DOCUMENT

DE TRAVAIL

N° 609

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Virginie Coudert and Julien Idier

November 2016

BANQUE DE FRANCE

EUROSYSTÈME

DIRECTION GÉNÉRALE DES ÉTUDES ET DES RELATIONS INTERNATIONALES

# An Early Warning System for Macro-prudential Policy in France

Virginie Coudert*      Julien Idier[ǂ]

* Bank of France, Financial Stability Directorate, Economix, University of Paris Nanterre and CEPII, virginie.coudert@banque-france.fr.

ǂ Bank of France, Financial Stability Directorate, julien.idier@banque-france.fr.

*We would like to thank Matthieu Bussière and seminar participants at the Banque de France for helpful comments.*

# An Early Warning System for Macro-prudential Policy in France

*Abstract*

We construct an early warning system for detecting banking crises that could be used for the macroprudential policy conduct in France. First, we select macro-financial risk indicators among a large number of candidates by considering their performances both over a panel of ten euro area countries and at the French level, for the 1985:Q1 to 2009:Q4. Second, we run all the logit models including four of these indicators, one being necessarily a measure of credit gap to fit the Basel Committee recommendations. We then retain two sets of models: one including those with all coefficients significant and expected signs, another one, obtained by relaxing these criteria. Third, we aggregate the probabilities estimated by the models, by giving each a weight proportional to its usefulness at predicting crises either at the panel or the country-level. The simulations performed both over and out of the sample show that aggregating more models yields better results than relying on one single model or only a few. Performance is also enhanced by aggregating models' results with country-specific weights relatively to common panel-weightings.

Keywords: Macroprudential policy, Banking Crises, Early Warning Indicators.
JEL codes E52 G12 C58

# Un système d'alerte pour la politique macroprudentielle

*Résumé*

Nous construisons un système d'alerte pour détecter les crises bancaires qui peut être utilisé pour la conduite de la politique macroprudentielle en France. Premièrement, nous sélectionnons des indicateurs de risque financier parmi un grand nombre de candidatsen considérant leur performance au niveau d'un ensemble de dix pays de la zone euro et au niveau de la France sur la période 1985:T1 to 2009:T4. Deuxièmement, nous faisons tourner tous les modèles logits qui incluent quatre des indicateurs préalablement sélectionnés, l'un d'eux devant nécessairement être une mesure du *credit gap* pour suivre les recommandations du Comité de Bâle. Nous retenons deux ensembles de modèles, l'un incluant seulement les modèles dont tous les coefficients sont significatifs et avec le signe attendu, l'autre obtenu en relâchant ces critères. Troisièmement, nous agrégeons toutes les probabilités estimées par les modèles en donnant à chacun une pondération proportionnelle à son utilité à prévoir les crises soit dans l'ensemble de l'échantillon soit au niveau de chaque pays. Selon les simulations menées à la fois sur et hors de l'échantillon, faire la moyenne de nombreux modèles donne de meilleurs résultats qu'un seul modèle ou un petit nombre. Les performances sont aussi améliorées par une pondération qui tient compte les spécificités des pays..

Mots-clé : Politique macroprudentielle, Crises bancaires, Système d'alerte.
JEL codes E52 G12 C58

# An Early Warning System for Macro-prudential Policy in France

Virginie Coudert     Julien Idier

## Non technical summary

One of the objectives of macroprudential policy is to contain the amplitude of the financial cycle, especially during its boom phase. One strategy to address this issue is to set higher capital requirements for banks when credit growth is gauged excessive at the macroeconomic level. In practice, this is done through the potential use of the "countercyclical capital buffers" (CCyB) whose ratios are raised during booms. For this policy to succeed, a major condition is to take the appropriate steps early enough during the boom period. Being early is necessary for at least two reasons: (i) institutionally banks have 12 months to comply with the new CCyB level and (ii) although the CCyB will have an immediate protective effect for banks once constituted, the delay needed for curbing down credit growth is uncertain. Consequently, an essential prerequisite for implementing this policy is to be able to assess in real-time in which phase of the financial cycle we stand. Early warning system (EWS) can be used for this purpose.

We thus construct an EWS for detecting the risks of banking crises with the aim of using it for the macroprudential policy conduct in France. One of the main difficulties in the setup of EWS comes from financial crises being (hopefully) rare events. This requires considering a panel of countries in addition to France in order to have a representative sample. Here, the sample includes a panel of 10 euro area countries over the 1985:Q1-2009:Q4 period.

We proceed in three steps. First, we identify the most relevant univariate indicators by adopting a signaling approach. We retain indicators with the best performances over the whole panel of 10 euro area countries that also emit relevant signals for France. This leaves us with 32 indicators. Second, we proceed to econometric estimations aimed at explaining the pre-crisis periods by these pre-selected indicators. To build the models, we take stock of former studies that have shown the key role of the total credit to GDP gap (BCBS, 2010b; Drehmann et Juselius, 2014; Dembiermont et al., 2013; Drehmann and Tsatsanoris, 2014). As this variable stands out as the most reliable one in a number of studies, it has been recommended by the Basel Committee on Banking Supervision (BCBS) in order to evaluate the appropriate level of

the CCyB and hence dubbed the « standardized Basel gap ». For the case of France, we prefer to retain a bank credit gap variable that it is more in line with the bank credit risk that we try to assess for the CCB policy conduct. Following Detken et al. (2014), we run all the possible models with the bank credit gap as explanatory variable along with three other variables. Then, instead of choosing one single model, we select two sets of models: a small one including all the models with their four coefficients significant and with the expected signs, and a large set, obtained by relaxing the selection criteria.

In a third step, we aggregate all the models from the two sets with weighting schemes reflecting their performance. The more useful is a model, the heavier its weight in the aggregated result. As the performance of models can be assessed either at the panel-level or at the country-level, we propose two options for the weighting scheme: one common to all countries, based on the usefulness of the models to predict crises on the whole panel; the other one, country-specific, resulting from the usefulness at the country-level.

This method mitigates model uncertainty by aggregating a large number of models, once a pre-selection of relevant models has been carried out. The contribution to the economic literature is two-fold: (i) we make the set of models as well as their weightings vary over time. In the real-time simulations, the weightings and the sets of models are continuously updated according to their time-varying performances. This is a valuable property as risk factors are known to vary over time. (ii) We account for different risk factors across countries by tailoring country-specific weightings when aggregating the models, while we still use all the information at the panel-level to estimate the models. This strategy, mixing pooled and country level, is consistent with both the fact that countries differ in terms of risk factors sensitivity, and that estimation is improved by considering a panel of countries.

The simulations performed to assess the validity of this strategy yield promising results. First, over the sample, aggregating a large number of models greatly improves the signaling performance– the loss function is reduced by 25% on average compared to the best performing model. Averaging models is also a way to avoid the unpleasant consequences of models' instability through time. Second, for the real-time simulations, resorting to a large set of models also appears as the best strategy. Indeed, after estimating the models to replicate the policy maker's conditions before the 2008 crisis, we find that no model at all had its four variables significant with the expected signs at that time. Hence, retaining models on the basis of stringent criteria with all variables significant would not have been possible in real-time. Actually, the results obtained using a large set of models selected with relaxed criteria are quite satisfying to predict the 2008 crisis at a reasonable horizon in most countries in the sample. Accounting for all possible risk factors hence appears as a good strategy in troubled times, when the sources of risk are evolving.

## 1. Introduction

Macroprudential policy aims at preventing financial and banking crises for all banks of a country altogether on the basis of the macroeconomic evolution, contrary to traditional banking supervision that is designed to monitor single banks based on their own ratios. Conceptually, it relies on the idea that financial markets, credit and asset prices tend to move together cyclically. The mounting phase of the cycle, or "boom" period, is characterized by abundant credit and low risk aversion, which both feed agents' indebtedness and fuels the rise in prices of financial assets as well as those of real estate. Within several years of this regime, the built-up of debt and the bubbles in asset prices pave the way to the next crisis. Indeed, once bubbles burst and agents start to deleverage, banks are hit by the fall of asset prices that deteriorate their balance-sheet and the value of collateral for their loans. At that time, the crisis is already looming, and it is too late for the policy makers to act. This sequential pattern has been long been documented in the economic literature about the financial cycle (Claessens et al. 2011, Borio, 2012). However, it is only since the 2008 crisis that governments have decided to tackle this issue and started to set up macroprudential policy.

One of the objectives of macroprudential policy is to contain the amplitude of the financial cycle, especially during its boom phase. One strategy to address this issue is to impose more capital requirements on banks when credit growth is gauged excessive at the macroeconomic level. In practice, this is achieved through setting "countercyclical capital buffers" (CCyB) whose ratios are raised during booms. This regulation has been recommended by the Basel Committee on Banking Supervision (BCBS) – the forum in charge of formulating international guidelines for bank supervision - in the framework of the Basel III agreements (BCBS, 2010a; BCBS, 2010b). The CCyB s have the advantage of both limiting the risk for each bank because of higher capital in risky periods and also curbing down credit expansion through disincentive effects. This measure has already been implemented in several countries. It has become mandatory in the European Union since the beginning of 2016, albeit the CCyB have been often calibrated at 0%, as in France.

For this policy to succeed, a major challenge is to take the appropriate steps – i.e. raise the capital buffers - early enough during the boom period. Being preventive is necessary for at least two reasons: (i) institutionally banks have 12 months to comply with the new level of the CCyB (when increased) and (ii) transmission channels are surrounded by uncertainty such that delays in pass-through could be expected. Hence doing it too late, especially just before a crisis is looming, would only worsen the situation for banks by being procyclical. Consequently, an essential prerequisite for this policy is to be able to assess in real-time at which point of the cycle we stand. To do so, there exist two types of methods. A first one is purely statistical and consists in extracting the cyclical components of financial series (Schüler et al., 2015) like for assessing the business cycle. This straightforward approach is useful, but the irregular durations of the previous cycles make it difficult to get robust results. An alternative method is to resort to early warning systems (EWS) designed at predicting crises.

The EWS are aimed at detecting the risk of crises on an empirical basis by considering the evolution in the fundamental variables in the economy. They have been developed for long to predict the financial crises in the emerging countries (see for example: Frankel and Rose, 1996; Kaminsky et al, 1998, Kaminsky, 1999; Burkart and Coudert, 2002; Gourinchas et al. , 2001; Bussiere and Fratzscher, 2006) and also applied to large panels of advanced and emerging economies (Demirgüç-Kunt, A. and Detragiache, E. 1998, 2005; Eichengreen and Arteta, 2000; Bordo et al. 2001; Borio and Lowe, 2002). After the 2008 crisis, a number of studies, have also been devoted to assess if advanced indicators could have been able to detect it (Borio and Drehman, 2009; Barrell et al., 2010; Frankel, J. A. and Saravelos, G. 2012, Bussière and Fratzscher, 2006 and 2008, Bussière, 2013). Recently, the EWSs have attracted renewed interest as the implementation of macroprudential policy requires policy makers to know where they stand in the financial cycle and especially how far they are from the next crisis. In particular, research in this field has been prolific within the Eurosystem, as attested by a number of recent papers (such as Alessi and Detken, 2011, 2014; Shin, 2013; Detken et al., 2014; Ferrari and Pirovano, 2015; Kalatie et al., 2015).

Former studies have already shown that a key variable to consider for assessing the financial cycle is the gap between the ratio of total credit to GDP and its long-run average (BCBS, 2010b; Drehmann et Juselius, 2014; Dembiermont et al., 2013; Drehmann and Tsatsanoris, 2014). As this variable stands out as the most reliable one in a number of studies, it has been recommended by the BCBS in order to evaluate the appropriate level of the CCyB and hence dubbed the « standardized Basel gap ». A gap as small as 2 percentage points (p.p.) mechanically entails triggering the capital buffers, whereas the CCyB would reach its maximum value of 2.5% when the credit gap crosses the 10 p.p. threshold. However, this credit gap on its own is not sufficient to establish the diagnostic; it has to be complemented by other indicators, other kinds of credit gaps or macroeconomic variables.

Here, we construct an EWS strategy for detecting the risks of banking crises in the euro area with the objective of using it for the macroprudential policy conduct in France. One of the main difficulties in the setup of EWS comes from financial crises being (hopefully) rare events. This requires considering a panel of countries in addition to France in order to have a representative sample of crises. We hence use a panel of 10 euro area countries over the 1985:Q1-2009:Q4 period and proceed in two steps. First, we identify the most relevant univariate indicators by adopting a signaling approach similar to Detken et al. (2014). We retain indicators with the best performances over the whole panel of 10 euro area countries that also emit relevant signals for France. Second, we proceed to a multivariate analysis. To do this, we run all the possible logit models with a credit gap as explanatory variable along with three other variables extracted from the previously selected indicators. We then select two sets of models on the basis of stringent or relaxed criteria and aggregate them with different weighting schemes reflecting either their performance at the panel or the country level. We compare the results obtained through the different options both in and out of sample, as well as for the pooled euro-area and specific countries.

Our contribution to the literature is to propose a method to mitigate model uncertainty by aggregating a large number of models, once a pre-selection of relevant models has been carried out. The originality of the method is to make the set of models as well as their weightings in the aggregation vary over time. This allows us to address the problem of models instability and capture the evolving risk factors. The results outperform those obtained by any single model. By adopting different weights in aggregating the models, we are also able to derive country-specific early-warning systems, even if the logit models are estimated on a panel of countries.

The rest of the paper is organized as follows. Section 2 describes the data, sample and criteria to assess performances that we will use as well for the univariate and the multivariate analysis. Section 3 describes the strategy followed for the univariate analysis and discusses the results. Section 4 presents the multivariate econometric approach, based on aggregating sets of logit models with different weightings. Section 5 evaluates the results in-sample and out-of-sample of the different EWS strategies. Section 6 gives complementary results and proceeds to robustness tests. Section 7 concludes.

## 2. Data, sample and criteria to assess performances

To build an early warning system (EWS), we need two sets of data: the dates of the crisis episodes in the considered countries and a set of economic variables that possibly release signals by evolving specifically during the pre-crisis periods. The horizon of prevision gives us the span of the pre-crisis period. We also need an approach to assess the results, which is provided by the signal approach. All these features apply both to the univariate method and the econometric method that we will successively adopt below.

### *2.1 Crises, horizon of prediction and pre-crisis periods*

The sample is made of quarterly data from 1985Q1 to 2009Q4 for ten countries (Austria, Belgium, Finland, France, Germany, Ireland, Italy, Netherlands, Portugal, Spain). By limiting the panel to the euro area members on a relatively short period, we expect that the sample is made of economies with similar functioning. We then work on a balanced panel of N countries and T periods, N=10; T=96.

To identify crisis periods, we follow a historical approach that considers lists of crises validated by their use in the economic literature. Most of these lists rely on expert surveys (for example see Laeven et Valencia, 2008, 2012). Here, we use the list updated by Babecky et al. (2012a)[1] that is extended up to the 2008 crisis (Table 1). The crisis dates for each country are identified by the same country's central bank. In particular, we note that all euro area countries have experienced a crisis in 2008, except Italy.

[1] An improvement and updating of this database until 2015 is still in progress at the euro area level within Eurosystem working groups.

**Table 1 : Periods of crisis in the 10 euro area countries, 1985-2009**

| Country | Crisis periods | Country | Crisis periods |
|---|---|---|---|
| Austria | 2008Q1-2008Q4 | Ireland | 1985Q1 |
| Belgium | 2008Q1-2008Q4 | | 2007Q1-2010Q4 |
| Finland | 1991Q1-1995Q4 | Italy | 1990Q1-1995Q4 |
| France | 1994Q1-1995Q4 | Netherlands | 2008Q1-2008Q4 |
| | 2008Q1-2009Q4 | Portugal | 2008Q1-2008Q4 |
| Germany | 2008Q1-2008Q4 | Spain | 2008Q1-2008Q4 |

Note : The dates of crises are those retained by Babecky et al. (2012a) for banking crises.

The dates of crises for each country are associated with their characteristic function $C_{nt}$ equal to 1 if there is a crisis in country $n$ at time t and 0 otherwise.

$$\begin{cases} C_{nt} = 1 \text{ if there is a crisis in country } n \text{ at time } t \\ C_{nt} = 0 \text{ otherwise} \end{cases} \quad (1)$$

However, we also need a pre-crisis variable as our aim is to identify variables that behave differently during pre-crises periods, not during crises. The horizon of prediction is set from 12 to 5 quarters, as adopted in Detken et al. (2014) or ESRB (2014). We are interested in characterizing the pre-crisis periods within this horizon $h \in$ H, where H = [5, 12] is the set of quarters going from 12 to 5 quarters before the crisis. This rather long delay is justified by the delays needed for implementing policies, such as the 12-month delay banks have to comply with the new level of the CCyB (when increased) [2]. Moreover, we account for the fact that periods just before crises and in their immediate aftermath can pollute the estimations. To avoid this, we remove them from the sample, marking them as missing values (NA).

More precisely, we define the pre-crisis indicator $I_{nt}$ of as:

$$\begin{cases} I_{nt} = 1, \quad \text{if } \exists\ h \in H=[5,12] \text{ such that } C_{n,t+h} = 1 \\ I_{nt} = NA, \quad \text{if } \exists\ h \in [-12, .., 4] \text{ such that } C_{n,t+h} = 1 \\ I_{nt} = 0, \quad \text{otherwise} \end{cases} \quad (2)$$

The pre-crisis period indicator $I_{nt}$ equals 1 when a crisis occurs in country $n$ within the $H$ horizon; it is set to missing values (NA) around the crises (from 4 quarters ahead to 12 quarters after), and set to 0 in all the other periods, that are referred to as "tranquil periods". This pre-crisis indicator is our dependent variable that we will aim at successively explaining by a signal method and an econometric one.

[2] Indeed, as indicated in art.136 CRD IV defining the CCB, banks have to comply to the new regulatory requirement within 12 months.

Although the data initially covers the 1985:Q1-2009:Q4 period, as all sample countries (but one) went through a crisis in 2008:Q1, the pre-crisis indicator has missing values from 2007:Q1 on. Indeed, as previously stated, we suppress observations up to one year ahead of a crisis, as well as the three subsequent years. This entails removing the years from 2007:Q1 to 2011:Q4 at least, and leaves us with a sample ending in 2006:Q4. Despite ending in 2006:Q4, the sample does take into account the 2008 episode, and we expect that the values of the variables observed during pre-crisis periods, 2005 or 2006, are able to detect the 2008 crisis. This strategy is in line with Detken et al. (2014).

### *2.2 Macrofinancial indicators and direction of risks*

We consider a large set of economic variables $X_k$, defined on the same sample as potential candidates for early warning indicators. This set accounts for the main risks on macroeconomics, credit, interest rates, real estate and financial markets (Table 2). The choice is restricted to series available for all 10 considered countries over the whole time sample. All series and their sources are presented in detail in Table A1 in the Appendix.

A preliminary step in the signaling process is to specify the direction of the risk. As we search for possible "booms" matching the pre-crisis periods, for a majority of our indicators, the risk increases with the high values of our series. Indeed, excessive values in credit ratios, asset or property prices favor the building-up of imbalances in the economy and are able to bring about financial bubbles that may unwind in future crises. Hence, the risk is on the right-tail of the distribution for all these series, the signal being emitted by the variable crossing its threshold upward. The only exceptions in our variables are the interest rates and the spreads, whose risk is the other way round. Indeed, low interest rates are more likely to be seen in "boom" periods as they enhance credit, deficits and fuel the rise in asset or house prices. Hence, the direction of risk associated with interest rate is on the left-tail of their distribution. To sum up, we are looking for upper thresholds for all variables but the interest rate related ones.

**Table 2: Candidates for early warning indicators**

| | Macro | Credit | Interest rates | Real estate | Market |
|---|---|---|---|---|---|
| Indicators | Current account | Bank (or total) credit | 3 month rate | Loans for House purchase | Real effective exchange rate |
| | Consumer price index | Bank (or total) credit to NFC (or HH) | Long-term (10y) | Residential real estate prices | Equity prices |
| | GDP | HH debt | "golden rule" | Price to income | |
| | M3 | Debt service ratios (NFC/HH) | | Price to rent | |
| | Unemployment | | | | |
| Transformations | % of GDP<br>gap to trend<br>1y, 2y, 3y-change | % of GDP<br>gap to trend<br>1y, 2y, 3y-change | levels<br>1y, 2y, 3y-change | % of income<br>gap to trend | 1y, 2y, 3y-change |

### *2.3 The signal method*

The signal approach has long been used for forecasting currency and balance of payments crises (Kaminsky et al., 1998, Kaminsky, 1999) as well as for banking crises (Demirgüç-Kunt, and Detragiache, 1998, 2005) and financial crises (Christensen and Li, 2013). It amounts to counting the number of crises that burst once a given variable hits a critical threshold appropriately chosen.

The signal method is key to EWS as it makes it possible to convert continuous variables into binary ones, called "signals" supposed to alert to crises. The method consists in finding the variables and their thresholds so that the thresholds are more frequently hit during the pre-crisis periods than during tranquil ones. We rely on this method for selecting our univariate indicators as well as our econometric models.

For the univariate indicators, we start from the economic variables $X_k$ , described in Section 2.2. Let us call $Z$ a generic indicator taken from our variables $X_k$. The same method will be applied later for assessing the results of the econometric models; the $Z$ variable will then be equal to the series of probabilities estimated by the models.

Every time the $Z$ variable hits a given threshold value $\theta$ in country $n$ at time $t$, it is said to have emitted "a signal" $S$. Hence the signal $S_{nt}(\theta)$ can be written as:

$$\begin{cases} S_{nt}(\theta) = 1, & \text{if } Z_{nt} \geq \theta \\ S_{nt}(\theta) = 0 & \text{otherwise} \end{cases} \quad (3)$$

To simplify, we assume in this section that only high values of indicators signal crises, so the threshold defines an upward limit, such as the credit gap exceeding a given value. The same method applies to indicators whose low values are more risky, like interest rates, by multiplying them by a negative coefficient.

More specifically, for *Z* to be a relevant indicator, there must be a threshold $\theta$ and a horizon $h \in H$ such that once *Z* has hit this threshold, the conditional probability of crisis at the *h* horizon is higher than the a priori probability of crises in the sample. In this non-parametric approach, all probabilities are defined empirically by counting the occurrences of the corresponding events over the sample. Hence, the "a priori probability of crisis" is defined as the number of crises divided by the total number of observations *NT*, and the conditional probability of crises if a signal is emitted is calculated by dividing the number of well predicted crisis by the number of emitted signals.

### *2.4 Assessing the performances of the indicators according to given thresholds*

To assess the relevance of indicator *Z* and its threshold, the sample is decomposed in four categories of observations : (A) a signal is emitted and a crisis bursts at the H horizon, the crisis is well predicted; (B) a signal is emitted and no crisis occurs within H horizon, it is a false alarm (Type II error); (C) no signal is emitted and a crisis bursts within the H horizon, it is a missed crisis (Type I error); (D) no signal is emitted and no crisis occurs at the H horizon, the tranquil period is well predicted. The number of observations in each category is counted for all countries taken together and denoted respectively A, B, C, D as in Table 3. The four categories partition the space of observations as displayed on Table 3 so that the sum A+B+C+D equals the total number of observations in the sample. Once the number of observations in each category is counted, one can easily calculate the performance ratios (last range of Table 3). The number of observations A, B, C and D can be calculated for the panel of all countries taken together. Another possibility discussed in Section 2.7 is to calculate these numbers of observations for each country.

For each value of $\theta$, the performance of indicator Z can then be assessed by ratios such as the percentage of missed crises T1 ($\theta$,Z) (type I errors), of false alarms T2($\theta$,Z) (type II errors). The noise to signal ratio T2($\theta$,Z)/(1-T1($\theta$,Z)) is also used to assess the global performance. The conditional probability of crisis if a signal is emitted is also useful to compare with the a priori probability of crisis (last column of Table 3). Indeed, we expect that a signal emitted by a relevant indicator at an appropriate threshold will increase the probability of crisis above the probability obtained without any information.

Strictly speaking, the denominations provided in Table 3 and both paragraphs above are not really accurate when the horizon of prediction H spans over more than one period, although they are generally chosen for their appealing simplicity. More specifically, the number A does not exactly refer to the "well predicted crises" but to the "well identified pre-crisis periods" meaning the observations both in pre-crisis periods ($I_{nt}$ =1) and with $Z_{nt} > \theta$. Consequently, the sum of (A+B) is not equal to the number of crises, but to 8 times it. Similarly the "missed crises" are the "missed pre-crisis periods" and the false alarms are the "tranquil periods wrongly identified as pre-crisis periods". However, for the sake of brevity and simplicity, we will continue to refer to terms such as "well-predicted crises" instead of "well-identified pre-crisis periods" in the following sections.

**Table 3: Decomposition of the observations in the sample according to variable Z and threshold θ, performance ratios and probabilities of crises**

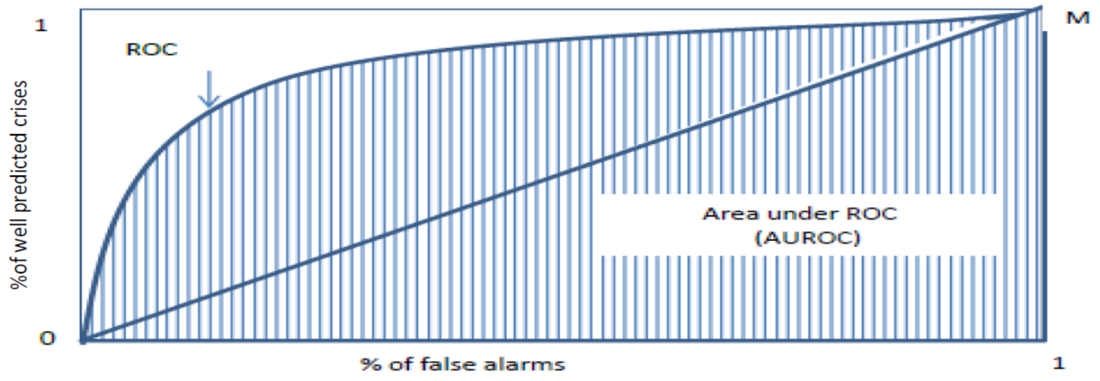
| | $\exists h \in H$: a crisis occurs in *t+h*, in country *n* | $\forall h \in H$,no crisis occurs in *t+h*, in country *n* | Probabilities of crises |
|---|---|---|---|
| | Pre-cris indicator Int = 1 | Pre-cris indicator Int =0 | |
| Signal emitted $Z_{nt} \geq \theta$ | "Crises well predicted" Nb =A | Error of Type 2 "False alarm" Nb=B | Probability of crisis if signal emitted A/(A+B) |
| No signal $Z_{nt} < \theta$ | Error of Type 1 "Missed Crises" Nb=C | "Tranquil period well predicted." Nb= D | |
| Performance ratios | Proportion of "missed crises" $T1(\theta,Z) = C/(C+A)$ | Proportion of "false alarms" $T2(\theta,Z) = B/(B+D)$ | A priori probability of crisis (A+C)/NT |

## *2.5 The AUROC criterion*

The threshold should be set by assessing the cost linked to the two types of errors. The trade-off is between (i) missing too many crises (T1) or (ii) wrongly predicting crises that do not exist (false alarms or T2). The lower the threshold, the more frequent the signal. Hence, by setting the threshold sufficiently low, one can easily predict the whole set of crises, but this may generate numerous false alarms. Inversely the higher the threshold, the less signals the indicator emits, at the risk of missing more crises.

When progressively lowering the threshold on the entire range of variation of Z, from its minimum to its maximum value, we can increase continuously the number of emitted signals. The percentage of well predicted crises then goes from 0% (with 0% of false alarms) to 100% (yielding also 100% of false alarms as all values emit a signal). This trade-off is represented on Figure 1, by shifting from point O, where no signal is emitted, to M, where a signal is emitted at each period. According to the threshold retained, the same indicator provides the whole range of results. The receiver operating curve (ROC) linking O to M represents the relevance of the indicator (Figure 1). As a relevant indicator should detect a high percentage of crises with few false alarms, it should display a ROC well above the bisector.

**Figure 1 : Trade-off between two types of errors**




Note : Point O: the threshold is set at maximum of the indicator, no signal is emitted (0% of predicted crises, 0% of false alarms); Point M: the threshold is set at minimum of the indicator, the signal is emitted at each period.

The relevance of the indicator can then be measured by the area under the ROC, ie the AUROC, which is shown on the hatched area in Figure 1. By construction, the AUROC is always between 0 and 1, and would be equal to 0.5 for a random signal. Therefore, to be relevant, an indicator must have an AUROC greater than 0.5, otherwise, it gives no information. The advantage of the AUROC criterion is to be independent of a particular threshold. Consequently, we will use this criterion when selecting our indicators, as we will first eliminate all the variables with an AUROC smaller than 0.5.

### *2.6 Policy maker's preferences and determination of threshold*

Although useful for preselecting indicators among a great number of potential ones, the AUROC criteria is not sufficient because it does not provide any particular threshold. Nevertheless, the thresholds are key to the EWS approach, as without them, one cannot say if signals have been emitted or not. This is why we need another approach to select the thresholds. One standard way is to minimize the policy maker's loss when making errors in predicting the crises.

The policy maker's loss function *L* is defined as the weighted average of the two types of errors generated by the signal given by Z crossing a given threshold. The weighting parameter $\mu$ varying between 0 and 1 indicates the policy maker's preferences for avoiding type I errors compared to those of type 2.

$$L(\mu, \theta, Z) = \mu \mathrm{T1}(\theta, Z) + (1 - \mu)\mathrm{T2}(\theta, Z) \qquad (4)$$

where $T1(\theta,Z)$ denotes the percentage of missed crises $T2(\theta,Z)$, the percentage of false alarms obtained for a given $\theta$ threshold.

The weighting parameter $\mu$ is unobservable and then must be set exogenously. The higher $\mu$, the more costly it is to miss predicting a crisis; which leads the policy maker to accept more false alarms. On the contrary, a low value of μ indicates a high political cost for false alarms, for example because if the measures taken to avoid a crisis cool off the economy unnecessarily. In this section, we set the μ parameter arbitrarily at 0.5. It will be allowed to vary in Section 6 to test for results sensitivity. As this value of 0.5 gives equal weights to the costs generated by the two types of errors, it seems rather neutral and offers a good starting point to proxy one set of thresholds.

Once the μ parameter is fixed, the policy maker is entitled to determine the threshold in order to minimize its loss function. The optimal threshold $\bar{\theta}$ can be easily determined by iteration through the minimization of the loss function.

$$\bar{\theta}(\mu, Z) = \operatorname{argmin}_{\theta} L(\mu, \theta, Z) \tag{5}$$

Once the threshold is optimized, we can determine the loss borne by the policy maker when using a given indicator Z associated with its critical threshold:

$$L(\mu, Z) = \quad L(\mu, \bar{\theta}, Z) \tag{6}$$

If a signal is emitted every time, the loss function will be equal to (1-μ); if no signal at all is released, the loss function will be equal to μ. Hence the policy maker has the possibility of lowering its loss to Min[μ, (1-μ)] independently of the information contained in any variable Z. Then, the "usefulness" $u(\mu, Z)$ of variable Z can be measured by the reduction in the loss function obtained by considering the signal emitted by Z instead of getting Min[μ, (1-μ)] with no information.

$$u(\mu, Z) = Min[\,\mu, (1-\mu)] - L(\mu, Z) \tag{7}$$

The relative usefulness $ru(\mu, Z)$ can be expressed as

$$ru(\mu, Z) = \frac{Min[\,\mu,(1-\mu)] - L(\mu, Z)}{Min[\,\mu,(1-\mu)]} \tag{8}$$

### 2.7 Evaluation at a country-level using panel-country data

The CCB will be triggered at a country-level, following a decision made on the basis of information gathered at the country-level. When considering a panel of countries for selecting indicators, we are left with the choice of which type of information will seem relevant to the national policy maker. She may optimize the prediction by considering the value of the loss function obtained over the whole panel of countries (like in Equation 4), or over her own country only.

In this latter case, the loss function, denoted $L_n(\mu, \theta, Z)$, will be country-specific, depending on the two types of errors $\mathrm{Ti}(n, \theta, Z)$, i=1,2, obtained by the indicator Z for country *n* at $\theta$ threshold

$$L_n(\mu, \theta, Z) = \mu \mathrm{T1}(n, \theta, Z) \quad + (1-\mu)\mathrm{T2}(n, \theta, Z) \tag{9}$$

Where T1(n, $\theta$, Z) (T2(n, $\theta$, Z)) is the percentage of missed crises (false alarms) for country *n* by using the θ threshold for the Z variable. Hence the differences in the country-specific loss functions stem from the various relevance of indicator Z across countries (at the same $\theta$ threshold), not from different preferences of the policy makers, as μ is assumed to be the same across countries.

If crises were not rare events, one could optimize the θ threshold for Z variable by only using the country-specific observations. In practice, the low number of crisis events makes it impossible to derive a robust threshold from optimization of the loss function in a single country. That is why the optimal threshold has to be common to all countries.

Hence we consider that the optimized country's loss function is obtained with the $\bar{\theta}$ threshold previously optimized at the panel-level.

$$L_n(\mu, Z) = \quad L_n(\mu, \bar{\theta}, Z) \tag{10}$$

The usefulness of an indicator at the country-level is then deduced by:

$$u_n(\mu, Z) = Min[\,\mu, (1-\mu)] - L_n(\mu, Z) \tag{11}$$

## 3. The preliminary selection of indicators one-by-one

We now apply the criteria described above to select the univariate indicators. Our methodology consists in starting from the information contained in the entire panel of countries in order to identify the best indicators at a euro-area level. Then, among these variables, we select those yielding the best usefulness for France.

### *3.1 The criteria used for selecting indicators*

In order to select the relevant indicators among a large set of possible candidates $\{X_k\}$, we measure their performance in terms of AUROC and loss function on the panel and then the usefulness obtained for France. We proceed in two successive steps that are summarized in Figure 2.

In the first step, we eliminate all indicators whose performance in terms AUROC is smaller than 0.50 over the sample of 10 countries. This step amounts to discarding all indicators that do not perform better than a random draw. For all the remaining indicators, we compute the critical threshold θ that minimizes the policy makers' loss function over the panel of 10 countries with $\mu$=0.5.

In the second step, we apply another criterion over the indicators selected in the previous stage by retaining only those that yield sufficiently good results for the French data. This leads us to retain only indicators with a positive usefulness for France.

### *3.2 Implementation of the selection process: the AUROC criterion*

We start the process with a set of 67 indicators (including several transformations of the same indicator) as described in Section 2 and presented in the Appendix A1. In the first step, we select 44 indicators by imposing the criterion of an AUROC higher than 0.5. These 44 indicators are classified by their performance in terms of AUROC and reported in Table A2 in the Appendix. Then we calculate the thresholds at the euro-area level consistent with the equally-weighted loss function (i.e. balanced preferences).

The five top indicators at this stage are the long-term interest rate, nominal and real, as well as credit ratios in percentage of GDP (total and bank credit to the private non-financial sector as well as bank credit to households in percentage of GDP). Among the next five indicators, two are related to interest rates: the 3-month money-market interest rate and the gap between the real long term interest rate and real GDP growth (that can be assimilated to a "golden rule"); other two indicators are real monetary aggregate M3 changes (over 1 year or 2 years) and 2-year change in share prices. The results also comfort the choice of the "Basel gap" as an early indicator of crises.

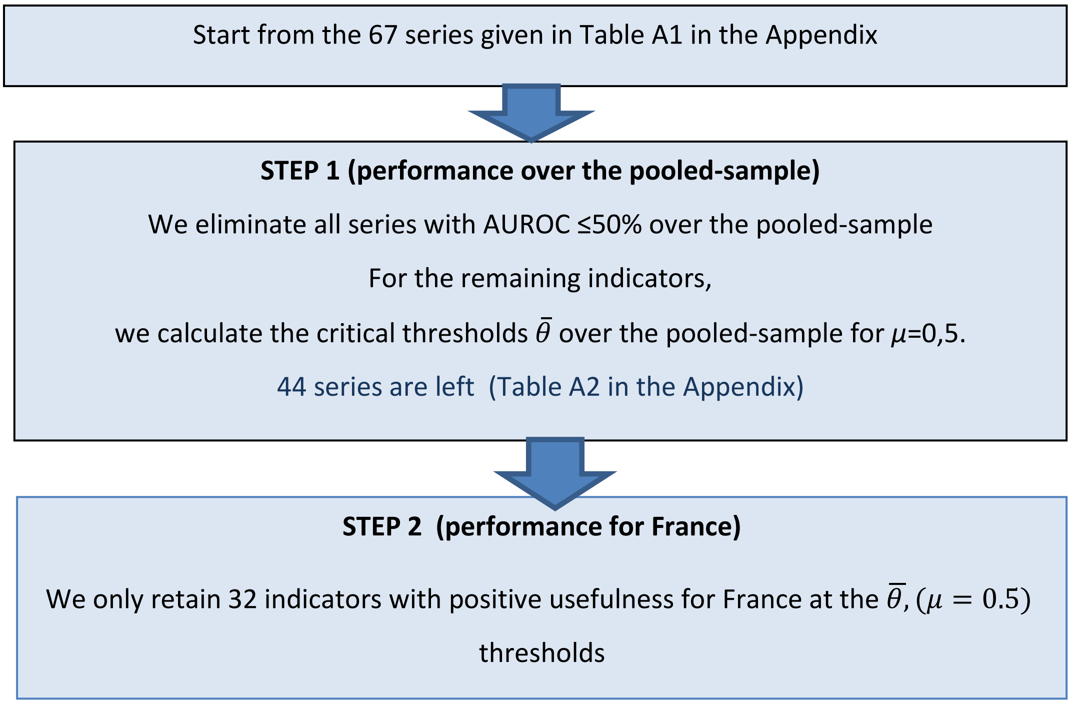
Among the next best indicators, several categories stand out such as credit, (gaps to trend and growth rates), debt service ratios, real estate prices and loans as well as the 2-year change in equity price. On the contrary, most macro-economic indicators are eliminated at this stage, as they are not better than a random draw to predict crises. Their dynamics do not show any specificity in the pre-crisis periods compared to the tranquil ones, although they are likely to behave differently in the aftermath of crises, but this is not what is at stake here. The only real activity indicator retained is the 1-year real GDP growth.

### *3.3 Implementation of the selection process: the usefulness ratio*

In the second stage, we start from the 44 indicators with their threshold calculated at the previous step. We now select those having a positive usefulness to predict crises for France when mu=0.5.

Only 32 out of our 44 former indicators fulfill this criterion. We rank them according to the usefulness of their signal (Table A3). The 3-year change in monetary aggregate M3 and the total credit to GDP gap to its long term trend are the two best performing indicators for predicting crises in France, with a similar usefulness ratio of 0.53. More generally, the results show that credit and money variables rank among the best indicators for France, as 6 of them are among the top ten. Interest rates and real estate (prices and loans) also have a prominent place in the list. However, the equity price growth is not a very useful signal for France as a stand-alone indicator.

**Figure 2 : Selecting process for univariate indicators**




## 4) The econometric approach: averaging logit models

The univariate approach developed above leads to identify several relevant indicators. We now need a methodology to combine them appropriately since stand-alone indicators may have lower predicting power when they do not interact with others. To combine indicators, we decide to rely on logit models.

### *4.1 Logit models, benchmark models and the "Basel gap"*

In the logit estimation, the left-hand side (LHS) variable is the same pre-crisis indicator variable $I_{nt}$ as defined by Equation (2). This means that we keep the same horizon of prediction H. We also keep excluding the observations in the immediate neighborhood of crises; as previously, the observations during the crises, the one year ahead and the three years after are removed from the sample, as they differ from "tranquil periods" and from pre-crisis periods. This strategy matches the one described in the ESRB Occasional paper on the operationalization of the CCB (Detken et al., 2014).

The basic logit equation to estimate is the following:

$$I_{n,t} = F\left[\alpha + \sum_{k=1}^{K_0} \beta_k X_{k,n,t-1} + \varepsilon_{n,t}\right] \quad (12)$$

where F is a logistic function, $\mathrm{F(Z)} = \frac{\beta_k e^Z}{1+e^Z}$ , and $K_0$ is the number of variables to be included in the regression, $\alpha$ and $\beta_k$, parameters to estimate. The one–quarter lags on the explanatory variables $X_{k,n,t-1}$ do not reflect the horizon of forecast, for this is taken into account by the leads in the dependent variable (5 to 12 quarters ahead of the crises); they only account for the delay in the avaibility of data for the policy maker.

As the logistic function is monotonously increasing, and ranging between 0 and 1, it matches a repartition function. Hence the fitted value of the logit estimation can be interpreted as the estimated conditional probability of crises.

$$\hat{p}_{n,t} = \mathrm{Prob}\left[I_{n,t} = 1 | \{X_k\}\right] = F\left[\hat{\alpha} + \sum_{k=1}^{K_0} \hat{\beta}_k X_{k,n,t-1}\right] \qquad (13)$$

This probability of crises can be dealt with through the signaling approach just like a univariate indicator. We hence compute the policy maker's loss function and the critical threshold probability $\theta$ using Equation (4) and (5). We can also assess the performance of the model by calculating its relative usefulness (Equation 8).

The logit regression is run on panel data without any country effects. Indeed it is not possible to include fixed effects as some countries in the sample have experienced no crises during the period under review, hence their null dependent variable would be correlated with the fixed effect.

The key issue here is to select the relevant indicators $X_k$ to include in the model among numerous potential variables. Putting all the potential variables in the regression at the same time would lead to multi-colinearity and biased results. Putting only several variables would be arbitrarily in the absence of a clear criterion. Given the high model uncertainty, it is reasonable to run a whole set of models before either picking the best ones or averaging results across a set of models, which is the strategy that we choose here.

Detken et al. (2014) among others have used the methodology described above to estimate a number of logit models as Equation (12) over a balanced sample of European Union (EU) countries. Their conclusions show that the best performing model over this pooled-sample includes 4 variables: the total credit to GDP gap, the debt service ratio, the equity prices (as a year-on-year change), the house price to income ratio.

Hence we start by estimating a similar model, adjusted for France in accordance with the recent communication of the High Council for Financial Stability [HCSF], the French macroprudential authority in charge of the CCB. This model, referred to as the benchmark model or Model 1 in the following, includes four explanatory variables: (i) the bank credit-to-GDP gap, (ii) residential property price-to-income ratio (annual change), (iii) three-year real equity price growth and (iv) debt service-to-income ratio. As indicated in HCSF (2015), we prefer a bank credit gap variable because it is more in line with the bank credit risk that we try to assess through this EWS, especially for the CCB policy conduct. However, the total credit to GDP gap is also considered as well among the other variables.

As a matter of fact, the Basel Committee on Banking Supervision (BCBS) and the European Systemic Risk Board (ESRB) recommend the use of a credit gap (associated with a buffer guide) to help the policy maker in activating and calibrating the CCB (BCBS, 2010) as this type of credit indicator is considered as useful to monitor the financial cycle (Drehmann et Tsatsaronis, 2014). Given this recommendation, we include the bank credit to GDP gap as an explanatory variable in all the logit models, which leaves us with the choice of three additional indicators as RHS variables.

## *4.2 Selecting the sets of models to aggregate*

As econometric estimations are surrounded by uncertainty, our aim is to reduce this model uncertainty by averaging results across a whole set of models. Our strategy complements the existing literature by (i) considering there is no perfect model and that relying on a single specification could be damaging in terms of risk management practices and (ii) trying to take into account country-specificities. In other words**,** our strategy explores the possibility to monitor the outcome of several logit models without a prior on the model specification.

If we consider K indicators as possible RHS variables in Equation (12), we have a set of logit models $m \in \Omega = (1,\ldots, M)$. Each model $m$ is defined by the set $K_m$ of its RHS variables $\{X_{k,}\} \in K_m$, taken among the K possible candidates. The equation for model $m$ is therefore expressed as:

$$I_{n,t} = F[\alpha_m + \sum_{k \in K_m} \beta_{m,k} X_{k,n,t-1} + \varepsilon_{n,t}] \qquad (14)$$

with $0 < |K_m| \leq K$.

However, as soon as the $K$ number of variables is large, this strategy rapidly leads to unmanageably large number of models to estimate. This is why we have begun by restricting the set of possible indicators by selecting them in Section 3 (Table A3 in the Appendix).

Here the RHS variables are the univariate indicators selected previously (Section 3) to which we add two other variables: the first one is the equity price 3-year growth because it stands in the top 20 indicators over the euro area panel on the AUROC basis and is also significant in the benchmark model ; the second one is the annual real GDP growth, just to be sure not to miss a macroeconomic signal (even if macroeconomic variables as standalone indicator have shown poor early warning performances). We also remove from the set of RHS variables all those with a trend, as the presence of a trend makes it more and more likely that a given threshold is crossed as the time goes on. This leads us to drop all simple ratios, like credit over GDP, and keep only their transformation, as growth rate or gap against trend. This leaves us with a set of 29 possible RHS variables.

Among this set of 29 indicators, we consider all possible combinations with 4 RHS variables: the first one invariably being the credit gap and the three others being picked out of the 28 remaining indicators. This specification with of 4 RHS variables is in line with the benchmark model. This setup implies estimating 3276 logit models. In order to get reasonable results and avoid any misspecification issues, we focus exclusively on two sets of models.

The first set of models $\Omega_1$ is restricted to fulfill stringent criteria: (i) each of the four estimated coefficients has to be significant at the 95% level; (ii) each of them has also to match the expected sign regarding the risk the indicator it is supposed to gauge, for example, positive, for debt ratios, negative for interest rates (as discussed at the start of Section 3). We systematically include the benchmark model in this set even if its coefficients are not significant.[3] Applying such stringent criteria drastically reduces the set of available models from 3276 to 6. The estimations for these six models are provided by Table A4 in the Appendix. As we want to avoid relying on too few models, we also consider the following set.

The second set of models $\Omega_2$ is larger, as it is selected through more relaxed criteria. It is made of all possible models with three in the four estimated coefficients significant at the 95% level and the expected sign. Consequently, one of the four variables has no constraint on its coefficient. As the criteria are more relaxed, the number of models is larger, amounting to 611 in the sample. Hence, the composite crisis probability (obtained from the aggregation of models that is explained in the next section) takes into account more heterogeneous risk indicators. By construction, the set $\Omega_1$ is a subset of $\Omega_2$.

In the following, we will retain these two sets of models, $\Omega_1$ and $\Omega_2$, successively in order to assess their respective performance.

### *4.3 The risk factors involved*

One key question concerning these selected models is to know which risk factors they account for. To answer this question, we report the frequencies of occurrence of each variable among the two sets of models in Table 4. The RHS variables that appear in the selected logit models can be considered as the most significant risk factors over the pooled-sample. Outside of the bank credit gap to GDP ratio that is included in all models by construction, one variable stands out by appearing in all the retained models: it is the 3-year change in equity price. By measuring variations over a 3-year period, this variable is able to capture the building-up of imbalances on the stock market. The slope of the yield curve is also a key variable as it enters in 83% of models; as the risk measured in this variable is left-tailed, the more risky situations are found with very low long term rates relatively to short ones. Then, a few other variables are retained in 17% of models to measure real estate risk, interest rates and growth of money aggregates. As expected, we retrieve the four variables highlighted in the benchmark model.

The performances of the models are rather satisfying over the pooled- sample. Their AUROCs range from 0.66 to 0.71 with a median of 0.68 when 6 models are retained with stringent criteria; between 0.59 and 0.83 with a median of 0.68 for the set $\Omega_2$ of 611 models selected with the relaxed criteria.

[3] However, if no model at all meet the stringent conditions, we will consider that the set $\Omega_1$ is empty (See Section 5.2 below)

**Table 4: Statistical appearance of risk factors in the two sets of selected models $\Omega_1$ and $\Omega_2$ (*)**

| Name | Unit | Set $\Omega_1$ restrictive criteria 6 models | Set $\Omega_2$ relaxed criteria 611 models |
|---|---|---|---|
| Bank credit to non financial private sector | Real – % GDP – gap to long-term trend | 100% | 100% |
| Equity price index | Real, 3-y change - % | 100% | 30% |
| Slope ot the yield curve | % | 83.33% | 22% |
| Price-to-income ratio | Y-o-y change | 33.3% | 15% |
| Debt service ratio, non-financial sector | % | 16,67% | 11% |
| Monetary aggregate M3 | Real, y-o-y change - % | 16.67% | 19% |
| Residential property price | Real, gap to long-term trend | 16.67% | 8% |
| Interest rate gap to GDP (Golden rule) | %, real bond yield minus 1-year real GDP growth | 16.67% | 10% |
| Ratio of house price to rent price | y-o-y difference | 16.67% | 12% |
| Loans to for house purchase | Real, 3-y change - % | 0% | 17% |
| Debt service to income ratio, non financial corporations | % | 0% | 16% |
| Monetary aggregate M3 | Real, 2-y change - % | 0% | 15% |
| Monetary aggregate M3 | Real, 3-y change - % | 0% | 12% |
| Interest rate gap to GDP (Golden rule) | %, real bond yield minus 3-year real GDP growth | 0% | 10% |
| Total Credit to Households | Real, 1-y change - % | 0% | 8% |
| Total Credit to non-financial Corporations | Real, 1-y change - % | 0% | 8% |
| Residential property price | Real, y-o-y change - % | 0% | 8% |
| Loans to for house purchase | Real, 1-y change - % | 0% | 8% |
| Residential property price | Real, 2-y change - % | 0% | 8% |
| Total Credit to Households | Real, 2-y change - % | 0% | 7% |
| Interest rate gap to GDP (Golden rule) | %, real bond yield minus 2-year real GDP growth | 0% | 7% |
| Total Credit to non-financial Corporations | Real, gap to long-term trend | 0% | 7% |
| 3-month interest rate | % | 0% | 6% |

Calculations: Banque de France. Note: (*) Set $\Omega_1$, restrictive criteria : all four variables are significant at 95% with the expected sign; Set $\Omega_2$, relaxed criteria : three in four variables are significant and with the expected sign. Not mentioned indicators did not appear in the selected models. In grey, the variables common with the benchmark ESRB(2014) model.

### *4.3 Two options for aggregating the models: usefulness at panel-level or country-level*

There are several ways to proceed to this aggregation, as described in Holopainen and Sarlin (2015). For example, a strategy followed by Babecky et al (2012a) is to select the variables that are the most significant in the largest number of models (considering their Student statistics). To do that, they construct a "posterior inclusion probability" (PIP) for each variable that is equal to the probability that the coefficient $\beta_{\mathrm{mk}}$ is significantly different from 0 in all models. Here our strategy relies on averaging the models results by giving more weight to the most performing ones, the performance being measured by the usefulness as detailed below.

Once the set of models $\overline{\Omega}$ has been selected ($\Omega_1$ or $\Omega_2$), we calculate the probability of crises of each model $m \in \overline{\Omega}$, denoted $\hat{p}_m$ , as the fitted value of Equation (14) for country $n$ at time $t$ :

$$\hat{p}_{m,n,t} = F\left[\widehat{\alpha_m} + \sum_{k \in K_m} \hat{\beta}_{m,k} X_{k,n,t-1}\right] \tag{15}$$

We then are able to calculate the policy maker's loss function $L(\mu, \theta, \hat{p}_m)$ at the panel-level given the $\mu$ parameter and for any $\theta$ threshold:

$$L(\mu, \theta, \hat{p}_m) = \mu \mathrm{T1}(\theta, \hat{p}_m) + (1-\mu)\mathrm{T2}(\theta, \hat{p}_m) \tag{16}$$

where $\mathrm{Ti}(\theta, \hat{p}_m)$ is the ratio of type i (i=1,2) errors when $\hat{p}_m$ crosses the $\theta$ threshold.

By optimizing this loss function at the panel-level, we find the critical threshold $\bar{\theta}$, which is the cut-off probability to release a crisis signal.

$$\overline{\theta}(\mu, \hat{p}_m) = \operatorname{argmin}_{\theta} L\left(\mu, \theta, \hat{p}_m\right) \tag{17}$$

This allows us to calculate the usefulness of each model at the panel-level.

$$u(\mu, \hat{p}_m) = Min[\mu, (1-\mu)] - L(\mu, \hat{p}_m) \tag{18}$$

The usefulness can also be assessed at the country-level as indicated in Section 2.7. To do this, we calculate the country's loss functions $L_n(\mu, \overline{\theta}, \hat{p}_m)$ by applying the same critical threshold $\bar{\theta}$ as calculated at the panel-level in Equation (17).

We denote the usefulness of model *m* at the country level with a *n* subscript: $u_n(\mu, \hat{p}_m)$.

$$u_n(\mu, \hat{p}_m) = \mathrm{Min}[\mu, (1-\mu)] - L_n(\mu, \overline{\theta}, \hat{p}_m) \tag{19}$$

The method consists in averaging all the probabilities of crisis obtained from the selected models m $\in \overline{\Omega}$ by giving more weight to the most useful models. Therefore the weight of each model is proportional to its usefulness. As the usefulness of models can be assessed both at the panel-level and at the country-level, we use two alternative weighting schemes and therefore obtain two composite probabilities of crises. The first one $\hat{P}^P$ gives more weights to the best performing models at the pooled-level and the other one, $\hat{P}^C$ , has its weights tailored at the country-level performance.

$$\hat{P}^J_{n,t} = \sum_{m \in \bar{\Omega}} w^J_{m,n} \hat{p}_{m,n,t} \quad for\ J=P,C. \tag{20}$$

Where $w^J_{m,n}$ is the weight given to model *m* for aggregating country *n's* estimated probabilities in option J, J=P or C; the index P refers to the pooled- level and C to the country -level.

The pooled weights $w^P_{m,n}$ are the same for all countries and depend on the usefulness of the model *m* over the pooled sample. [4]

$$w^P_{m,n} = w^P_m = \frac{u(\mu,\hat{p}_m)}{\sum_{m \in \bar{\Omega}} u(\mu,\hat{p}_m)} \tag{21}$$

The country-specific weights $w^C_{m,n}$ vary across countries and depend on the usefulness of the models $u_n(\mu, m)$ assessed separately over each country.

$$w^C_{m,n} = \frac{u_n(\mu,\hat{p}_m)}{\sum_{m \in \bar{\Omega}} u_n(\mu,\hat{p}_m)} \tag{22}$$

From the previous step, we get two aggregated series of crises probabilities: $\hat{P}^P$ and $\hat{P}^C$ obtained by averaging the selected models with their usefulness either at the pooled or the country-level. We then calculate the two thresholds to be applied to these probabilities by optimizing the policy makers' loss function at the panel-level in both cases.

$$\overline{\theta}\ (\mu, \hat{P}^J) = \text{argmin}_\theta\, L\big(\mu, \theta, \hat{P}^J,\big)\, , J=P,\ C \tag{23}$$

The aggregation strategy presented above has three main advantages. First, and most importantly, it mitigates model uncertainty by taking into account a number of different models. Second, it also makes it possible for countries to differ in terms of risk factors sensitivity, while mixing pooled and country-level information. Indeed the country-specific probability $\hat{P}^C_{n,t}$ also draws its legitimacy from the fact that all the models considered in the aggregation answer to criteria on a pooled-information basis (significance and sign of their coefficients) which ensures their validity over the whole panel. Third, the weight given to each model changes over time according to its usefulness, hence the weighting scheme can be updated continuously according to the time-varying performances of the selected models (if the exercise is done in real-time). This is a valuable property as risk factors are likely to vary over time. Of course, any models can be re-estimated on a regular basis, but the strategy presented here is more flexible: the coefficients of each model are not only re-estimated at each period; the set of selected models itself changes over time.

[4] We restrict model selection to models with positive usefulness, since usefulness can be negative if one logit performs worse than a pure random model.

# 5 Assessing the performance of the econometric approach

We now check whether the aggregated probabilities of crises provided by the models are able to emit relevant signals of crises. To do so, we compare the signals obtained with the two aggregation strategies (pooled or country-level) and the two sets of models ($\Omega_1$ or $\Omega_2$). We begin by a standard over-the-sample evaluation then go on with out-of-the sample or "real-time" simulations.

## *5.1. In-sample evaluation*

Table 5 displays the results obtained in sample by aggregating the models over the two sets Ω1 or Ω2. Two major findings stand out from these results. First, performance is greatly improved by aggregating more different models. This is shown by the much better results obtained by averaging the models over the larger set $\Omega_2$ when comparing the loss functions. Adopting a larger set of models, $\Omega_2$ decreases by around 25% on average the value of the loss function for both options relatively to the small set $\Omega_1$. Hence, it seems rationale to relax model selection criteria in order to bring about better results. Second, tailoring the models' weight on country-specific usefulness improves model performances when using a large set of models, while it yields about the same results with the small set of models. The advantage of these country-specific signals is that they also account for the pooled information, as the set of models involved has been selected on the basis of the significance and sign of their coefficients over the whole panel.

**Table 5. In-sample results for the aggregated models, percentage of missed crises (T1), false alarms (T2) and loss function (L) depending on the weighting scheme and the set of models, $\mu$=0.5**

| Options for the weightings scheme: models' usefulness calculated at | *Small set of models $\Omega_1$ (*)* | | | *Large set of models $\Omega_2$ (**)* | | |
|---|---|---|---|---|---|---|
| | T1 | T2 | *L* | T1 | T2 | *L* |
| Panel -level | 0.4 | 0.200 | *0,300* | 0.28 | 0.21 | *0,251* |
| Country-level | 0.45 | 0.174 | *0,312* | 0.208 | 0.195 | *0,202* |

Note. (*) selected through stringent selection criteria (6 models); (**) selected through relaxed selection criteria (611models)

The better performance achieved by aggregating more models needs to be investigated further. Is it a random result or can it be checked and justified? To address this issue, we compare the former results with the performances achieved by each single logit model in $\Omega_{1.}$ Each of these models fulfills the condition of four indicators significant with the expected sign. Results show that single models have less good performances than the aggregated ones (Table 6). Only the benchmark model, model 1, slightly outperforms a combination of a small set of models ($\Omega_1$) when the aggregation is made at the country-level. However, the value of the loss function obtained from each model is much higher than when a large set of models $\Omega_2$ is averaged. In other words, no single model is able to do better than a large combination of models.

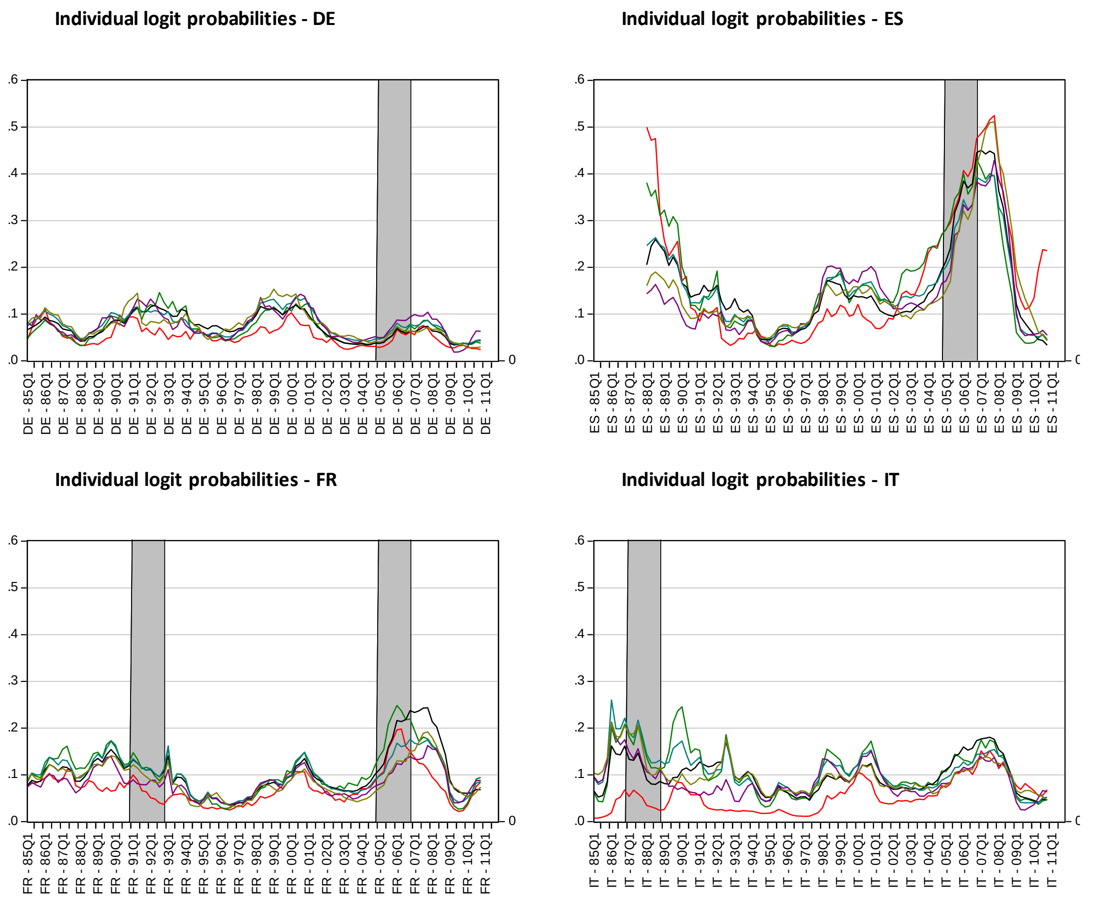
**Table 6. Value of the loss function obtained from each individual logit model in the set $\Omega_1$ (*), in sample**

| | Model 1(**) | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| **Loss function** | 0.301 | 0.337 | 0.370 | 0.359 | 0.340 | 0.362 |

Note : (*) Loss function obtained from each individual logit model satisfying the stringent selection criteria (4 significant and expected sign coefficients). (**) Model 1 is the only one for which the Bank Credit-to-GDP gap is not significant, however not excluded given its benchmark status.

One way to explain the weaker performances obtained by single models compared to averaging results of models is to admit that increasing the number of models reduces model uncertainty. Figure 3 depicts the respective crisis probabilities estimated by the 6 models for France, Germany, Italy and Spain. Even if the 6 probabilities exhibit strong co-movements, there are notable differences across models that may lead to different assessments regarding the threat of a banking crisis. Indeed, the different combinations of factors point to different risks that could ultimately lead to a banking crisis. If we define uncertainty by the width of the range of probabilities given by the 6 models for a given date and a given country, one salient feature is that uncertainty is especially high when the probability of crisis increases. This peak in uncertainty when crises are about to burst clearly calls for a multiplicity of models to better monitor the risks of financial crises.

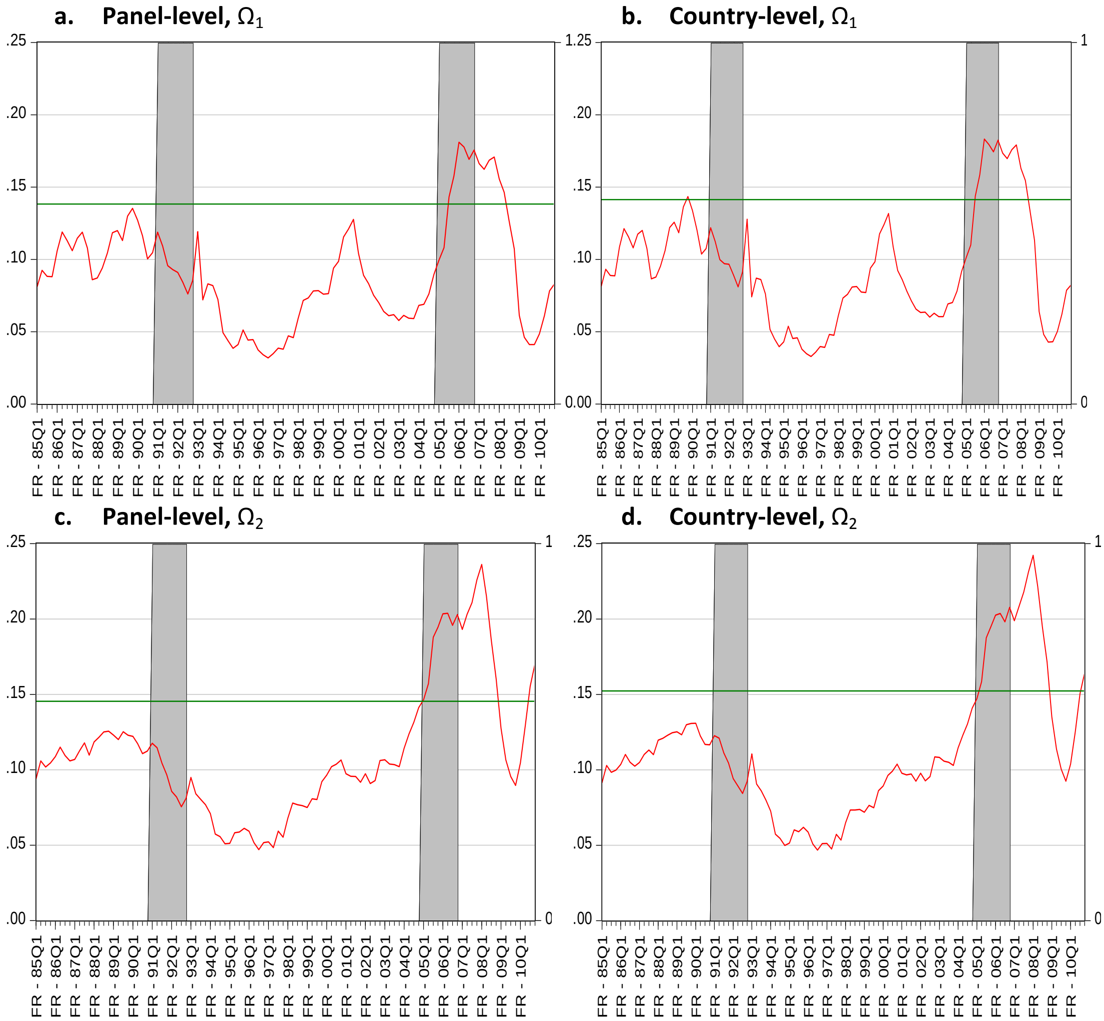
**Figure 3: Crisis probabilities estimated with the 6 logit models in the set $\Omega_1$ (in sample)**




Note: crisis probabilities obtained with the 6 models in the set $\Omega_1$ selected for their 4 significant and expected signed coefficients

Turning to France, the signaling performances when aggregating the models over the set $\Omega_1$ or $\Omega_2$ with the two options previously described are pictured on Figure 4. Estimated probabilities are reported along with their thresholds, and compared with the grey shaded area of pre-crisis periods. A good signaling power therefore matches a probability exceeding the threshold during the grey areas of the two pre-crisis periods, preceding the 1994 and 2008 crises. Regarding the 1994 French crisis, aggregating probabilities over a larger set of models reduces the signaling performance. However, turning to the more severe 2008 crisis, the aggregation over the larger set $\Omega_2$ is able to release earlier signals than those obtained on the small set $\Omega_1$. Indeed, the threshold is hit as soon as 12 quarters before the 2008 crisis when using the set of models $\Omega_2$ with each of the two options (Figure 4.b), whereas it is crossed a few quarters later when considering the small set of models $\Omega_1$.

**Figure 4: Crisis probabilities for France aggregated by the usefulness of models at the panel level and at the country-level, models drawn from the sets $\Omega_1$ and $\Omega_2$ (in sample, mu=0.5)**



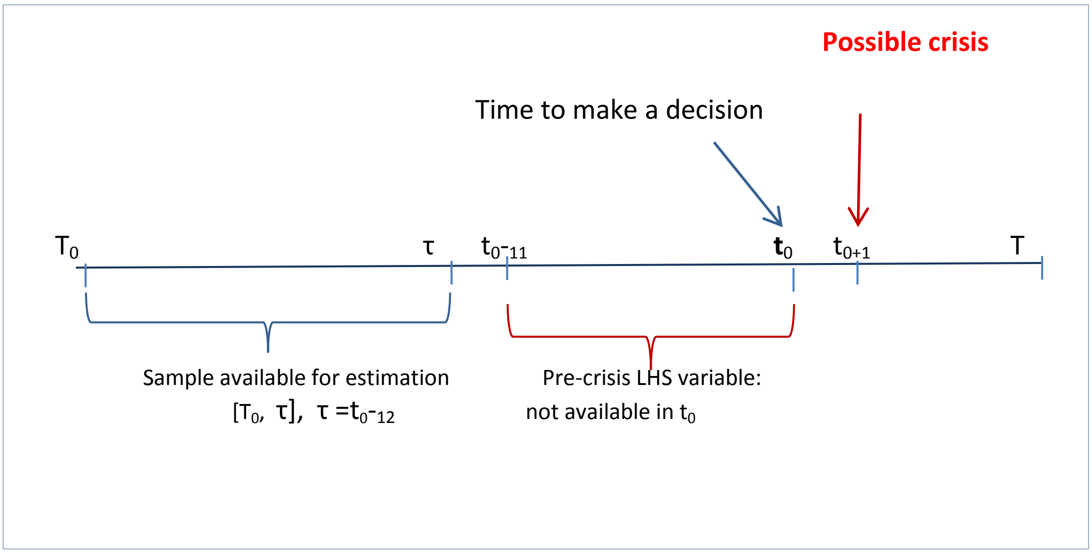

Note: Grey areas indicate pre-crisis periods; probabilities are aggregated according to the usefulness of models at the panel-level and the country-level, successively from the set $\Omega_1$ of 6 models satisfying the stringent model selection criteria; and from the set $\Omega_2$ of 611 models satisfying the relaxed selection criteria.

## *5.2 Real-time evaluation of the monitoring strategy*

### *5.2.1. Principles for the real-time simulations*

To understand the lags a policy maker has to cope with when predicting a crisis, we have to remember that the LHS variable, being a pre-crisis indicator, is available only with a 12-quarter delay. Let us suppose that in time $t_0$, we are just a quarter ahead of a possible crisis; as we do not know it, the pre-crisis variable cannot be defined from $t_{0-11}$ to $t_0$ (Figure 3). Then the largest period for estimation spans from $T_0$, the beginning of the sample in 1985Q1, up to $t_{0-12}$.

**Figure 5: Available information in real-time at time t**




To leave enough observations for the estimation, we start the out-of–sample exercise in 2003Q1 until 2009Q4. Let us describe thoroughly the different steps to estimate the first simulation as if it took place in t0=2003q1. For the reasons indicated above, we have to end the first model estimation at date τ =2000q1.

Let us call $\hat{p}^{\tau}_{m,n,t}$ the probability of pre-crisis obtained for time *t* with the model *m* estimated until time τ. It is expressed as:

$$\widehat{p}^{\tau}_{m,n,\mathrm{t}} = F\left[\widehat{\alpha^{\tau}}_{m} + \sum_{k\in K_m} \widehat{\beta^{\tau}}_{m,k} X_{k,n,t-1}\right] \tag{24}$$

Where $\widehat{\alpha^{\tau}}_{m}$ and $\widehat{\beta^{\tau}}_{m,k}$ are the parameters obtained by estimating model *m* from T0=1985Q1 to τ. We thus get the predicted probabilities $\widehat{p}^{\tau}_{m,n,\tau+\mathrm{h}}$ , h= 1 to 12. The last one τ+12 provides us with the needed prediction for t0=2003q1, but we also look at the predictions for the shorter horizons. We then aggregate the probabilities obtained from the different models taking into account the relative usefulness of the models computed over the sample [T0, τ] successively at the panel and the country-levels. Similarly, we estimate the thresholds over the same sample [T0, τ].

Once the first simulation is made for 2003q1, we proceed in exactly the same way for 2003q2 by adding one quarter to the estimation sample. We end the process in 2009q4. This provides us with 28 forecasts for 10 countries for each horizon (h=1 to 12 quarters ahead); in fact, the number of forecasts is smaller, as we have removed observations surrounding crises (since the dummy is set to NA in those periods as explained in Section 2). Taking into account crisis dates, we end up with 164 forecasts in total for the 10 countries among which we have 64 pre-crisis quarters. As the sample dates indicate, the out of sample evaluation is merely a test of the signaling properties of the models for the 2008 crisis.

### *5.2.2 Illustration for France and Germany*

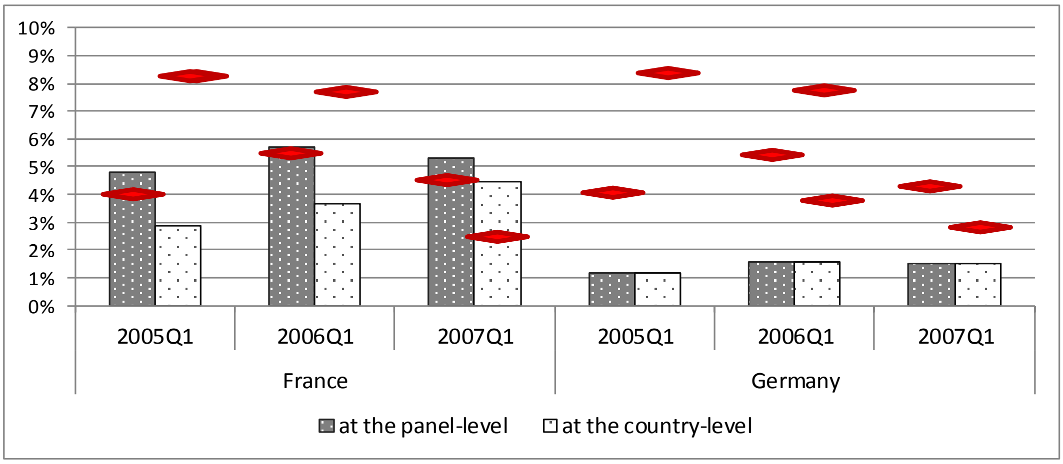
To illustrate the real time evaluation, we start by putting ourselves in the shoes of a French (then German) policy-maker before the 2008 crisis, for example in 2005Q1 (2006Q1, 2007Q1). She has to decide whether to implement or not macro-prudential tools in her country. Being in 2005Q1 means that the policy maker can only estimate the logit models up to 2003Q1 since the “pre-crisis” dummy used in these models is not defined after this date. To assess the model results under this real-time constraint, we successively proceed to the aggregation of the two sets models ($\Omega_1$ or $\Omega_2$) with the two options in 2005Q1, 2006Q1, 2007Q1.

First, a surprising result is that the set of models $\Omega_1$ is an empty set, and therefore not usable. Indeed, up to 2008Q1, no model satisfies the stringent selection criterion (all 4 variables significant with the expected sign). Therefore, it is unavoidable for the policy maker to relax the model selection criteria as we have done in the previous in sample analysis and use the set $\Omega_2$ (that includes all models with 3 in 4 significant variables with the expected sign).

Second, on the contrary, the larger set $\Omega_2$ is well furnished with models, as it includes 166 of them in 2005Q1, 386 in 2006Q1 and 632 in 2007Q1. Figure 6 presents the corresponding aggregated probabilities of crisis given by these models when aggregated according to the models’ usefulness at the panel and country-levels.

As regards France, the panel-weighted probabilities give very satisfying results as the signal is released as early as 2005Q1; on the contrary, the signal is postponed until 2007Q1 if using the country-weighted aggregation. In the case of Germany, two features stand out. First, both methods give the same probabilities of crises. This is due to Germany not having experienced any crisis prior to 2008; hence it is not possible to calculate the usefulness of an indicator over the German sample in this real-time estimation carried out to predict the 2008 crisis. Second, the method fails to deliver any clue of the coming crisis. This may come from the fact that macro financial indicators were not showing so large imbalances in this country prior to 2008, which is also in line with the 2008 crisis being much less severe in Germany than in some other countries of the sample.

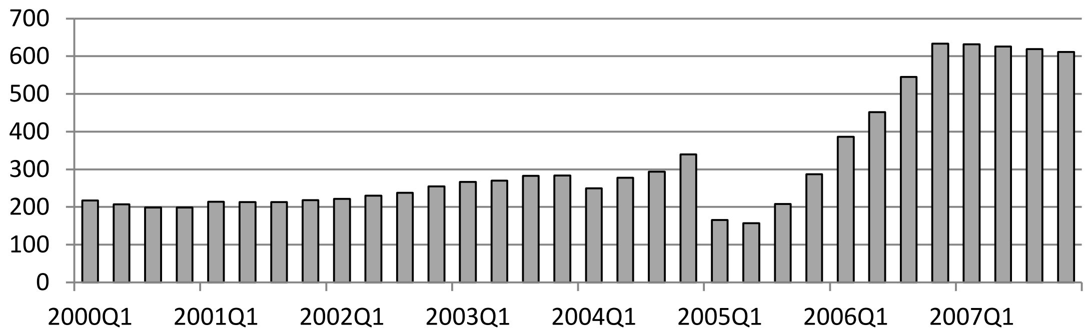
**Figure 6. Crisis probabilities and thresholds estimated in real-time for the two aggregation options on the set of models $\Omega_2$ ( $\mu$ =.5)**




### *5.2.3 Overall results for out-of-sample evaluation*

Applying the model selection criteria in real-time leads to the rise and death of models. This is a particular strong feature, showing that model uncertainty could impair the robustness of an early warning system over time. Figure 7 presents the number of selected models using the relaxed selection criteria at each point in time, in real-time. The number of selected models grows up from about 200 models in early 2000 to around 600 just before the 2008 crisis. Once the imbalances leading to a severe crisis start to build-up, they affect a large set of risks, more indicators are turning red and multivariate signals become stronger.

**Figure 7. Number of selected models in $\Omega_2$**




Note: number of models satisfying the relaxed selection criteria over time.

Table 7 presents the out of sample results for the two aggregation options for the panel of countries between 2003Q1 and 2009Q4. Here, the panel-level weighting scheme seems to outperform the country-level aggregation, if we consider the loss function. This matches our previous finding for France, showing that the panel-weighted models would have been better to predict the 2008 crisis but contradicts the in-sample results that were better with country-level weightings. Consequently, the in-sample and out-sample results leave us with mixed evidence concerning the option to follow.  As there are no clear-cut conclusions regarding the best aggregating strategy, we consider it useful to systematically run the two aggregating options to signal possible crises.

**Table 7  Out-of-sample results for the aggregated models in the set $\Omega_2$, percentage of missed crises (T1), false alarms (T2) and loss function (L) depending on the weighting scheme, ($\mu$=0.5), real-time simulations**

| Options for the weightings scheme: models' usefulness calculated at | *Aggregation on the large set of models $\Omega_2$ (*)* | | |
|---|---|---|---|
| | T1 | T2 | *L* |
| Panel -level | 0.44 | 0.39 | ***0,42*** |
| Country-level | 0.64 | 0.28 | *0,46* |

Note. (*) selected through relaxed selection criteria.

## 6 Variants, robustness checks and heatmaps

In this section, we provide complementary results regarding the value of the mu parameter and the way to calculate thresholds as well as robustness checks. First, we assess the results with different values of the policy maker's μ parameter, reflecting her level of risk aversion towards missing crises. This step is necessary because the μ parameter is very difficult to calibrate and may also vary over time. Second, we propose an alternative method for calculating the thresholds to apply on aggregated results: instead of optimizing the cut-off levels of the aggregated probabilities (as we have done in the previous sections), we now compute the weighted average of single models' optimal thresholds. Third, we check for the impact of the dummy crisis variable on the results: we thus estimate all the models again as well as the ensuing weightings with an alternative crisis dummy.Finally we present a simple visualization of the results for the policy maker through "heatmaps".

### *6.1 Alternative values for the μ parameter*

For assessing the results with alternative values of μ, we rely on the same models' simulations, in and out-of-the sample, as previously. We therefore start from the same sets of models $\Omega_1$ and $\Omega_2$ for the in-sample results and $\Omega_2$ for the real-time simulations. The only differences stem from (i) the way the models are aggregated because the usefulness of models changes according to the mu parameter; (ii) the optimal threshold that is lowered as the μ aversion to miss crises increases. This latter difference makes higher values of mu release more true signals at the cost of more false alarms.

We display the results of the in-sample simulations for the two alternative values of μ =0.6

and 0.7 while reminding the previous ones obtained with μ = 0.5 (Table 8). Both our main previous findings are comforted by these results. First, averaging the models' probabilities over a larger set of models provides much better performance regardless of the value of mu and the aggregation method. This is shown by the lower values of the loss functions obtained by aggregating the large set of models $\Omega_2$ in the two last rows of Table 8. Second, the usefulness of models at the country-level provides a better weighting method in the large set of models, as it reduces the value of the loss function relatively to a panel-weighing, whatever the value of mu. As regards the out-of-sample simulations, they provide the same kind of results as before: the panel-weighting method performs better for mu= 0.6, as for mu=0.5 (Table A5 in the Appendix). Nevertheless, the country-specific weightings provide better results for mu=0.7, which enhances the interest of this aggregation method.

We now consider the values of the loss function obtained by the stringently selected individual models $\Omega_1$ (Table 9). This allows us to confirm the conclusion drawn above. All single models are outperformed by their aggregation on a large set, irrespective of the value of mu. The most disturbing point about these single models' results is that the best performing one changes according to the aversion mu of the policy maker to miss a crisis. This is particularly upsetting as the mu parameter is quite impossible to estimate and set at the discretion of the econometrician. The benchmark model, Model 1, that stands out as the most performing one for mu=0.5, is outperformed by Model 5, as soon as mu=0.6. More worryingly, it is the worst of the six when mu is set to 0.7, ie when the policy maker is keener to avoid crises. In these conditions, on the top of knowing that most single models are not stable through time, our doubts over the true value of the mu parameter makes it very problematic to rely on a single model to predict crises. This clearly highlights the great uncertainty surrounding the appropriate model to retain, and comforts us in our approach to aggregate a large set of models.

**Table 8. In-sample results for the aggregated models, percentage of missed crises (T1), false alarms (T2) and loss function (L) depending on the weighting scheme, the set of models, and the $\mu$ parameter.**

| Weightings schemes : models' usefulness calculated at | *μ= 0.5* | | | *μ= 0.6* | | | *μ= 0.7* | | |
|---|---|---|---|---|---|---|---|---|---|
| | T1 | T2 | *L* | T1 | T2 | *L* | T1 | T2 | *L* |
| *Small set of models $\Omega_1$ (*)* | | | | | | | | | |
| Panel -level | 0.40 | 0.200 | *0,300* | 0.325 | 0.275 | *0,305* | 0.075 | 0.66 | *0,251* |
| Country-level | 0.45 | 0.174 | *0,312* | 0.25 | 0.41 | *0,314* | 0.0 | 0.926 | *0,278* |
| *Large set of models $\Omega_2$ (**)* | | | | | | | | | |
| Panel -level | 0.28 | 0.22 | *0,251* | 0.283 | 0.221 | *0.258* | 0.044 | 0.717 | *0,247* |
| Country-level | 0.208 | 0.196 | 0,202 | 0.059 | 0.351 | 0,176 | 0.0 | 0.449 | 0,135 |

(*) selected through stringent selection criteria (6 models); (**) selected through relaxed selection criteria (611models)

**Table 9. Value of the loss function obtained from each individual logit model in the set $\Omega_1$, in sample, with different values of mu.**

| | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** | **Model 6** |
|---|---|---|---|---|---|---|
| **μ=0.5** | 0.301 | 0.337 | 0.370 | 0.359 | 0.340 | 0.362 |
| **μ=0.6** | 0.310 | 0.315 | 0.338 | 0.324 | 0.284 | 0.347 |
| **μ=0.7** | 0.293 | 0.270 | 0.282 | 0.269 | 0.225 | 0.274 |

## *6.2 An alternative method for setting critical thresholds*

Up to now, we have set the two thresholds for the aggregated probabilities $P^P$ and $P^C$ by optimizing the loss function at the panel-level. In this section, we adopt another method for setting the thresholds which mirrors the way we have constructed the aggregated probabilities.

More specifically, we rely on the same average probabilities $P^P$ and $P^C$ but only modifies the cut-off levels that release signals. To do so, we proceed in two steps. First we calculate all the critical thresholds $\bar{\theta}(\mu, \hat{p}_m)$ for the probabilities $\hat{p}_m$ obtained for all models $m$ by optimizing the policy makers' loss function at the panel level. Second, we aggregate all the models' thresholds using either the weighting scheme resulting from the panel or country-level models' utility.

To derive the new "panel weighted threshold", $\tilde{\theta}(\mu, P^P)$ applied to the panel-level probability we hence calculate the average of the models' thresholds by weighting them with the panel-level weights $w_m^P$defined in Equation (21):

$$\tilde{\theta}(\mu, P^P) = \sum_{m \in \bar{\Omega}} w_m^P \bar{\theta}(\mu, \hat{p}_m) \quad (25)$$

Turning to the country-weighted threshold, $\tilde{\theta}_n(\mu, P^C)$ applied to $P^C$, we define it as the average of models' thresholds weighted by the models' country-specific weights $w_{m,n}^C$ defined in Equation (22)

$$\tilde{\theta}_n(\mu, P^C) = \sum_{m \in \bar{\Omega}} w_{m,n}^C \bar{\theta}(\mu, \hat{p}_m) \quad (26)$$

In the former setting, the two cut-off probabilities were common to all countries. In this new framework, the country–weighted threshold is allowed to vary across countries, in order to better reflect the relevance of the different models for each country.

The results obtained for these new thresholds in the sample are displayed on Table 10. The two main outcomes found previously are comforted by this exercise. First, aggregating models on a larger set of models gives better risk predictions. Second, the country-weighted aggregation improves upon the results relative to the panel-weighted one.

Another issue is to gauge these results relatively to those obtained previously through optimizing the thresholds. To do this, we compare the loss functions found on Table 10 with those reported on Table 5. At the panel-level, this new method of setting thresholds definitely underperforms the former one. This is not surprising, since the former method relied on an optimized threshold, so no other threshold is able to give better results on the loss function at least in the sample. However, at the country-level, the country-specific cut-offs outperform the optimized one, because the optimization was made under the constraint of a single level for all countries. Consequently, tailoring both the crisis probability and its cut-off at the country-level appears to be a valuable approach to account for heterogeneity. It is therefore worthwhile to implement this alternative method.

**Table 10. In-sample results for the aggregated models, percentage of missed crises (T1), false alarms (T2) and loss function (L) depending on the weighting scheme and the set of models, $\mu$=0.5, for alternative aggregated thresholds (1)**

| Options for the weightings scheme: models' usefulness calculated at | *Small set of models $\Omega_1$ (*)* | | | *Large set of models $\Omega_2$ (**)* | | |
|---|---|---|---|---|---|---|
| | T1 | T2 | *L* | T1 | T2 | *L* |
| Panel -level | 0.275 | 0.385 | *0,33* | 0.28 | 0.24 | *0,26* |
| Country-level | 0.187 | 0.426 | *0,302* | 0.134 | 0.256 | *0,195* |

Notes. (1) The alternative thresholds are calculated by averaging the models' critical thresholds with either panel-weighted or country-weighted utilities; (*) selected through stringent selection criteria (6 models); (**) selected through relaxed selection criteria (611models)

Turning to real-time simulations to predict the 2008 crisis, we face the same obstacles as previously described and results are still blurred (Table A.6 in the Appendix). First, the country-level aggregation offer equivalent risk prediction for high values of mu, but not for mu=0.5. Second, contrary to the in-sample simulations, the alternative thresholds do not enhance the performances, neither at a panel nor at a country-level.

### *6.3 Robustness checks over the crisis dummy variable*

As the results are contingent on the crisis episodes recorded in the dummy variable, we proceed to a robustness check by employing an alternative dummy variable. We now use the ESRB crisis dummy as in ESRB (2014) and run the in and out of sample estimations again with this new dependent variable. The dates of crisis are presented in Table A7 of the Appendix. One key difference with the former crisis dummy is that neither Austria, Belgium nor Germany are supposed to have experienced a crisis in 2008 in this new setting.

The in-sample results reinforce those previously found (see Table A8 in the Appendix). First, aggregating a large set of models obtained with the relaxed criteria yields much better results than restricting the set of models to stringent criteria. Second, using a country-weighting scheme to aggregate the models also improves the predicting performance for both sets of models, although it was true only for the large set with the former dummy.

Turning to the real-time simulations, they appear much better at predicting the 2008 crisis than those performed previously with the former dummy variable (Table A9 in the Appendix). Besides the fact that the set of models selected with stringent conditions is no longer empty, the loss function is lower for all values of mu. This can been seen when comparing the results with the former ones reported on Table A5. In particular, the fact that we were not able to forecast a crisis in 2008 in Germany with the previous dummy now turns to be a good thing, for the 2008 observations that were tagged as crises with the previous dummy for this country are classified as tranquil periods with the new one. As a matter of fact, it is beyond the scope of this paper to decide which crisis dummy is the more appropriate, for this depends on the severity of crises assessed at the country-level.

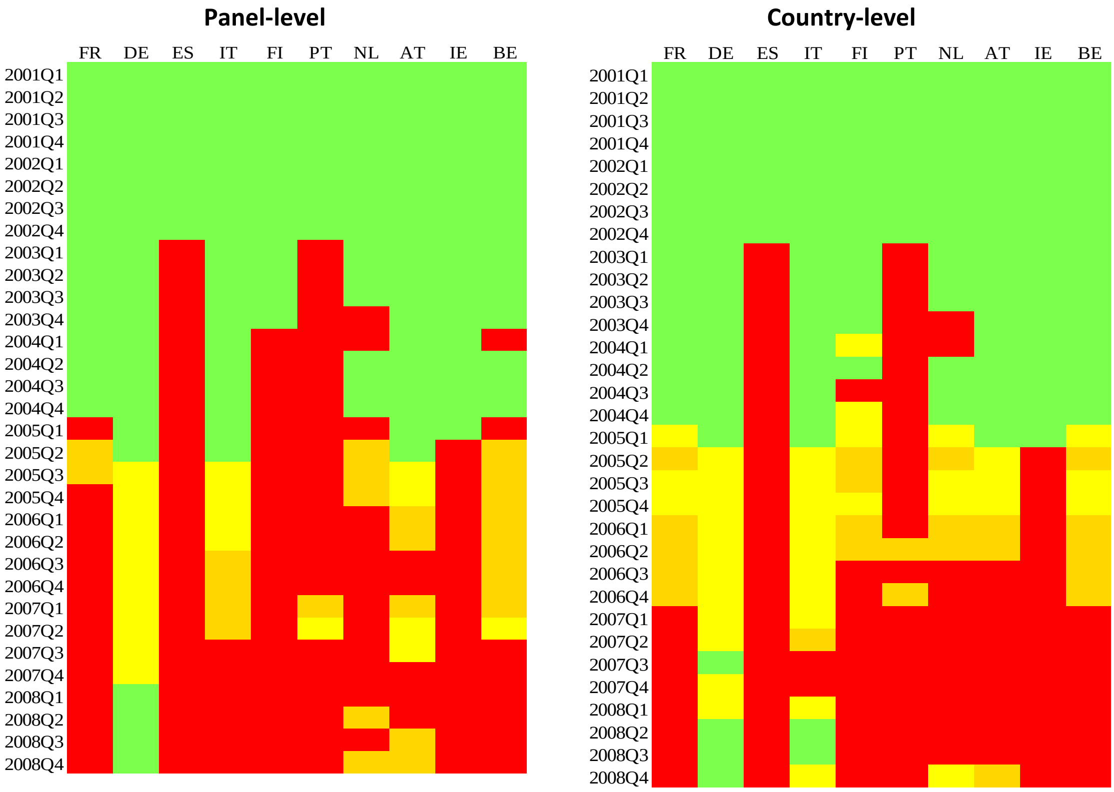
In addition, the real-time simulations obtained with this alternative crisis dummy actually comfort our previous conclusions found with the in-sample results, which contrasts with the blurred outcomes drawn from the former real-time simulations. First, aggregating probabilities over a greater number of models heightens the signaling power (except for mu=0.5 at the country-level). Second, country-weighted aggregation outperforms the panel-level weighting. Third, the number of models involved in the aggregation tends to rise in 2006 and 2007 when approaching financial turmoil (Figure A1 in the Appendix).

### *6.4 Heatmaps*

The information given by the real-time simulations performed on several values of the mu parameter can be synthetized into a "heatmap" representation, where warmer colors indicate more risky periods. Figure 8 displays the heatmaps obtained from the aggregated probabilities of crisis calculated in real-time according to the four options for the ten EU countries from 2001 to 2008. The heatmap color code is based on the levels and critical thresholds of the composite probabilities of crises obtained in real-time with the four aggregation options. The different colors match the composite probability of crisis being below its threshold for $\mu$ =0.7 and above it for $\mu$ =0.7, 0.6 and 0,5. We consider several different values of $\mu$ because the threshold is always higher for smaller $\mu$, since the policy maker is less worried to miss a crisis. Hence, if a signal is emitted despite the high threshold, this should be more alerting. The colors are defined by the composite probability of crisis being (i) below the threshold for $\mu$ =0.7, the color is green; (ii) above the threshold for $\mu$ =0.7, it is yellow; (iii) above than the threshold for mu=0.6 , it is orange; (iv) above the threshold for mu=0.5 , it is red. These representations are useful for policy makers to quickly identify some rising threats of banking crisis across countries and across time.

According to the heatmaps, both options for aggregating models would have started to emit a signal of crisis from 2005Q1 on, well ahead of the 2008 crisis, in the case of France. They also signal a crisis in most euro area countries from this date. Note that despite facing similar difficulties as the other euro area members, Italy has declared not having had any crisis in 2008. As our dependent variable of pre-crisis is based on central banks' declaration, this statement makes the red signal a wrong one when we assess the performance of our out of sample evaluation. Consequently, this introduces a downward bias in the evaluation.

**Figure 8. Heatmaps indicating the risk of banking crises in the 10 countries, with the two aggregating options, in real-time**



As a variant, we also consider the performances obtained by the models retained in Ω2 with an alternative method. Instead of averaging the probabilities estimated by all the models, we just count the number of models that would have emitted a pre-crisis signal in real-time for each country-level. This voting method adopted by Holopainen and Sarlin (2015) yields mixed results (Figure A2 in the appendix). The number of signals tends to rise before the 2008 crisis for most countries, which is in line with the increasing numbers of models selected in the large set Ω2 at the approach of the crisis (Figure 7). However, the approach that we have retained through aggregating probabilities seems to release more interpretable and clearer results.

## 6. Conclusion

In this paper, we present a monitoring strategy for bank crises, based on early warning properties of indicators. This strategy takes into account numerous risk factors. One main difference with the related literature is that we rely on a large number of models, instead of a single one.

After selecting a set of risk indicators on the basis of their abilities to predict the banking crises in 10 euro area countries, we run all possible logit models combining four of these factors. Once the models have been estimated over the panel of countries, we select two sets of them: a small one following a stringent criterion, restricted to those with all variables significant and with the expected sign, as well as a larger set obtained through relaxed criteria, requiring only three variables in four being significant and with the expected sign. We then proceed with a weighted average of all the probabilities estimated by the different models across the two sets. To do so, we set the models' weights as proportional to their usefulness, which is a measure of their performance at predicting crises. The more useful is a model, the heavier its weight in the aggregated result. As the performance of models can be assessed either at the panel-level or at the country-level, we propose two options for the weighting scheme: one common to all countries, based on the usefulness of the models to predict crises on the whole panel; the other one, country-specific, resulting from the usefulness at the country-level.

Four main features stand out from the paper. First, aggregating a large number of models greatly improves the signaling performance over the sample – the loss function is reduced by 25% on average compared to the best performing model. In addition, averaging models allows us to avoid the unpleasant consequences of models' instability through time. Indeed, our real-time simulations show that the best performing model not only varies over time, it also depends on the policy maker's aversion to miss predicting a crisis, which is an unobserved parameter. On the whole, averaging models enables us to mitigate the uncertainty surrounding any single model.

Second, aggregating numerous models also appears the best strategy for the real-time simulations. Indeed, when we have estimated the models to replicate the policy maker's conditions before the 2008 crisis, we found that no model at all had its four variables significant with the expected signs at that time. Hence, retaining models on the basis of stringent criteria would not have been possible in real-time. Therefore, the only way is to take into account a large number of models selected with relaxed criteria. As a matter of fact, the results obtained using a large set of models are quite satisfying to predict the 2008 crisis at a reasonable horizon in most countries. Accounting for all possible risk factors hence appears as a good strategy in troubled times, when the sources of risk are evolving.

Third, we account for different risk factors across countries by tailoring country-specific weightings when aggregating the models, while we still use all the information at the panel-level to estimate the models. This strategy, mixing pooled and country level, is consistent with both the fact that countries differ in terms of risk factors sensitivity, and that estimation is improved by considering a panel of countries.

Fourth, the approach also enables us to address the issue of risk factors changing over time by allowing for flexible weighing schemes and changing sets of models. Indeed, in the real-time simulations, we continuously update the weightings and the sets of models according to their time-varying performances. This is a valuable property as risk factors are known to vary over time. Overall, once model uncertainty is acknowledged, we rely on a strategy involving the most possible risk factors at each time, while accounting for changes in these risk factors and their weightings over time.

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**Appendix. Table A1. List of indicators tested**

| Indicators | Transformation | Source |
|---|---|---|
| Total credit to non financial private sector [1] | Real – % GDP<br>Real – % GDP – gap to long-term trend<br>Real, y-o-y change - %,<br>Real, 2-y change - %<br>Real, 3-y change - % | BIS |
| Total credit to non financial firms | Real – % GDP<br>Real – % GDP - Gap to long-term trend<br>Real, y-o-y change - %<br>Real, 2-y change - %<br>Real, 3-y change - % | BIS |
| Total credit to households | Real – % GDP<br>Real – % GDP - Gap to long-term trend<br>Real, y-o-y change - %<br>Real, 2-y change - %<br>Real, 3-y change - % | BIS |
| Banking credit to the private sector | Real – % GDP<br>Real – % GDP - Gap to long-term trend<br>Real, y-o-y change - %<br>Real, 2-y change - %<br>Real, 3-y change - % | ECB |
| Loans for house purchases | Real – % GDP<br>Real – % GDP - Gap to long-term trend<br>Real, y-o-y change - %<br>Real, 2-y change - %<br>Real, 3-y change - % | ECB |
| Debt service [2] to income ratio, households and non financial firms | % revenu | ECB |
| Debt service to income ratio, non financial firms | % disposable income | ECB |
| Debt service to income ratio, households | % disposable income | ECB |
| Households' debt | % gross disposable income | ECB |
| GDP | Real, y-o-y change - %<br>Real, 2-y change - %<br>Real, 3-y change - % | ECB |
| Consumer price index | Y-o-y change - %<br>2-y change - %<br>3-y change - % | ECB |
| Monetary aggregate M3 | Real, y-o-y change - %<br>Real, 2-y change - %<br>Real, 3-y change - % | ECB |
| Current account | % GDP | ECB |
| Public Debt | % GDP | ECB |
| Unemployment ratio | % | ECB |
| Long-term government bond yield (*) | Nominal - %<br>Real - % | Bloomberg |
| 3-month money market interest rate (*) | Nominal - %<br>Real - % | ECB |
| Slope of the yield curve (10 Y – 3 M) (*) | b.p. | ECB |
| Real effective exchange rate | Index<br>Index, y-o-y change - %<br>Index, 2-y change - %<br>Index, 3-y change - % | ECB |
| Residential property index | Real, y-o-y change - %<br>Real, 2-y change - %<br>Real, 3-y change - %<br>Gap to long-term trend | OECD |
| Ratio of real estate price to disposable income per head | Index based 100 in 2010<br>Index based 100 at the mean of each country<br>Y-o-y change | OECD |
| Ratio of house price to rents | Y-o-y change | OECD |
| Rent index | Real, y-o-y change - %<br>Real, 2-y change - %<br>Real, 3-y change - % | OECD |
| Stock price index | Real, y-o-y change - %<br>Real, 2-y change - %<br>Real, 3-y change - % | OECD |
| Golden rule (gap of real long term interest rate to real GDP) | b.p. over 1 year<br>b.p. over 2 years<br>b.p. over 3 years | ECB |

(1) The BIS total credit series is extracted from national accounts. It includes all debts of the private non-financial sectors (households and firms) whatever (i) the instrument, loan, bond, securitization. (ii) the type of lender : banks, households, firms (iii) the geographical area : external and domestic debt. The series is expressed as % of GDP – The gap of this series to its long-term trend is the "Basel ratio».

(2) As defined by Drehmann and Juselius (2012) : the DSR reflects the aggregate cost of credit

(*) indicates series with a left-hand side risk.

**Table A 2. List of indicators retained after Step 1 with their performance over the 10-country panel, ranked by decreasing AUROC (1)**

Note (1) *T1* is the percentage of missed crises ; *T2*, the % of false alarms ; C*ond Prob* is the conditional probability of crises once the signal is emitted and *Threshold* the value that minimizes the policy makers's loss function, *Ruse* denotes the relative usefulness of the indicator. (*)

| | Indicator | Threshold | AUROC | T1 | T2 | %Pred | CondProb | Ruse |
|---|---|---|---|---|---|---|---|---|
| 1 | Long-term government bond yield - Nominal - % (*) | 4,1 | 0,82 | 0,21 | 0,06 | 0,79 | 0,59 | 0,73 |
| 2 | Long-term government bond yield - Real - % (*) | 2,5 | 0,75 | 0,24 | 0,22 | 0,76 | 0,28 | 0,54 |
| 3 | Total credit to the private non- financial sector - Real – % GDP | 126,9 | 0,73 | 0,27 | 0,31 | 0,73 | 0,22 | 0,42 |
| 4 | Bank credit to the private non- financial sector - Real – % GDP | 92,9 | 0,71 | 0,47 | 0,11 | 0,53 | 0,36 | 0,42 |
| 5 | Total credit to households - Real – % GDP | 40,6 | 0,7 | 0,22 | 0,42 | 0,78 | 0,21 | 0,36 |
| 6 | Golden rule - 1-y | - 0,3 | 0,68 | 0,26 | 0,32 | 0,74 | 0,21 | 0,42 |
| 7 | 3-month money market interest rate - Nominal - % (*) | 3,2 | 0,68 | 0,35 | 0,2 | 0,65 | 0,28 | 0,45 |
| 8 | Monetary aggregate M3 - Real, 2-y change - % | 11,4 | 0,67 | 0,4 | 0,32 | 0,6 | 0,19 | 0,29 |
| 9 | Monetary aggregate M3 - Real, 1-y change - % | 7,4 | 0,66 | 0,57 | 0,18 | 0,43 | 0,22 | 0,25 |
| 10 | Stock price index - Real, 2-y change - % | 25,1 | 0,66 | 0,2 | 0,39 | 0,8 | 0,2 | 0,4 |
| 11 | Monetary aggregate M3 - Real, 3-y change - % | 13,4 | 0,66 | 0,3 | 0,43 | 0,7 | 0,17 | 0,28 |
| 12 | 3-month money market interest rate - Real - % (*) | 1,1 | 0,66 | 0,43 | 0,19 | 0,57 | 0,27 | 0,38 |
| 13 | Debt service, households and non-financial firms % | 16,1 | 0,65 | 0,27 | 0,43 | 0,73 | 0,17 | 0,3 |
| 14 | Total credit to non-financial firms - Real – % GDP | 87,7 | 0,65 | 0,41 | 0,3 | 0,59 | 0,23 | 0,29 |
| 15 | Debt service, households % | 13,7 | 0,64 | 0,55 | 0,22 | 0,45 | 0,28 | 0,24 |
| 16 | Debt service, non-financial firms % | 28,3 | 0,63 | 0,11 | 0,63 | 0,89 | 0,18 | 0,26 |
| 17 | Total credit to households - Real, 2-y change - % | 11,8 | 0,63 | 0,19 | 0,54 | 0,81 | 0,19 | 0,27 |
| 18 | Stock price index - Real, 3-y change - % | 9,8 | 0,63 | 0,18 | 0,58 | 0,82 | 0,15 | 0,23 |
| 19 | Total credit to households - Real, 1-y change - % | 7,0 | 0,62 | 0,28 | 0,47 | 0,72 | 0,19 | 0,24 |
| 20 | Total credit to the private non- financial sector - Real – % GDP - Gap to long-term trend | 6,0 | 0,62 | 0,42 | 0,35 | 0,58 | 0,17 | 0,23 |
| 21 | Bank credit to the private non-financial sector - Real – % GDP - Gap to long-term trend | 5,0 | 0,62 | 0,5 | 0,27 | 0,5 | 0,18 | 0,23 |
| 22 | Rattio of house price index to disposable income per head – 1-y change | 6,5 | 0,6 | 0,63 | 0,13 | 0,38 | 0,28 | 0,24 |
| 23 | Total credit to households - Real, 3-y change - % | 16,9 | 0,6 | 0,18 | 0,56 | 0,82 | 0,18 | 0,26 |
| 24 | Residential property price index - Gap to long-term trend | 17,2 | 0,6 | 0,65 | 0,06 | 0,35 | 0,44 | 0,29 |
| 25 | Golden rule - 2-y | 1,2 | 0,6 | 0,26 | 0,49 | 0,74 | 0,14 | 0,25 |
| 26 | Ratio of house prices to rent prices – 1-y change - % | 8,3 | 0,59 | 0,64 | 0,13 | 0,36 | 0,28 | 0,23 |
| 27 | Banking credit to the private non fiance, Real, 1-y change | 14,0 | 0,59 | 0,74 | 0,06 | 0,26 | 0,34 | 0,2 |
| 28 | Stock price index - Real, 1-y change - % | 6,2 | 0,59 | 0,18 | 0,54 | 0,82 | 0,16 | 0,28 |
| 29 | Stock price index - Real, 2-y change - % | 15,6 | 0,58 | 0,58 | 0,15 | 0,42 | 0,27 | 0,27 |
| 30 | Slope of yield curve (10Y-3M) b.p. (*) | 1,3 | 0,58 | 0,14 | 0,52 | 0,86 | 0,16 | 0,34 |
| 31 | Residential property price index - 1-y change % | 8,4 | 0,57 | 0,66 | 0,15 | 0,34 | 0,23 | 0,19 |
| 32 | Loans to for house purchase - Real, 1-y change - % | 9,8 | 0,56 | 0,36 | 0,48 | 0,64 | 0,14 | 0,16 |
| 33 | Bank credit to the private non fiancial sector, Real, 2-y change | 28,5 | 0,56 | 0,76 | 0,07 | 0,24 | 0,3 | 0,17 |
| 34 | Loans to for house purchase - Real, 2-y change - % | 21,5 | 0,56 | 0,4 | 0,45 | 0,6 | 0,14 | 0,15 |
| 35 | Residential property price index - 3-y change - % | 21,9 | 0,56 | 0,57 | 0,19 | 0,43 | 0,24 | 0,24 |
| 36 | Total credit to the private non-financial sector - Real – % GDP – 1-y change | 13,1 | 0,55 | 0,77 | 0,06 | 0,23 | 0,32 | 0,17 |
| 37 | Loans to for house purchase - Real, 3-y change - % | 31,7 | 0,54 | 0,4 | 0,48 | 0,6 | 0,13 | 0,12 |
| 38 | Total credit to non -financial firms - Real, variation 1 an - % | 2,4 | 0,53 | 0,24 | 0,67 | 0,76 | 0,15 | 0,09 |
| 39 | Golden rule - 3-y | 2,9 | 0,53 | 0,25 | 0,59 | 0,75 | 0,13 | 0,16 |
| 40 | Effective exchange rate- Real - Real, 2-y change - % | - 2,3 | 0,52 | 0,06 | 0,7 | 0,94 | 0,13 | 0,23 |
| 41 | GDP - Real, 1-y change - % | 2,3 | 0,51 | 0,32 | 0,61 | 0,68 | 0,12 | 0,07 |
| 42 | Banking credit to the private non fiancial sector, Real, 3-y change | 39,4 | 0,51 | 0,73 | 0,09 | 0,27 | 0,27 | 0,18 |
| 43 | Total credit to non-financial firms - Real – % GDP - Gap to long-term trend | 1,5 | 0,51 | 0,38 | 0,52 | 0,63 | 0,15 | 0,11 |
| 44 | Total credit to the private non financial sector - Real, 2-y change - % | 24,1 | 0,5 | 0,81 | 0,08 | 0,19 | 0,23 | 0,11 |

indicates left-tail risk.

Categories of variables are indicated by the following colors:

| Rates | Credit | Markets | Real estate | Macro |
|---|---|---|---|---|

**Table A 3 : List of indicators retained after Steps 1 and 2, with their performance for France, ranked by usefulness**

| | Indicator | Treshold | AurocPanel | T1 | %Pred | T2 | CondPr | Relative Usefulness |
|---|---|---|---|---|---|---|---|---|
| 1 | Monetary aggregate M3 - Real, 3-y change - % | 13,37 | 0,66 | 0,13 | 0,88 | 0,35 | 0,4 | 0,53 |
| 2 | Total credit to the private non financial sector - Real – % GDP - Gap to long-term trend | 6,03 | 0,62 | 0,25 | 0,75 | 0,22 | 0,48 | 0,53 |
| 3 | Total credit to households - Real – % GDP | 40,64 | 0,7 | 0,5 | 0,5 | 0 | 1 | 0,5 |
| 4 | Slope of yield curve (10Y-3M) b.p. (*) | 1,28 | 0,58 | 0,06 | 0,94 | 0,45 | 0,36 | 0,49 |
| 5 | Total credit to the private non-financial sector - Real – % GDP | 126,9 | 0,73 | 0,5 | 0,5 | 0,02 | 0,89 | 0,48 |
| 6 | Debt service, non-financial firms % | 28,31 | 0,63 | 0 | 1 | 0,52 | 0,34 | 0,48 |
| 7 | Residential property price index - Gap to long-term trend | 17,21 | 0,6 | 0,5 | 0,5 | 0,02 | 0,89 | 0,48 |
| 8 | Debt service, households and non-financial firms % | 16,12 | 0,65 | 0,5 | 0,5 | 0,03 | 0,8 | 0,47 |
| 9 | Loans to for house purchase - Real, 1-y change - % | 9,84 | 0,56 | 0,5 | 0,5 | 0,05 | 0,73 | 0,45 |
| 10 | Long-term government bond yield - Nominal % (*) | 4,07 | 0,82 | 0,5 | 0,5 | 0,05 | 0,73 | 0,45 |
| 11 | Loans to for house purchase - Real, 2-y change - % | 21,53 | 0,56 | 0,56 | 0,44 | 0 | 1 | 0,44 |
| 12 | Total credit to households - Real, 3-y change - % | 16,89 | 0,6 | 0,19 | 0,81 | 0,4 | 0,35 | 0,41 |
| 13 | Total credit to non-financial firms - Real – % GDP - Gap to long-term trend | 1,47 | 0,51 | 0,06 | 0,94 | 0,53 | 0,32 | 0,4 |
| 14 | Ratio of house prices to rent prices – nominal- 1-y change - % | 8,34 | 0,59 | 0,5 | 0,5 | 0,12 | 0,53 | 0,38 |
| 15 | Loans to for house purchase - Real, 3-y change - % | 31,68 | 0,54 | 0,63 | 0,38 | 0 | 1 | 0,38 |
| 16 | Residential property price index - 2-y change - % | 15,61 | 0,58 | 0,5 | 0,5 | 0,12 | 0,53 | 0,38 |
| 17 | Golden rule – 1-y | -0,25 | 0,68 | 0,5 | 0,5 | 0,12 | 0,53 | 0,38 |
| 18 | Total credit to non financial firms - Real – % GDP | 87,67 | 0,65 | 0,56 | 0,44 | 0,07 | 0,64 | 0,37 |
| 19 | Ratio of house prices to disposable income per head – nominal- 1-y change | 6,5 | 0,6 | 0,5 | 0,5 | 0,13 | 0,5 | 0,37 |
| 20 | Residential property price index - 3-y change - % | 21,85 | 0,56 | 0,5 | 0,5 | 0,13 | 0,5 | 0,37 |
| 21 | Residential property price index - 1-y change - % | 8,39 | 0,57 | 0,5 | 0,5 | 0,13 | 0,5 | 0,37 |
| 22 | Long-term government bond yield - Real - % (*) | 2,5 | 0,75 | 0,5 | 0,5 | 0,15 | 0,47 | 0,35 |
| 23 | Total credit to non -financial firms - Real, variation 1 an - % | 2,37 | 0,53 | 0 | 1 | 0,67 | 0,29 | 0,33 |
| 24 | Monetary aggregate M3 - Real, 2-y change - % | 11,35 | 0,67 | 0,44 | 0,56 | 0,23 | 0,39 | 0,33 |
| 25 | Total credit to households - Real, 2-y change - % | 11,84 | 0,63 | 0,31 | 0,69 | 0,37 | 0,33 | 0,32 |
| 26 | Monetary aggregate M3 - Real, 1-y change- % | 7,42 | 0,66 | 0,69 | 0,31 | 0 | 1 | 0,31 |
| 27 | Total credit to households - Real, 1-y change - % | 6,98 | 0,62 | 0,5 | 0,5 | 0,25 | 0,35 | 0,25 |
| 28 | Banking credit to the private non financial sector - Real – % GDP - Gap to long-term trend | 5,02 | 0,62 | 0,69 | 0,31 | 0,07 | 0,56 | 0,25 |
| 29 | 3-month money market interest rate - Nominal - % (*) | 3,23 | 0,68 | 0,56 | 0,44 | 0,2 | 0,37 | 0,24 |
| 30 | 3-month money market interest rate - Real - % (*) | 1,06 | 0,66 | 0,63 | 0,38 | 0,15 | 0,4 | 0,22 |
| 31 | Golden rule - 3-y | 2,85 | 0,53 | 0,38 | 0,63 | 0,47 | 0,26 | 0,16 |
| 32 | Golden rule -2-y | 1,15 | 0,6 | 0,5 | 0,5 | 0,38 | 0,26 | 0,12 |

**Table A 4 : The 6 logit models selected with stringent criteria, in-sample**

| | Logit1 | Logit2 | Logit3 | Logit4 | Logit5 | Logit6 | Rate of appearance in selected models |
|---|---|---|---|---|---|---|---|
| GAP400_CB2GDP | 0.0015<br>*0.013* | 0.035<br>*0.014* | 0.031<br>*0.014* | 0.036<br>*0.015* | 0.034<br>*0.016* | 0.044<br>*0.013* | 100% (by construction) |
| D12_EQPR | 0.007<br>*0.0016* | 0.0044<br>*0.0015* | 0.005<br>*0.0015* | 0.0044<br>*0.0014* | 0.0038<br>*0.0015* | 0.004<br>*0.0014* | 100% |
| SLOPE | | 0.264<br>*0.07* | 0.174<br>*0.060* | 0.226<br>*0.069* | 0.178<br>*0.066* | 0.149<br>*0.069* | 83% |
| D4_RREP2INC | 0.081<br>*0.019* | 0.068<br>*0.023* | | | | | 33% |
| DSR | 0.191<br>*0.044* | | | | | | 17% |
| GAP400_RREPR | | | 0.032<br>*0.016* | | | | 17% |
| D4_RREP2RENT | | | | 0.029<br>*0.012* | | | 17% |
| GOLDEN1 | | | | | 0.091<br>*0.041* | | 17% |
| D4_M3R | | | | | | 0.041<br>*0.018* | 17% |

Note: logit 1 is the benchmark model in line with Detken et al. (2014), i.e. a model automatically selected in the selection process, even with non significant coefficients. The figures below the coefficients are the standard errors. GAP400_CB2GDP = Bank credit gap to GDP against the trend obtained with a hp filter 400 000; slope = yield curve slope 3M 10Y multiplied by (-1); D12_EQPR is 3-year growth of equity prices; D4_RREP2INC = yoy residential real estate price to disposable income; DSR = debt service ratio à la Drehmann et Juselius (2012); GAP400_RREPR = residential real estate prices gap against the trend obtained with hp filter 400 000; D4_RREP2rent = yoy residential real estate price to rent; GOLDEN1 = golden rule as real yoy GDP vs real 10-year yield; D4_M3R is yoy growth of M3.

**Table A5. Out-of-sample results for the aggregated models in the set $\Omega_2$, percentage of missed crises (T1), false alarms (T2) and loss function (L) depending on the weighting scheme and the $\mu$ =parameter, real-time simulations**

| Weightings schemes : models' usefulness calculated at | *μ= 0.5* | | | *μ*= 0.6 | | | *μ= 0.7* | | |
|---|---|---|---|---|---|---|---|---|---|
| | T1 | T2 | *L* | T1 | T2 | *L* | T1 | T2 | *L* |
| Panel -level | 0.44 | 0.39 | 0,42 | 0.20 | 0.42 | 0.290 | 0.06 | 0.46 | 0,186 |
| Country-level | 0.64 | 0.28 | 0,46 | 0.35 | 0.33 | 0,34 | 0.03 | 0.46 | 0,162 |

**Table A6. Out-of-sample results for the aggregated models, percentage of missed crises (T1), false alarms (T2) and loss function (L) depending on the weighting scheme with the set of models $\Omega_2$ , for alternative aggregated thresholds (1), real-time simulations**

| Options for the weightings scheme: models' usefulness calculated at | *μ= 0.5* | | | *μ=* 0.6 | | | *μ= 0.7* | | |
|---|---|---|---|---|---|---|---|---|---|
| | T1 | T2 | *L* | T1 | T2 | *L* | T1 | T2 | L |
| Panel -level | 0.47 | 0.49 | *0,48* | 0.37 | 0.60 | *0,46* | 0.33 | 0.66 | *0,43* |
| Country-level | 0.57 | 0.51 | *0,54* | 0.40 | 0.55 | 0.46 | 0,35 | 0.63 | *0,43* |

Notes. See Table 10.

**Table A7: Alternative measure of crisis periods (ESRB)**

| Country | Crisis periods | | |
|---|---|---|---|
| Austria | no | Italy | 1994Q1- 1995Q4 |
| Belgium | no | Netherlands | 2002Q2-2003Q4 |
| Finland | 1991Q1-1992Q4 | | 2008Q3- 2010Q4 |
| France | 1993Q3- 1995Q3 | Portugal | 1999Q1- 200Q1 |
| | 2008Q3- 2010Q4 | | 2008Q4- 2010Q4 |
| Germany | 2000Q1-2003Q4 | Spain | 1978Q1-1982Q3 |
| Ireland | 2008Q3- 2010Q4 | | 2009Q2- 2010Q4 |

**Table A8. In-sample results, percentage of missed crises (T1), false alarms (T2) and loss function (L) for the four options, depending on preference parameter μ, in sample with an alternative dummy crisis**

| Weightings schemes : models' usefulness calculated at | *μ= 0.5* | | | *μ=* 0.6 | | | *μ= 0.7* | | |
|---|---|---|---|---|---|---|---|---|---|
| | T1 | T2 | *L* | T1 | T2 | *L* | T1 | T2 | *L* |
| *Aggregation over a small set of models Ω1 (*)* | | | | | | | | | |
| Panel -level | 0.47 | 0.06 | 0,272 | 0.17 | 0.43 | 0.275 | 0.00 | 0.73 | 0,220 |
| Country-level | 0.03 | 0.46 | 0,247 | 0.01 | 0.57 | 0,236 | 0.00 | 0.60 | 0,181 |
| *Aggregation over a large set of models Ω2 (**)* | | | | | | | | | |
| Panel -level | 0.14 | 0.36 | 0,249 | 0.14 | 0.35 | 0.225 | 0.00 | 0.58 | 0,176 |
| Country-level | 0.11 | 0.29 | 0,202 | 0.04 | 0.38 | 0,178 | 0.00 | 0.49 | 0,148 |

(*) selected through stringent criteria (25 models); (**) selected through relaxed selection criteria (524 models).

**Table A9. Out-of sample results, percentage of missed crises (T1), false alarms (T2) and loss function (L), depending on preference parameter $\mu$, with an alternative dummy crisis**

| Weightings schemes : models' usefulness calculated at | *$\mu$= 0.5* | | | $\mu$= 0.6 | | | *$\mu$= 0.7* | | |
|---|---|---|---|---|---|---|---|---|---|
| | T1 | T2 | *L* | T1 | T2 | *L* | T1 | T2 | *L* |
| *Aggregation over a small set of models Ω1 (*)* | | | | | | | | | |
| Panel -level | 0.05 | 0.58 | 0.318 | 0 | 0.68 | 0.270 | 0 | 0.77 | 0.232 |
| Country-level | 0.00 | 0.44 | 0.220 | 0 | 0.62 | 0.247 | 0 | 0.69 | 0.209 |
| *Aggregation over a large set of models Ω2 (**)* | | | | | | | | | |
| Panel -level | 0 | 0.60 | 0.303 | 0 | 0.64 | 0.254 | 0 | 0.67 | 0.202 |
| Country-level | 0.10 | 0.47 | 0.285 | 0 | 0.57 | 0.227 | 0 | 0.64 | 0.194 |

Notes. (*) selected through stringent criteria; (**) selected through relaxed selection criteria.

**Figure A1. Number of selected models in $\Omega_2$ according to the crisis dummy variable**

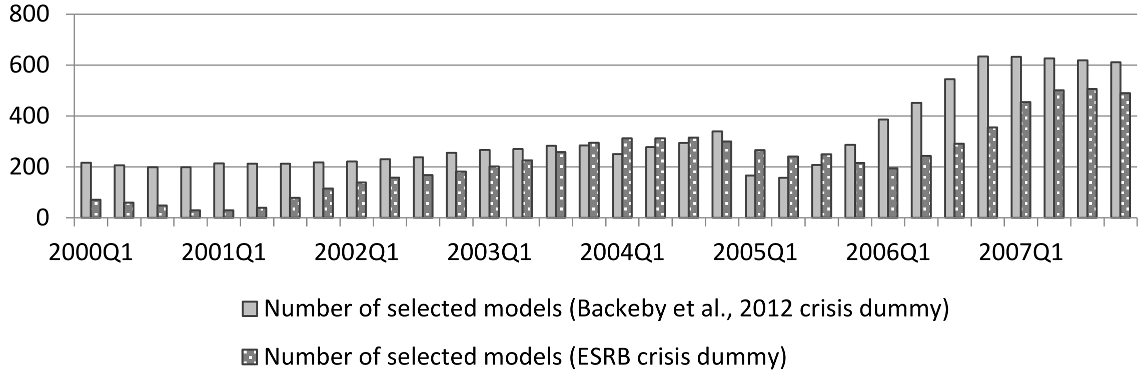
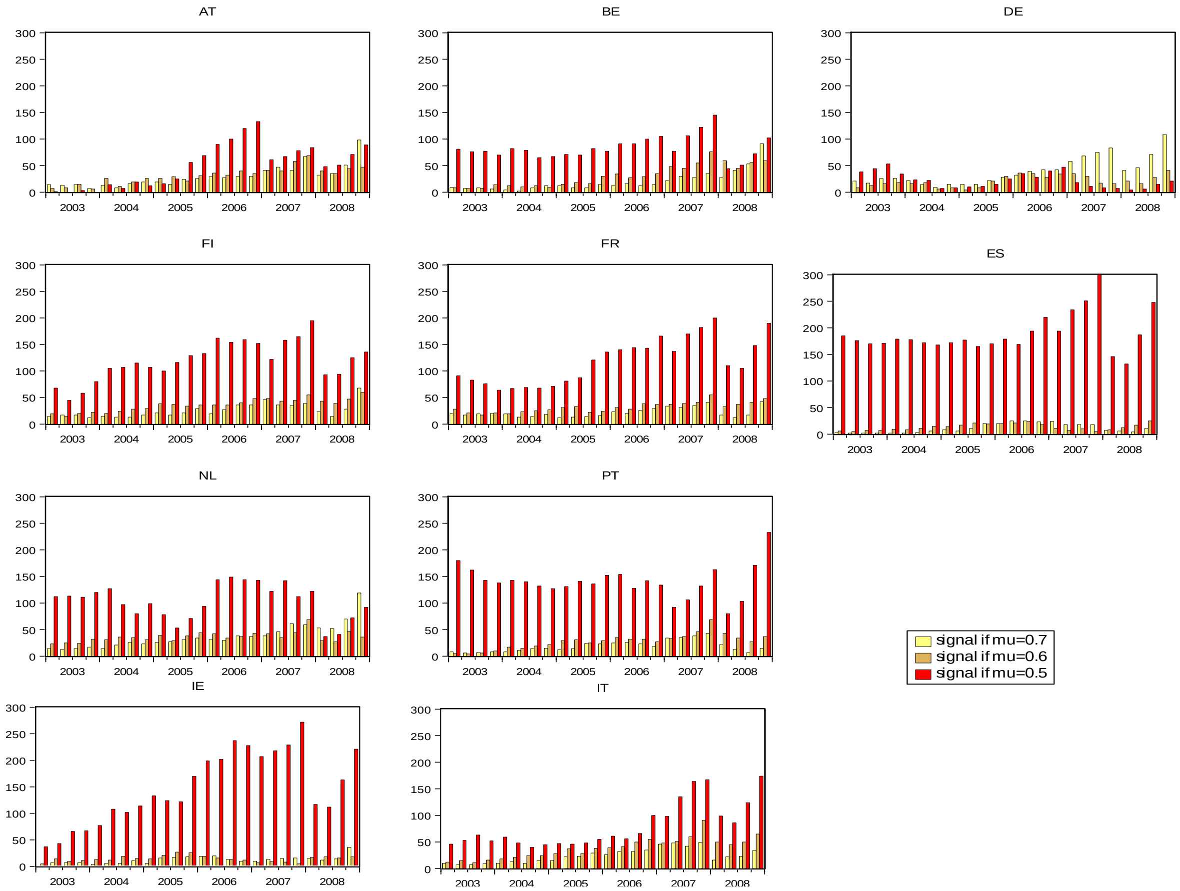



**Figure A 2 . Number of signals emitted by the selected models in $\Omega_2$ according to different preference parameters (in real-time)**



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