs is chaired by Philipp Hartmann (ECB). Paolo Angelini (Banca d'Italia), Laurent Clerc (Banque de France), Carsten Detken (ECB), Simone Manganelli (ECB) and Katerina Šmídková (Czech National Bank) are workstream coordinators. Javier Suarez (Center for Monetary and Financial Studies) and Hans Degryse (Katholieke Universiteit Leuven and Tilburg University) act as external consultants. Fiorella De Fiore (ECB) and Kalin Nikolov (ECB) share responsibility for the MaRs Secretariat.

The refereeing process of this paper has been coordinated by a team composed of Gerhard Rünstler, Kalin Nikolov and Bernd Schwaab (all ECB).

The paper is released in order to make the research of MaRs generally available, in preliminary form, to encourage comments and suggestions prior to final publication. The views expressed in the paper are the ones of the author(s) and do not necessarily reflect those of the ECB or of the ESCB.

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Non-technical summary

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. As mitigating systemic financial stability risks is the objective of macroprudential policy, several macroprudential tools have been designed to curb excessive leverage and/or build-up buffers against likely future losses. Such instruments include the countercyclical capital buffer, the systemic risk buffer as well as a potentially time-varying leverage ratio, and instruments directly targeting borrowers such as loan-to-value (LTV) and loan-to-income (LTI) caps. However, the application of macroprudential policy is still at an early stage and much effort is currently being devoted to providing policy-makers with concrete indications on how to actually design macroprudential instruments. Against this background, we propose an early warning model to be used for identifying those periods in which the build-up of leverage can be defined as excessive and may warrant the activation of relevant macro-prudential instruments.

As in any early warning exercise, the target event is first defined. In the present case, the model is designed to issue warning signals well ahead of systemic banking crises caused by excessive credit growth. To fully align the definition of banking crisis with the target of macroprudential tools like countercyclical capital buffers and leverage ratios, we extend it to include also 'near misses', i.e. periods in which domestic developments related to the credit/financial cycle could well have caused a systemic banking crisis had it not been for policy action or an external event that dampened the credit cycle. At the same time, non-systemic banking crises and crises not related to the credit cycle are excluded. According to this definition, 25 episodes are identified in the countries under analysis, namely euro area countries together with the UK, Denmark and Sweden, over the period between 1970Q1 and 2013Q4.

The second step is the selection of the candidate early warning indicators: in this respect, the dataset used in this application comprises publicly available aggregate credit-related, macroeconomic, market and real-estate variables.

The modelling technique is based on decision trees, in particular binary classification trees. Based on the results of a Random Forest, which consists in bootstrapping and aggregating several decision trees, we select the most relevant early warning indicators. On these we grow a benchmark early warning tree where the key indicators and the respective early warning thresholds are considered in a unified framework, i.e. by taking into account the conditional relationships between them. As a result, the model is designed to not only predict banking crises, but also to give an indication on which macro-prudential policy instrument would be best suited to address specific vulnerabilities.

Finally, the in- and out-of-sample predictive performance of the model is evaluated. In particular, an out-of-sample exercise is carried out using only information available as of mid-2006. 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 countercyclical capital buffers in place in these countries already for one year before the Lehman collapse.

Overall, policy makers at the national designated authorities becoming responsible for macro-prudential policies in the EU as well as at the European level, i.e. at the ECB and ESRB, will have to use their judgement in setting the macro-prudential policy stance for the respective countries. We show that tools like our proposed decision tree and Random Forest can serve several purposes in this process.

were already in place, would have allowed, for example, to have countercyclical 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

10 Policy implications

Policy makers at the national designated authorities becoming responsible for macro-prudential policies in the EU as well as at the European level, i.e. at the ECB and ESRB, will have to use their judgement in setting the macro-prudential policy stance for the respective countries. Tools like our proposed early warning tree and Random Forest can serve several purposes in this process. 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 macro-prudential policy tools are not activated. Second, the intuitive nature of a decision tree model and its easy visualization is likely to increase acceptance of an analytical approach as a starting point for policy discussions. As section 7 has shown, 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.

11 Conclusions

We build an early warning system aiming at supporting policy decisions on when to activate macroprudential tools targeting excessive credit growth and leverage. 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.

By using decision trees, we build a multivariate predictive model which is at the same time extremely accurate and very easy to interpret. Based on the experience of EU countries over the last 40 years, it applies decision tree learning to the problem of identifying excessive credit growth and leverage with a sufficient lead time to allow policy reactions. 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. At the same time, the model is able to give an indication on which macroprudential tool could be best suited to address specific vulnerabilities.

The proposed early warning system can be regarded as a useful common reference point informing policy makers when using their judgement. Indeed, it is crucial that the use of judgement be firmly anchored to a clear set of principles to promote sound decision-making in the operationalization of macroprudential instruments.

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 6 and is shown in Figure 7. 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 8. 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%.

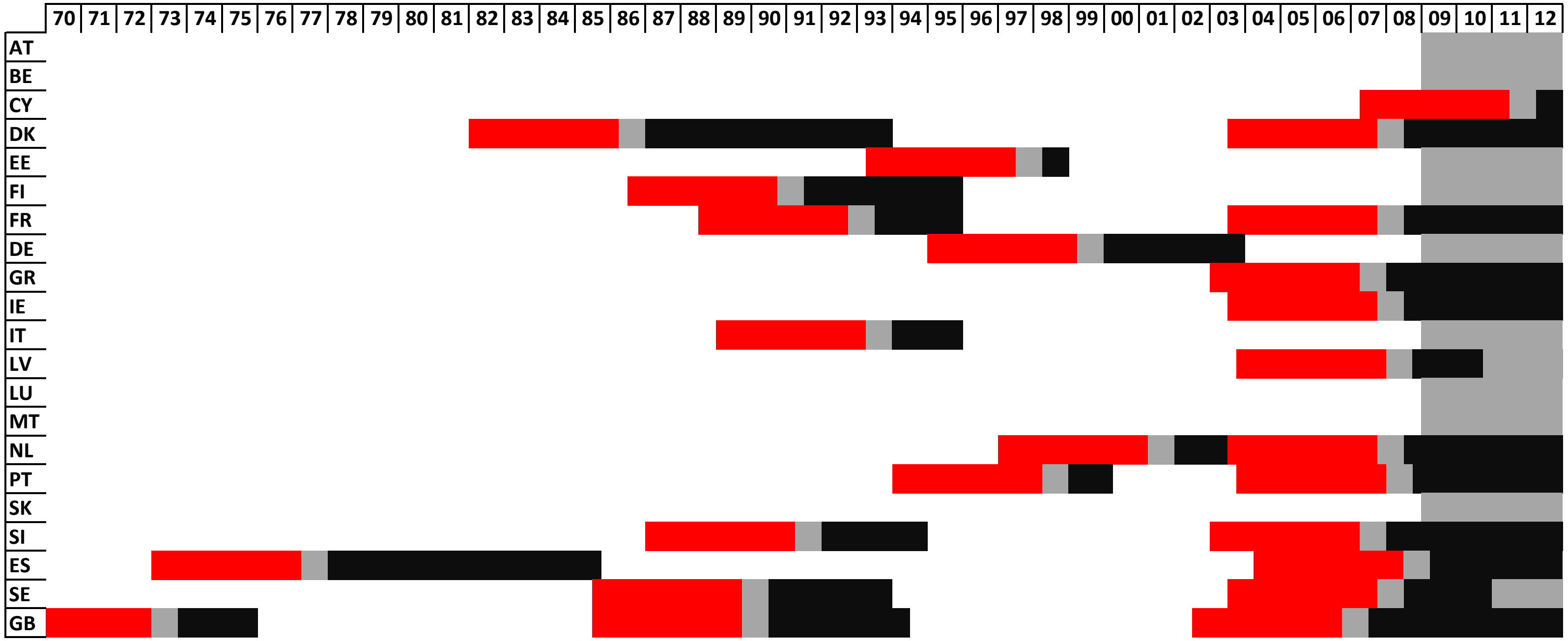

Figure 1: Identified crises (in black), pre-crisis periods (in red) and periods excluded from the analysis (in grey).

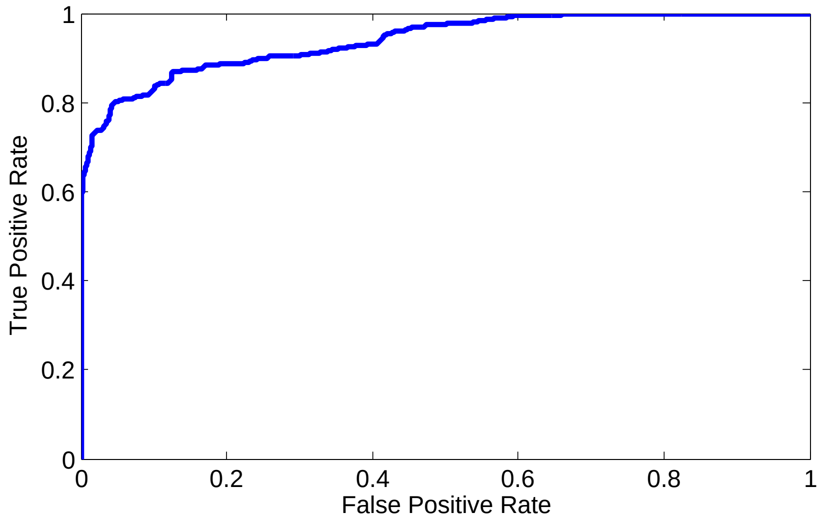

Figure 2: ROC curve associated with the Random Forest.

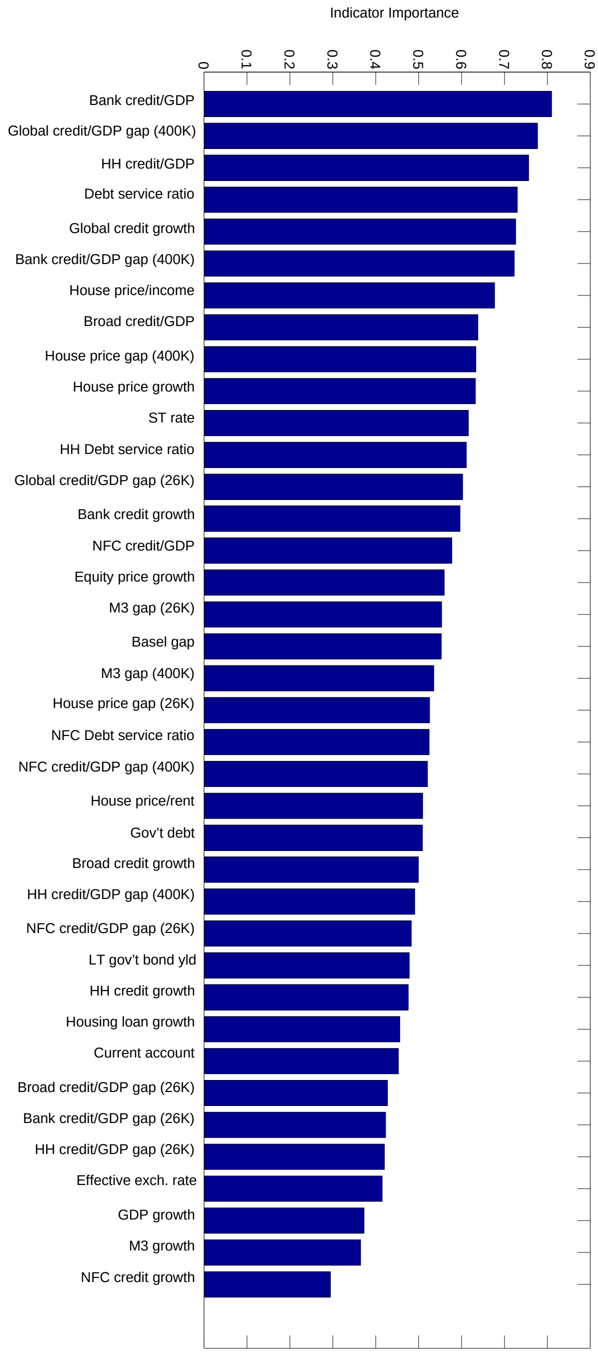

Figure 3: Ranking of the indicators according to the conveyed amount of useful information.

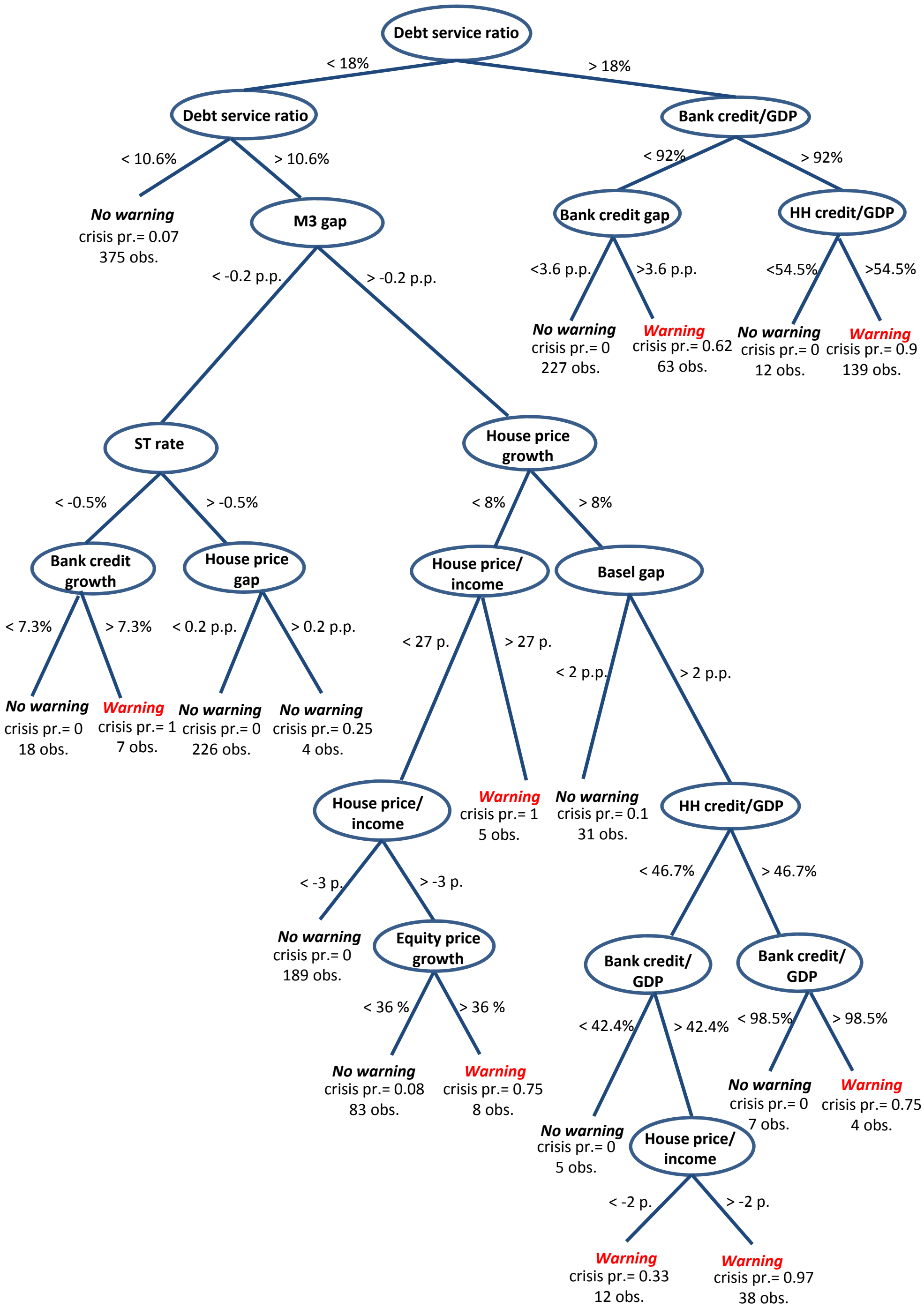

Figure 4: The benchmark early warning tree. The threshold for the house price to income ratio is in terms of index points above/below its long term average, while p.p. stands for percentage points. In each terminal node (leaf) of the tree the crisis probability is indicated, based on the frequency of 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.

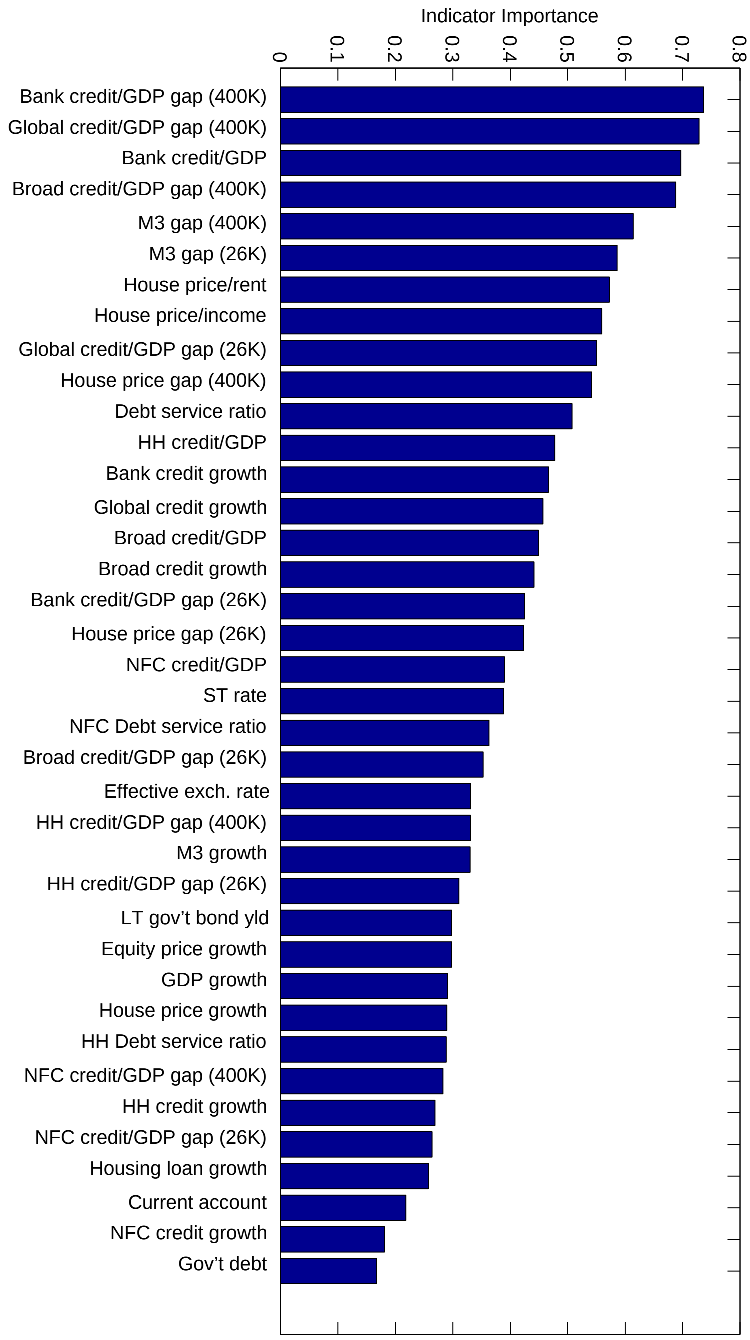

Figure 5: Ranking of the indicators according to the conveyed amount of useful information, using data available in mid-2006.

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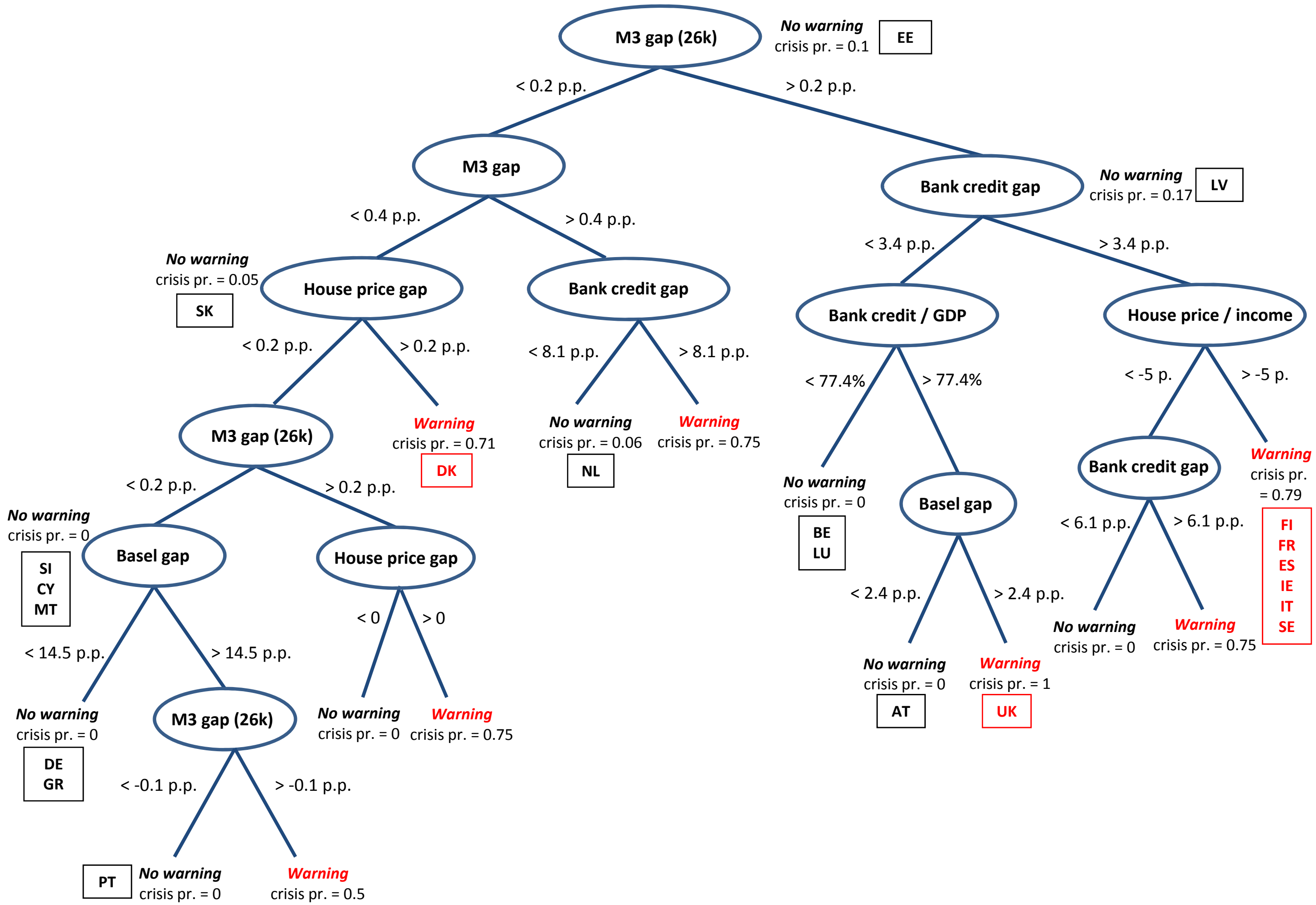

Figure 6: The early warning tree derived with data as of 2006Q2. Gaps are computed by setting $\lambda = 400000$ unless otherwise indicated. In each terminal node (leaf) of the tree the crisis probability is indicated, based on the frequency of pre-crisis quarters ending up in that particular leaf, considering the historical data on which the tree has been grown. When the crisis probability associated with a leaf exceeds 30% the leaf is labelled as a 'warning' leaf.

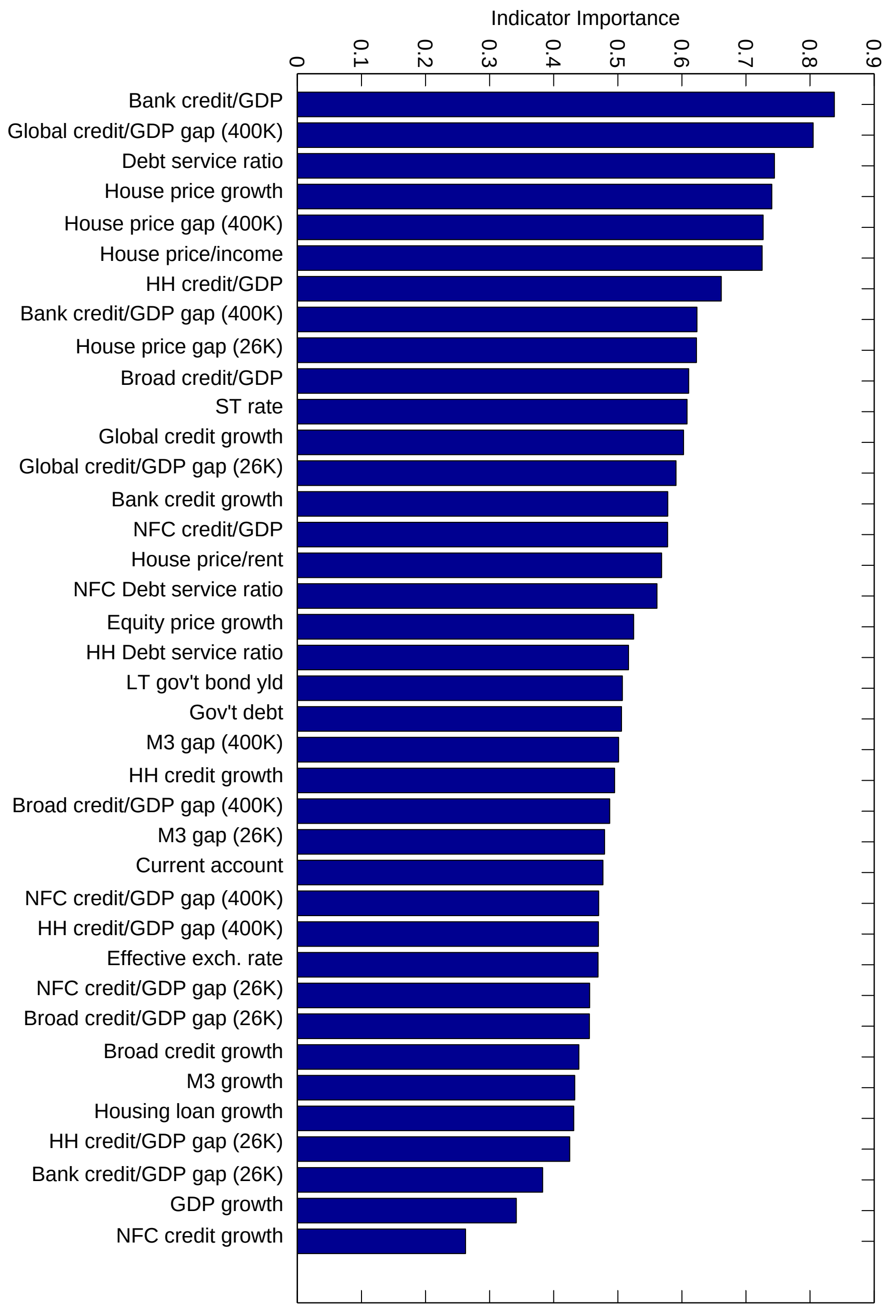

Figure 7: Ranking of the indicators according to the conveyed amount of useful information, assuming the policymaker has balanced preferences between Type 1 and Type 2 errors.

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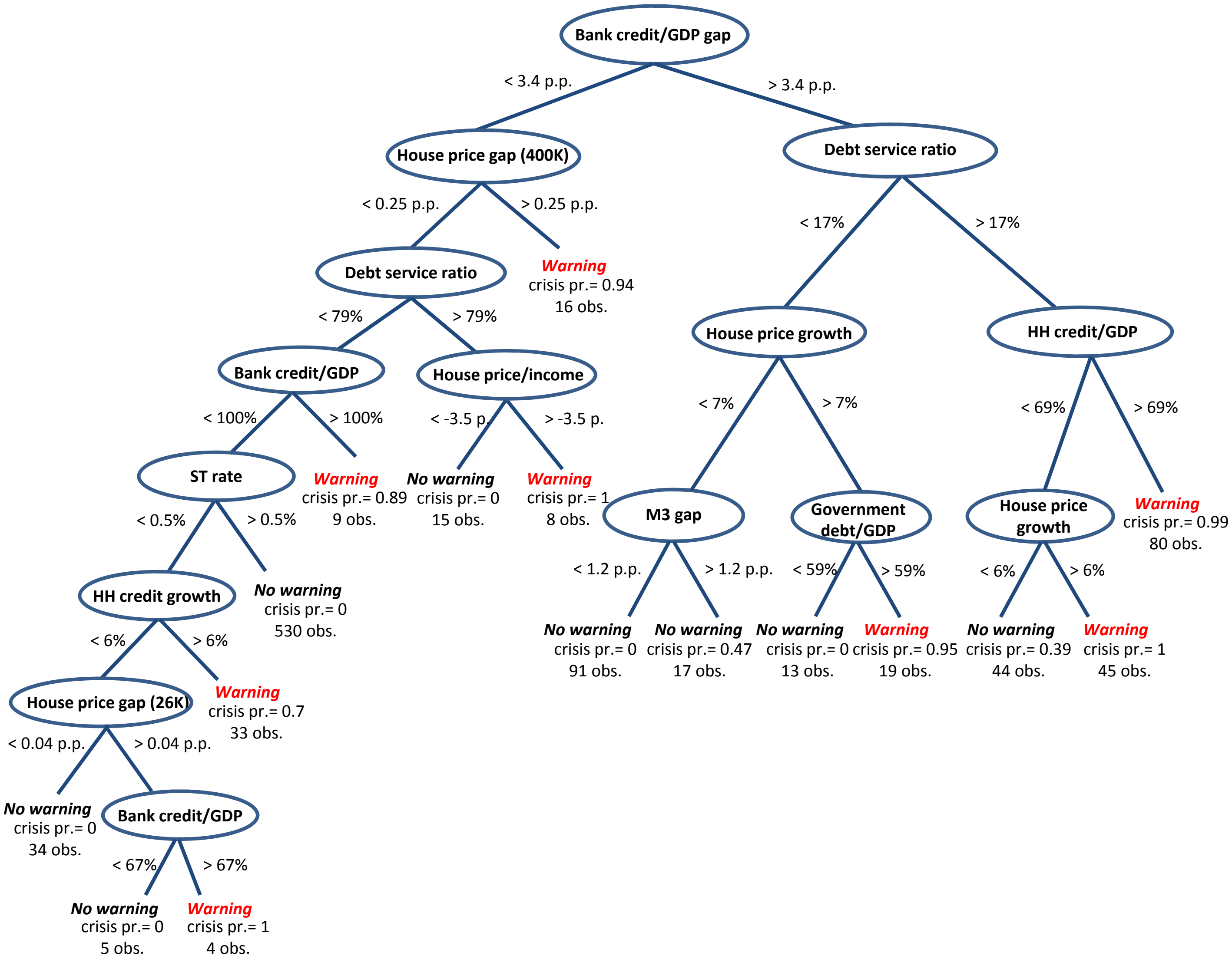

Figure 8: The early warning tree derived by assuming balanced preferences. The threshold for the house price to income ratio is in terms of index points above/below its long term average, while p.p. stands for percentage points. In each terminal node (leaf) of the tree the crisis probability is indicated, 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 50% the leaf is labelled as a 'warning' leaf.

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