Setting Countercyclical Capital Buffers based on Early Warning Models: Would it Work?

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ABSTRACT

As a response to recent financial crises, the Basel III / CRD IV regulatory frameworks implement countercyclical capital buffers (CCB) in order to increase the resilience of the banking sector to absorb shocks arising from financial and economic stress. In this context, this paper seeks to assess the usefulness of private credit variables and other macro-financial and banking sector indicators in guiding the setting of the CCB in a multivariate early warning model framework, using data for 23 EU Members States covering 1982Q2-2012Q3. We find that in addition to credit variables, other domestic and global financial factors such as equity and house prices as well as banking sector variables help to predict vulnerable states of the economy in EU Member States. The models that we analyse demonstrate good out-of-sample predictive power, e.g. signalling the Swedish and Finnish banking crises of the early 1990s at least 6 quarters in advance. We therefore suggest that policy makers take a broad approach in their analytical models supporting CCB policy measures. Finally, a simple *ceteris paribus* simulation analysis reveals that in order to effectively reduce the probability of banking crises for the historical examples considered, the CCB should have been set at the upper end or even above the 0-2.5 % range specified in the CRD IV.

Keywords: Basel III; CRD IV; countercyclical capital buffer; financial regulation; banking crises; early warning model

JEL Classification: G01, G21, G28

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Non-technical summary

The countercyclical capital buffer (CCB), a policy instrument proposed by the Basel III and the EU Capital Requirements Directive (CRD IV) as a response to the recent financial crisis, aims at increasing the resilience of the banking system in times of financial crisis by ensuring that banks set aside capital when credit growth is strong and allowing them to use this capital in periods of financial stress. Motivated by the discussion in the literature on the appropriate methodology for setting the CCB, this paper assesses credit and various other macro-financial variables in predicting banking system vulnerabilities preceding systemic banking crises on a sample of 23 EU Member States across a period from 1982Q2 to 2012Q3.

This paper contributes to the literature in three ways. First, it is the first paper to apply the most recent early warning modelling techniques for the use of setting the CCB, calibrating models to predict a vulnerable state of the financial system which could lead to a systemic banking crisis. Second, the paper applies the latest (and most complete) database on credit and evaluates the importance of this variable, which plays a central role in the CCB legislation, in both uni- and multivariate settings predicting financial vulnerabilities. Third, it presents a simple model simulation in order to see if an activation of the CCB (effectively increasing banking sector capitalisation) prior to the latest financial crisis would have achieved the goal of increasing resilience and reducing the predicted probability of future banking crises.

The paper finds that among domestic credit variables, indeed, the credit-to-GDP gap performs as the best early warning indicator. Interestingly, however, global credit variables seem to outperform domestic credit variables. In particular, global credit growth and the global credit-to-GDP gap provide strong early warning signals both as single variables in a non-parametric signalling approach and through consistent and significant effects in multivariate logit models. It is important to keep in mind, however, that the strong predictive abilities of the global variables are subject to a caveat related to the evaluation period that includes the global financial crisis, where there is a strong clustering of crisis episodes across

countries.

In addition to the salience of credit variables, the paper finds that other macro-financial variables such as domestic house price growth and global equity price growth can be positively associated with future banking crises. Moreover, the paper presents evidence that a high level of banking sector capitalisation decreases the probability of entering a state of financial vulnerability. This result is supported by a simple *ceteris paribus* simulation analysis, which reveals that in order to effectively reduce the probability of banking crises for the historical examples considered, the CCB should have been set at the upper end or even above the 0-2.5 % range specified in the CRD IV. Thus, our results suggest that even though credit variables are very important in predicting future financial instability, there is good reason for policy makers and researchers to take a broad empirical approach by incorporating also other macro-financial variables in such analyses.

1. Introduction

Being faced with the longest and most severe financial crisis in decades, policy makers around the globe have actively searched for policy tools which could help to prevent or at least reduce the intensity of future financial crises. A tool that is an integral part of the Basel III regulations and the EU Capital Requirements Directive (CRD IV) is the countercyclical capital buffer (CCB), which has been proposed by the Basel Committee on Banking Supervision (BCBS) at the Bank of International Settlements (BIS).

According to the CRD IV, the countercyclical capital buffer would be introduced in times of *"aggregate growth in credit [...] associated with a build-up of systemic risk, and drawn down during stressed periods."* (EU [19]). In this way, the CCB aims to increase the resilience of the banking system in case of a financial crisis. In order to promote international consistency in setting countercyclical capital buffer rates, the BCBS has developed a methodology based on the ratio of aggregate credit to GDP (Basel Committee on Banking Supervision [5]). The CRD IV, while acknowledging the importance of credit growth and the credit-to-GDP ratio, specifies that buffer rates should also account for *"other variables relevant to the risks to financial stability."* (EU [19]).[1] This provides the motivation for this paper: We assess the usefulness of credit and other macro-financial variables for the prediction of banking sector vulnerabilities in a multivariate framework, hence enabling a more informed decision on the setting of CCB rates.

The BCBS guidelines are based on an analysis that uses a sample of 26 countries from all over the world, for which the credit-to-GDP gap (defined as the deviation of the credit-to-GDP ratio from its long-term trend) performs as the best single indicator in terms of signalling a coming financial crisis. However, from the evidence presented by the BCBS it is not clear whether the credit-to-GDP gap provides a warning signal that is early enough to account for the 12 month implementation period for raising the capital buffers specified

[1] In particular, the CRD IV specifies that the deviation of the credit-to-GDP ratio from its long-term trend should serve as *"a common starting point for decisions on buffer rates by the relevant national authorities, but should not give rise to an automatic buffer setting or bind the designated authority. The buffer shall reflect, in a meaningful way, the credit cycle and the risks due to excess credit growth in the Member State and shall duly take into account specificities of the national economy."* (EU [19]).

in the CRD IV regulation.[2] In other words, the credit gap may be an early warning indicator that is not early enough for policy implementation purposes. Moreover, the guidelines (or the work by Drehmann et al. [17] on which the guidelines are based) do not directly compare the predictive power of the credit-to-GDP gap to that of other potentially relevant variables related to risks to financial stability (as stated in the CRD IV) in a *multivariate framework*. Acknowledging the potentially very large implications that this policy has for the international banking sector, our paper aims to address these non-trivial omissions.

This paper contributes to the literature in the following ways. First, we apply state-of-the-art modelling techniques from the early warning system (EWS) literature to see whether they could be useful for decisions on countercyclical capital buffers in EU countries. In line with the forthcoming legislation for the CCB, the models are calibrated so that they aim to predict a vulnerable state of the economy (or banking sector), i.e. a build-up of system-wide risk that, with a suitable trigger, could turn into a banking crisis. In practice, we analyse the out-of-sample predictive abilities of a variety of models for those states of the economy that have preceded earlier banking crises by twelve to seven quarters. This would, hopefully, allow a timely build-up of the CCB. The analysis is conducted in a multivariate logit model framework using data for 23 EU Member States spanning over 1982Q2-2012Q3, where we complement the credit variables with several domestic macro-financial and banking sector variables, and following e.g. Frankel and Rose [20] and Lo Duca and Peltonen [30], also include global variables in our models in order to account for potential spillover effects. In a similar fashion as Alessi and Detken [2], Lo Duca and Peltonen [30] and Sarlin [36], the models are evaluated using a framework that takes into account a policy maker's preferences between type I (missing a crisis) and type II errors (false alarms of crises). Moreover, the paper focuses exclusively on EU countries, including the largest possible sample (limited by data availability) instead of focusing on a few large economies as is common in the

[2] According to Article 126(6) of the CRD IV, *"when a designated authority sets the countercyclical buffer rate above zero for the first time, or when thereafter a designated authority increases the prevailing countercyclical buffer rate setting, it shall also decide the date from which the institutions must apply that increased buffer for the purposes of calculating their institution specific countercyclical capital buffer. That date may be no later than 12 months after the date when the increased buffer setting is announced [in accordance with paragraph 8]. If the date is less than 12 months after the increased buffer setting is announced, that shorter deadline for application shall be justified by exceptional circumstances"*.

literature.

Second, given the importance of the credit variables in the CRD IV regulatory framework, we use the same BIS database on credit as the BCBS and evaluate their salience in predicting vulnerable states of the economy, both in univariate and multivariate frameworks. Hence, we build on the work of Drehmann et al. [17], who use a univariate signal extraction methodology (see also Kaminsky et al. [22]) to find that the credit-to-GDP gap provides the best early warning signals for the build-up of capital buffers. Third, we analyse with a simple model simulation whether an activation of the CCB prior to the 2007/08 crises in our sample countries would have achieved its goal, i.e. whether it would have increased the resilience of the EU banking systems and reduced the predicted probabilities of countries being in vulnerable states. The analysis is conducted in a ceteris paribus fashion, meaning that it demonstrates the pure effect of higher levels of capital without accounting for potential effects of a CCB introduction on the other independent variabes. Finally, we employ different definitions of banking crises (Babecky et al. [3]; Laeven and Valencia [26, 28]; Reinhart and Rogoff [33, 34]) as well as several other variations of the analysis to assess the robustness of the main results.

The main findings of the paper are the following. First, we find that global variables and especially global credit variables are strong predictors of macro-financial vulnerability, providing good signals when used as single variables and demonstrating consistent and significant effects in multivariate logit models. Domestic credit-to-GDP also affects the probability of being in a vulnerable state, even though the effect is clearly smaller than that of global credit variables. However, despite the importance of credit variables, we also find evidence suggesting that other variables play a salient role in predicting vulnerable states of the economy. For example, domestic house price growth and global equity growth are positively associated with macro-financial vulnerabilities. Moreover, we find that banking sector variables exert significant effects: strong banking sector profitability may incur excessive risk-taking leading to increased vulnerability, while a high banking sector capitalisation decreases the probability of entering a vulnerable state—a result also confirmed by the simulation analysis. This result is potentially important for policy makers (especially those involved in setting the CCB), as it reinforces the notion that higher CCB rates and bank capital ratios overall reduce the likelihood of financial vulnerability. As such, our findings suggest that even though credit variables are near-essential in early warning models, other macro-financial and banking sector variables are important covariates to control for and to improve the predictive power of these models. Moreover, as a validation of our analysis, we find a good out-of-sample performance of the models in predicting the vulnerable states preceding the financial crises in Finland and Sweden in the early 1990s as well as those in Italy and the U.K. in the mid-1990s. Finally, a simple *ceteris paribus* simulation analysis of the model reveals that in order to effectively reduce the probability of banking crises for the historical examples considered, the CCB should have been set at the upper end or even above the 0-2.5 % range specified in the CRD IV.

The remainder of the paper is organised as follows. Section 2 provides an overview of the literature on early warning models and countercyclical capital buffers. We present our data set in Section 3 and introduce the methodology in Section 4. Estimation results and robustness analysis are presented in Section 5, while Section 6 provides a simple model simulation for the usefulness of CCBs in reducing banking sector vulnerabilities. Our concluding remarks are reserved to Section 7.

2. Related literature

This paper seeks to tie into at least two strands of the literature, namely the early warning literature and the recent debate that has emerged on the CCB. Regarding the former, we build on the methodology of Frankel and Rose [20] who studied the determinants of currency crises by means of a multivariate probit model and that of Demirgüç-Kunt and Detragiache [14] who provide a multivariate logit model to assess the probability of a banking crisis. Both papers have made considerable contributions to the early warning literature, despite sharing the same limitations, namely the lack of an evaluation framework to issue early warning signals and the use of annual data which makes these models less precise. Kaminsky et al. [22] introduce an evaluation framework by means of a so-called ‘signalling approach' in which explanatory variables signal the likelihood of an imminent crisis when they exceed a particular threshold. Yet, their study is restricted to an evaluation of single variables and does not provide a multivariate framework either in the analysis or in the evaluation. Berg et al. [6] argue convincingly that early warning models should be evaluated on their out-of-sample predictive power rather than their in-sample performance. They find that long-horizon (time-series) models are superior in this regard.

Alessi and Detken [2] tackle some of the shortcomings of the previous literature in expanding the methodology by Kaminsky et al. [22] by adding the notion of a policy maker's preference with regard to his/her risk aversion between type I and type II errors. They find that global measures of liquidity, in particular the global private credit gap, have the best out-of-sample performance in predicting costly asset price booms (which tend to precede banking crises). Building on this work, Lo Duca and Peltonen [30] provide a broad multivariate framework which includes domestic and global macro-financial variables and apply an extensive evaluation approach which includes out-of-sample predictions and calculations of optimal early warning thresholds. In line with Alessi and Detken [2], they find that global credit and equity variables improve the predictive power of early warning models. Yet, their paper differs from our approach in several important aspects. First, they use a rather different (and arguably less conservative) method to identify events of systemic stress, one that is not based on actual banking crises and therefore captures a different distribution of events. Second, they use a shorter time series for a different (and for our purposes, smaller) cross section of countries. For example, in their analysis they do not differentiate between euro area countries, instead treating them as a single unit. Finally, they do not include banking sector variables into their specification, which we do and for which we find significant effects.

The debate on the CCB in the literature relates to a considerable extent to a discussion on variable selection, where the importance of domestic credit variables in models prescribing when banks need to set aside capital in times of fast credit expansion is the main bone of contention. Drehmann et al. [17] analyse the signalling performance of various credit-related and other macro-financial variables in predicting systemic banking crises. Using a single-variable signalling approach (similar to Kaminsky et al. [22]), they find that the credit-to-GDP gap (using a backward-looking trend as suggested by the BCBS) is the superior predictor over a 3-year time horizon, suggesting that this variable is the most credible signal for policy makers who decide on setting the CCB. Still, focusing solely on the credit-to-GDP gap, as advocated by the Basel Committee on Banking Supervision (BCBS) in their 2010 proposal regarding the CCB (Basel Committee on Banking Supervision [5]), may incur risk as such gap measures are sensitive to the exact specification of the trending variable. For example, Edge and Meisenzahl [18] show that for the U.S., revisions to the credit-to-GDP ratio gap are "sizeable and [...] on the same order of magnitude of the gap itself. [...] The main source of the revision stems not from revised estimates of the underlying data but rather from the unreliability of end-of-sample estimates of the trend credit-to-GDP ratio." In other words, using real-time data may lead to policies that are incorrect and potentially costly in hindsight. The authors note that if the CCB would have been put in place in the U.S. in line with the BCBS proposal, it would have amplified an economic downturn in two instances in the early 2000s. Repullo and Saurina [35] reach a similar conclusion, by observing that the credit-to-GDP gap correlates negatively with GDP growth, implying that under the CCB proposal banks would have to set aside capital when GDP growth is negative. Moreover, Coffinet et al. [11] find that capital buffers have a negative effect on loan growth, suggesting that they may reduce the credit supply following a severe recessionary shock. Seidler and Gersl [39] show that the methodology for calculating the credit gap is not appropriate for countries in Central and Eastern Europe as these countries have experienced rapid credit expansion as part of a convergence to credit levels which are normal in advanced economies. Kauko [25] suggests an alternative methodology to operationalise excessive credit growth, namely by either differencing the credit stock or by taking the moving average of output. Barrell et al. [4] find evidence that in addition to credit growth, bank capital ratios and property price growth significantly affect the probability of banking crises in OECD countries. Unlike most of the literature, domestic credit growth actually reduces the probability of banking crises in their model. This rather surprising effect could be explained by omitted variable bias (the model does not account for global variables or domestic credit-to-GDP) or the fact that their model uses annual data only. Nevertheless, it further supports the main point of developing a broader empirical model which encompasses several macro-financial variables. As such, we feel encouraged to take a broader approach to analysing macro-financial vulnerabilities by including other potentially important factors into our study.

3. Data

This section introduces the data used for our study. We begin with the identification of vulnerable states, i.e. the dependent variable in the study, based on banking crises in the European Union. We then proceed by introducing the independent variables used in the empirical analysis. Finally, we present some descriptive statistics on the development of key variables around banking sector crises in the sample countries.

3.1. Definition of vulnerable states

The paper develops an early warning model that attempts to predict a vulnerable state of the economy from which a banking crisis could emerge given a suitable trigger. Thus, we are not trying to predict banking crises per se, even though we need to identify these crises in order to determine the vulnerable states. Specifically, we define the vulnerable states as the period between twelve and seven quarters before the onset of a banking crisis. The time horizon accounts for the announcement period of twelve months that is specified in the CRD IV (EU [19], Art. 126(6)) as well as for a time lag required to impose such policies. At the same time, extending the horizon too far into the past may weaken the link between observed variation in the independent variables and the onset of banking crises. To analyse this, we provide a number of alternative time horizons in the robustness section.

In order to identify banking crises, we use the dataset which has been compiled by Babecky et al. [3] as part of a data collection exercise by the European System of Central Banks (ESCB) Heads of Research Group (labeled as HoR database hereafter). This database consists of a quarterly database of banking crises in the EU countries between 1970Q1 and

2012Q4.[3] The crisis occurrence index takes a value of 1 when a banking crisis occurred in a given quarter (and a value of 0 when no crisis occurred). The HoR database aggregates information about banking crisis occurrence from "several influential papers", including (in alphabetical order): Caprio and Klingebiel [10]; Detragiache and Spilimbergo [15]; Kaminsky [23]; Kaminsky and Reinhart [24]; Laeven and Valencia [26, 27, 28]; Reinhart and Rogoff [33, 34]; and Yeyati and Panizza [40]. The crisis occurrence indices from these papers have subsequently been cross-checked with the ESCB Heads of Research before inclusion into the database. A list of the banking crisis dates for our sample countries based on this dataset is provided in Panel A of Table 1. In the robustness section, we test the robustness of the results by regressing the benchmark model on banking crisis data provided by Laeven and Valencia [28] and Reinhart and Rogoff [34].

As such, we define the dependent variable to be equal to 1 between (and including) twelve to seven quarters prior to a banking crisis as identified by the ESCB HoR database and 0 for all other quarters in the data. In order to overcome crisis and post-crisis bias (see e.g. Bussière and Fratzscher [8]), we omit all country quarters which either witnessed a banking crisis or which fall within six quarters after a banking crisis.

3.2. Macro-financial and banking sector variables

The panel dataset used in the analysis contains quarterly macro-financial and banking sector data spanning over 1982Q2-2012Q3 for 23 EU member states. The data is sourced through Haver Analytics and originally comes from the BIS, Eurostat, IMF, ECB and OECD.[4] Panel A of Table 1 provides an overview of the data availability for our main variables,

[3] Croatia, which joined the EU on 1 July 2013, has not yet been included in the database.

[4] In particular, the individual series stem from the following original sources: Data on total credit to the private non-financial sector is obtained from the BIS and—for those countries where BIS data is not available—from Eurostat. Information on nominal GDP growth and inflation rates comes from the IMF's International Financial Statistics (IFS). Data on stock prices is obtained from the OECD, while data on house prices is provided by the BIS. Banking sector variables are obtained from two sources: The OECD provides relatively long series on banking sector capitalisation and profitability on an annual basis that we use in the empirical analysis. Additionally, for illustrative purposes, we use a shorter series of banking sector capitalisation in Figure 4 that is available on a quarterly basis and which is obtained from the ECB's Balance Sheet Items (BSI) statistics. Finally, quarterly data on the 10-year government bond yield and the 3-months interbank lending rate (money market rate) are obtained from the OECD.

while Panel B summarises the list of variables included in our study.

Following Drehmann et al. [17], we first include variables measuring the supply of credit to the private sector. We use the "long series on total credit and domestic bank credit to the private non-financial sector" compiled by the BIS. This data includes "credit [that] is provided by domestic banks to all other sectors of the economy and non-residents. The private non-financial sector includes non-financial corporations (both private-owned and public-owned), households and non-profit institutions serving households [...]. In terms of financial instruments, credit covers loans and debt securities" (see Dembiermont et al. [13] for a description of the database). To our knowledge, the BIS credit series offers the broadest definition of credit provision to the private sector, while having been adjusted for data gaps and structural breaks. We include four different measurements of credit in our models, accounting for credit growth and leverage, both at the domestic and at the global level. Credit growth is entered as a percentage (annual growth), while leverage is measured by the deviation of the credit-to-GDP ratio (using nominal GDP data) from its long-term backward-looking trend (using a backward-looking Hodrick-Prescott filter with a smoothing parameter λ of 400,000) as proposed by the Basel Committee on Banking Supervision [5] Consultative Document.[5] Global credit variables have been computed using a GDP-weighted average of the variable in question for several countries (see also Alessi and Detken [2]), including the United States, Japan, Canada, and all European countries which are in this study. In addition to the four "pure" variables, we include four sets of interaction terms in the same fashion as Lo Duca and Peltonen [30], namely the product of the domestic variables, the product of the global variables and that between the domestic and the global credit variables. The results using different variations of the credit variables are discussed in Sections 4.1 and 4.2.[6]

[5] Recommendations in the BCBS Consultive Document are based on a paper by Borio et al. [7], who find that trends calculated with a λ of 400,000 perform well in picking up the long-term development of private credit. In particular, a λ of 400,000 is consistent with the assumption of credit cycles being four times longer than business cycles if one follows a rule developed by Ravn and Uhlig [32] which states that the optimal λ of 1,600 for quarterly data should be adjusted by the fourth power of the observation frequency ratio (i.e., if credit cycles are four times longer than business cycles, λ should be equal to $4^4 \times 1,600 \approx 400,000$).

[6] In Section 5.1 we evaluate how individual credit variables perform in the prediction of banking sector vulnerabilities. In this section, we look at several other transformations of the credit variables, including the credit gap (defined as the deviation of private credit from its long-term trend), the credit-to-GDP ratio, several credit growth moving averages, and a variable defined as the difference between credit growth and nominal GDP growth. We evaluate all these variables on the domestic as well as on the global level.

In order to test the importance of credit variables in a comparative fashion as well as to analyse the potential importance of other factors, we include a number of additional variables in our study. These variables are available for fewer observations than the credit variables, which is why the number of observations in the full model differs from the number of observations in models that include only credit variables.[7] Variables are selected based on the existing literature and on data availability. In order to account for the macroeconomic environment and monetary stance, we include nominal GDP growth (domestic and global) and CPI inflation rates. Furthermore, following Reinhart and Rogoff [33], we include data on equity and residential house prices, both domestically and globally (using the same methodology to calculate the global variables as in the case of the credit variables), focusing on annual growth rates. Finally, to control for banking sector profitability and solvency and as suggested by e.g. Barrell et al. [4], we include aggregate bank capitalisation (calculated by the ratio of equity over total assets) and aggregate banking sector profitability (defined as net income before tax as a percentage of total assets).

As we are estimating binary choice models using panel data, non-stationarity of independent variables could be an issue (Park and Phillips [31]). We perform panel unit root tests suggested by Im et al. [21] as well as univariate unit root tests by developed by Dickey and Fuller [16] in order to analyse the time series properties of the variables of interest. In the panel unit root test, the null hypothesis that all cross-sections contain unit roots can be rejected at least at the 10 percent level for all series except for the credit-to-GDP gap and global credit growth.[8] We complement the analysis of the credit-to-GDP gap, the global credit-to-GDP gap and global credit growth by using the Dickey and Fuller [16] test country-by-country, and find that in case of the credit-to-GDP gap we can reject the null hypothesis of a unit root at least at the 10 percent level for all countries except for Estonia, Lithuania and Greece. For the global credit-to-GDP gap, we can also reject the null hypothesis at least at the 10 percent level for all countries except for Estonia and Lithuania, while for the global

[7] We re-estimate all credit models on the reduced sample in order to guarantee the comparability of the results.

[8] Alternatively, we perform a Fisher-type test by running a Dickey and Fuller [16] test by cross-section and then combining the p-values from these tests to produce an overall test statistic. The null hypothesis that all cross-sections contain unit roots can be rejected at least at the 10 percent level for all series except for the credit-to-GDP gap and the global credit-to-GDP gap.

credit growth the null hypothesis can be rejected for all countries.[9] Overall, the transformations done to the original variables, the results from the unit root tests and general economic theory make us confident that we have addressed potential non-stationarity concerns for the variables of interest.

3.3. Development of the key variables

Before entering the discussion of the main results, we shortly present some descriptive statistics, which provide the context of our main argument of moving beyond credit variables when predicting macro-financial vulnerabilities. Figure 1 presents the average developments of the six main variables of interest over time before and after the onset of a banking crisis. For the purpose of predicting crises, one would hope to find an indicator variable that (on average) peaks (or bottoms out, or at least changes direction) a number of quarters before a crisis, so that it can be used as a signal. In the current case of predicting a vulnerable state of the economy, which precedes a potential banking crisis, we would be interested in variables that change direction a bit longer before the onset of a crisis (i.e., two to three years before the crisis), so that policy makers can use this time to increase the resilience of banks during the crisis.

In this context, we observe that among the six variables depicted here, the credit-to-GDP gap shows one of the least clear pictures in terms of signalling a coming crisis. On average, the credit gap increases slowly prior to a banking crisis and only starts falling about one year into the crisis. Yet, this does not need to be a very surprising development, as this variable is a ratio and therefore requires the numerator to grow more slowly (or decrease faster) than the denominator in order for the variable to decrease in value. The BCBS itself concedes that the credit-to-GDP trend may not capture turning points well (Basel Committee on Banking Supervision [5]). Consequently, the ratio will not fall unless credit falls faster than GDP, something which is not at all certain during banking crises. Still, it shows that purely from a descriptive perspective, any signal to be derived from the credit gap needs

[9] Global variables are of course identical across countries in a given quarter. However, countries differ in the time period for which data is available, which explains why the results of the unit root tests can differ across countries.

to come from the level of this variable (i.e., a threshold value), not from changes in its development.

Unlike the credit gap, credit growth (as depicted in % year-on-year growth) does appear to hit a peak about two years before the onset of a banking crisis, even though its fall only becomes clear during the last pre-crisis year. A similar development can be observed in nominal GDP growth and equity price growth figures. These variables do peak before a crisis (on average), but the signal that a crisis is coming only becomes evident shortly before the crisis happens. This makes it difficult, at least from a descriptive point of view, to extract any strong signal from these variables. By some margin, residential house price growth outperforms the other domestic variables in terms of signalling 'power' in this descriptive exercise. In our sample, the growth rate of residential house prices tends to peak about 3 years before a crisis happens on average, starting a clear descent (although prices are still rising) that lasts into the crisis where growth stalls. Based on this evidence, we would conclude that residential house prices would be a useful tool (at least much more useful than the other variables shown here) for decisions on the CCB, as it passes the early warning requirement (one year of implementation plus one or two quarters of publication lag) with verve. So, at least from a descriptive standpoint, it is clear that it makes sense to gauge the developments of different macro-financial variables to predict or signal coming crises. Whether this result holds in a more rigorous comparative (multivariate) framework, will be discussed in the subsequent analysis.

4. Methodology

In this section we introduce the methodology used in the empirical analysis. We start by introducing the logistic regressions used in our multivariate framework. Thereafter, we explain how we evaluate individual indicators' and model predictions' usefulness for policy makers.

4.1. Multivariate models

In order to assess the predictive abilities of credit, macro-financial and banking sector variables in a multivariate framework we estimate logistic regressions of the following form:

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

where $Prob(y_{it} = 1)$ denotes the probability that country i is in a vulnerable state, where a banking crisis could occur seven to twelve quarters ahead of quarter t. As described in Section 3.1, we set the dependent variable to one seven to twelve quarters before the onset of a banking crisis in the respective country and to zero otherwise. As independent variables, the vector X_{it} includes credit and macro-financial variables on the domestic and on the global level as well as domestic banking sector variables (see Section 3.2 for a precise definition of the variables). The estimations also include a set of country dummy variables α_i in order to account for unobserved heterogeneity at the country level (country fixed effects).[10,11] Finally, we use robust standard errors clustered at the quarterly level in order to account for potential correlation in the error terms that might arise from the fact that global variables are identical across countries in a given quarter.[12]

The analysis is conducted as much as possible in a real-time fashion, meaning that only

[10]There is an argument for omitting these dummies from the estimations as they automatically exclude all countries without a crisis from the estimation, hence introducing selection bias (see e.g. Demirgüç-Kunt and Detragiache [14] and Davis and Karim [12]). However, not including them also induces bias, namely omitted variable bias caused by unit effects. As it is unlikely that financial crises are homogeneously caused by identical factors (see also Candelon et al. [9]) and as a Hausman test indicates unit heterogeneity, we have decided to include unit dummy variables in our estimations. However, we also report results for pooled models (without country dummies), where coefficients in these models are of course different, but they nevertheless carry the same sign in virtually all models that we have estimated.

[11]In principle, we could have included time dummies in addition to country dummies in order to account for heterogeneity in crisis probabilities over time. However, we decided against the inclusion of these dummies for two reasons: First, only quarters where at least one country experiences a banking crisis could be used for identification in such a specification. As our sample includes many quarters where none of the countries experienced a crisis the inclusion of time dummies would significantly reduce our sample size. Second, the focus in our paper is on the prediction of future banking crises. Specifically, we aim to develop an early warning model that policy makers can use for the detection of vulnerabilities in the banking sector. While time dummies might improve the ex post fit of a model, they are of little use for out-of-sample forecasting since they are not known ex ante (see e.g. Schularick and Taylor [38]).

[12]Alternatively, we cluster standard errors at the country level, which results in smaller estimates in particular for the global variables.

information that is available at a particular point in time is used. As such, all de-trended variables have been calculated using backward trends, thereby only using information that was available up to that point. Furthermore, the explanatory variables have been lagged by one quarter, also to account for endogeneity bias through simultaneity. We are well aware that this simple procedure cannot crowd out all endogeneity-related bias, but we note that the dependent variable itself is an early warning variable. The time horizon for which this variable is equal to one has been chosen in the context of our exercise and has not been exogenously determined. Therefore, we consider endogeneity to be a somewhat smaller problem in this study. Nevertheless, we have tested our models for different specifications of the dependent variable, both in terms of the pre-crisis period chosen (12-1/20-13 quarters before the onset of a crisis) and the definition and data source of banking crises in the robustness section.

4.2. Model evaluation

Banking crises are (thankfully) rare events in the sense that most EU countries have encountered none or only one over the past two decades. Still, when they occur, banking crises tend to be very costly, both directly through bailouts and fiscal interventions and indirectly through the loss of economic output that oftentimes (particularly in systemic banking crises) tends to follow these crises. Thus, policy makers have a clear incentive to be able to detect early enough potential signs of vulnerabilities that might precede banking crises in order to take measures to prevent further building up of vulnerabilities or to strengthen the resilience of the banking sector. Yet, at the same time, policy makers may not want to be signalling crises when in fact they do not happen afterwards. Doing so may (a) reduce the credibility of their signals, weakening decision-making and damaging their reputation, and (b) needlessly incur costs on the banking sector, endangering credit supply. As a consequence, policy makers also have an incentive to avoid false alarms, i.e., they do not want to issue warnings when a crisis is not imminent. As pointed out by Alessi and Detken [2], an evaluation framework for an early warning model needs to take into account policy makers' relative aversion with respect to type I errors (not issuing a signal when a crisis is imminent) and type II errors (issuing a signal when no crisis is imminent).

The evaluation approach in this paper is based on the so-called 'signalling approach' that was originally developed by Kaminsky et al. [22], and extended by Alessi and Detken [2], Lo Duca and Peltonen [30] and Sarlin [36]. In this framework, an indicator issues a warning signal whenever its value in a certain period exceeds a threshold τ, defined by a percentile of the indicator's country-specific distribution. Similarly, a multivariate probability model issues a warning signal whenever the predicted probability from this model exceeds a threshold $\tau \in [0,1]$, again defined as a percentile of the country-specific distribution of predicted probabilities. In this way, individual variables and model predictions for each observation j are transformed into binary predictions P_j that are equal to one if the respective thresholds are exceeded for this observation and zero otherwise. Predictive abilities of the variables and the models can then be evaluated by comparing the signals issued by the respective variable or model to the actual outcome C_j for each observation.[13] Each observation can be allocated to one of the quadrants in the contingency matrix depicted in Table 2: A period with a signal by a specific indicator can either be followed by a banking crisis seven to twelve quarters ahead (TP) or not (FP). Similarly, a period without a signal can be followed by a banking crisis seven to twelve quarters ahead (FN) or not (TN). Importantly, the number of observations classified into each category depends on the threshold τ.

In order to obtain the optimal threshold τ one needs to take the policy maker's preferences vis-à-vis type I errors (missing a crisis, $T_1(\tau) = FN/(TP+FN) \in [0,1]$) and type II errors (issuing a false alarm, $T_2(\tau) = FP/(FP+TN) \in [0,1]$) into account. This can be done by defining a loss function that depends on the two types of errors as well as the policy maker's relative preference for either type. The optimal threshold is then the one that minimizes the loss function. Taking into account the relative frequencies of crises $P_1 = P(C_j = 1)$

[13] C_j is equal to one if the country experiences a banking sector crisis seven to twelve quarters ahead of the respective period and zero otherwise.

and tranquil periods $P_2 = P(C_j = 0)$, the loss function is defined as follows:[14]

$$L(\mu, \tau) = \mu P_1 T_1(\tau) + (1-\mu) P_2 T_2(\tau) \tag{2}$$

where $\mu \in [0,1]$ denotes the policy makers' relative preference between type I and type II errors. A μ larger than 0.5 indicates that the policy maker is more averse against missing a crisis than against issuing a false alarm, which—in particular following the recent financial crisis—is a realistic assumption in our view.

Using the loss function $L(\mu, \tau)$, the usefulness of a model can be defined in two ways. First, following Alessi and Detken [2], the absolute usefulness is defined as:

$$U_a = min(\mu P_1, (1-\mu) P_2) - L(\mu, \tau) \tag{3}$$

Note that U_a computes the extent to which having the model is better than having no model. This is because a policy maker can always achieve a loss of $min(\mu P_1, (1-\mu)P_2)$ by either always issuing a signal (in which case $T_1(\tau) = 0$) or never issuing a signal (in which case $T_2(\tau) = 0$). The fact that P_1 is significantly smaller than P_2 in our sample (i.e., there are relatively few vulnerable states preceding banking crises) implies that, in order to achieve a high usefulness of the model a policy maker needs to be more concerned about the detection of vulnerable states potentially preceding banking crises in comparison to the avoidance of false alarms.[15] Otherwise, with a suboptimal performing model, it would easily pay off for the policy maker to never issue a signal given the distribution of vulnerable states and tranquil periods (see Sarlin [36] for a detailed discussion of this issue).

A second measure, the relative usefulness U_r, is computed as follows (see Sarlin [36]):

$$U_r = \frac{U_a}{min(\mu P_1, (1-\mu) P_2)} \tag{4}$$

[14] As pointed out by Sarlin [36], policy makers should be concerned about about the absolute number of misclassification rather than the share of misclassifications in relation to class size (i.e., unweighted type I and type II errors). Therefore, a failure to account for the relative frequency of crisis episodes and tranquil periods—as in previous studies—results in a bias on the weighting of type I and type II errors in the loss function.

[15] The share of observations that is followed by a banking crisis seven to twelve quarters ahead—P_1—is approximately equal to 10 % in our sample.

The relative usefulness U_r reports U_a as a percentage of the usefulness that a policy maker would gain from a perfectly performing model.[16] The relative usefulness is our preferred performance indicator as it allows the comparison of models for policy makers with different values for the preference parameter μ.

In addition to assessing the relative and absolute usefulness of a model, we also employ receiver operating characteristics (ROC) curves and the area under the ROC curve (AUROC) as these are also viable measures for comparing performance of early warning models. The ROC curve shows the trade-off between the benefits and costs of a certain threshold τ. When two models are compared, the better model has a higher benefit (TP rate (TPR) on the vertical axis) at the same cost (FP rate (FPR) on the horizontal axis).[17] Thus, as each FP rate is associated with a threshold, the measure shows performance over all thresholds.[18] In this paper, the size of the AUROC is computed using trapezoidal approximations. The AUROC measures the probability that a randomly chosen vulnerable state is ranked higher than a tranquil period. A perfect ranking has an AUROC equal to 1, whereas a coin toss has an expected AUROC of 0.5.

5. Empirical results

In this section we present the empirical results. We first explore the usefulness of credit variables for the identification of vulnerable states of the banking sector, and proceed by extending the framework to a multivariate model including other macro-financial and banking

[16] A perfectly performing indicator would achieve $T_1 = T_2 = 0$, implying $L = 0$. Consequently, U_a would reduce to $min(\mu P_1, (1-\mu)P_2)$.

[17] The TPR (also called sensitivity) gives the ratio of periods where the model correctly issues a warning to all periods where a warning should have been issued, formally $TPR = TP/(TP+FN)$. The FPR (also called specificity) gives the ratio of periods where the model wrongly issues a signal to all periods where no signal should have been issued, formally $FPR = FP/(FP+TN)$. An ideal model would achieve a TPR of one (no missed crises) and a FPR of zero (no false alarms).

[18] The measure can also be interpreted as showing the performance over all preference parameters μ of the policy maker: The lower the threshold τ, the more aggressive is the policy maker in making crisis calls as almost all signals are above the threshold. Hence, a low τ corresponds to a policy maker with a strong aversion against type I errors, i.e. a policy maker with a strong preference for correctly calling all crises. Equivalently, the larger the threshold τ the more conservative is the policy maker in making crisis calls. Therefore, a high τ corresponds to a policy maker with a strong aversion against type II errors, i.e. a policy with a strong preference for the avoidance of false alarms.

sector indicators. Thereafter, we evaluate the out-of-sample performance of the estimated models and—finally—present some robustness checks.

5.1. Credit variables

As the CRD IV regulations emphasise the role of credit variables for setting the countercyclical buffer rate—in particular the role of credit growth and the credit-to-GDP gap—we start by evaluating the usefulness of these variables for the identification of vulnerable states within the EU banking sector.

5.1.1. Individual indicators

First, we evaluate the usefulness of domestic credit variables by using a simple signalling approach. Using a preference parameter of μ equal to 0.9, Panel A of Table 3 reports the optimal threshold for several credit variable indicators.[19] Given the optimal threshold, the table also shows the number of observations in each quadrant of the matrix depicted in Table 2, the percentage of type 1 and type 2 errors, as well as several performance measures, such as the absolute and the relative usefulness, the adjusted noise-to-signal (aNtS) ratio[20], the percentage of vulnerable states correctly predicted by the indicator (% Predicted), the probability of a vulnerable state conditional on a signal being issued (Cond Prob) and the difference between the conditional and the unconditional probability of a vulnerable state (Diff Prob).

Among the domestic indicators, indeed, the credit-to-GDP gap performs best in the

[19] A preference parameter of μ equal to 0.9 indicates a strong preference for the detection of crises by the policy maker. In our view this is a reasonable assumption as the current crisis illustrated once more that financial crises often translate into large costs for the economy. As Sarlin [36] points out, using a μ equal to 0.9 and simultaneously taking into account the unconditional probability of a crisis (which is about 10 % in our sample) is equivalent to using a μ equal to 0.5 without adjusting for the unconditional probabilities (as in Alessi and Detken [2] or Lo Duca and Peltonen [30]). In the Appendix, we provide results for different values of the preference parameter.

[20] The aNtS ratio is the ratio of false signals measured as a proportion of quarters where false signals could have been issued to good signals as a proportion of quarters where good signals could have been issued, or $(FP/(FP+TN))/(TP/(TP+FN))$. A lower aNtS ratio indicates better predictive abilities of the model.

sense that it generates the highest relative usefulness.[21] This indicator issues a signal whenever the credit-to-GDP gap is above the 40^{th} percentile of its country-specific distribution and achieves 25.6 % of the usefulness a policy maker would gain from a perfectly performing model. The indicator correctly calls 81.3 % of the vulnerable states and displays an adjusted noise-to-signal ratio of 0.678. Conditional on a signal being issued, the probability of a vulnerable state is 16.8 %, which is 4.7 % higher than the unconditional probability of a vulnerable state in our sample. Other variables that perform relatively well are annual credit growth, the credit-to-GDP ratio and the credit gap (defined as the deviation of the stock of credit from its long term trend, see Section 3.2).[22]

Interestingly, global variables seem to outperform domestic variables in terms of usefulness. Panel B of Table 3 shows that these indicators usually exert a higher relative usefulness, a lower adjusted noise-to-signal ratio, and are able to predict a larger share of the vulnerable states in our sample. This suggests that focusing on the development of domestic credit variables might not be sufficient. In an increasingly integrated economy, vulnerabilities that develop at a global level potentially transmit to countries around the world. Therefore, policy makers should take these developments into account, e.g. when deciding on countercyclical buffer rates.[23]

The evaluation of the predictive abilities of global variables is subject to a caveat: As these variables do not vary across countries, and as most countries had a crisis starting in 2008, the good performance of these variables can in part be explained by a clustering of crisis episodes within the same year, i.e., indicators based on global credit variables correctly predicted the current crisis in several of our sample countries. To a certain extent this puts the higher usefulness of global as compared to domestic variables in a perspective. However,

[21]This is consistent with findings by Drehmann et al. [17] for a different set of countries and seems to support the approach taken in the CRD IV regulation. However, the main argument of our paper will be that performance of the individual indicators can be improved if they are combined in a multivariate approach. Moreover, also global variables are useful for the identification of vulnerabilities in the banking sector.

[22]Table A.1 in the Appendix shows that most of the individual indicators are not very useful if the preference parameter μ is smaller or equal to 0.85. For example, the usefulness of annual credit growth at the optimal threshold is negative for $\mu = 0.8$, which means that the best thing to do for a policy maker would be to ignore the signal entirely and never issue a warning. As crises are relatively rare events in our sample (the unconditional probability of a crisis is about 10 %), policy makers need to have a clear preference for the detection of crises for the indicators to be useful.

[23]In the CRD IV, the CCB rate is calculated based on a weighted average of banks' country exposures.

the current crisis is certainly the best example for a non-domestic vulnerability that spread to banking systems around the world. Thus, if the aim of the CCB is to increase the resilience of the banking system, both domestic and global developments should be taken into account.

5.1.2. Credit models

While the signalling approach is a simple and useful way to assess the predictive abilities of individual indicators, a multivariate framework has the advantage of being able to assess the joint performance of several indicators. We therefore estimate simple logit models including several of the individual credit variables and assess their performance and usefulness.

Results for these models are presented in Table 4. Again, we start by considering only the domestic variables and focus on credit growth and the credit-to-GDP gap, as these variables performed well in the signalling approach and play a prominent role in the CRD IV regulations (Model 1). Credit growth seems to dominate the credit-to-GDP gap in this simple model. In order to account for unobserved heterogeneity across countries that might otherwise bias our results, we include a set of country dummies in Model 2. The predictive power of the model—as indicated by the Pseudo R-Squared as well as the AUROC—improves considerably, while the coefficients for the credit variables remain relatively stable. Next, we gradually include the global credit variables, interactions between growth and leverage on the domestic and the global level as well as interactions between the domestic and the global variables.[24] The predictive power of the model improves with each step.[25]

In order to compare the models' predictive abilities with those of the individual indi-

[24]We orthogonalise interaction terms with first-order predictors in order to avoid problems of multicollinearity (see e.g. Little et al. [29]). In particular, when interacting two variables X and Y, we first form the simple product $X \times Y$ and then regress it on the original variables: $X \times Y = \alpha + \beta_1 \times X + \beta_2 \times Y + \varepsilon$. We then take the residual from this regression—ε, which is orthogonal to X and Y—to represent the interaction between the two original variables. Variance inflation factors (VIF) smaller than ten for all variables indicate that we are able to get rid of multicollinearity problems in this way.

[25]Note that the interpretation of interaction effects in logit models is cumbersome. As pointed out by Ai and Norton [1], the interaction effect is conditional on the independent variables (unlike interaction effects in linear models) and may have different signs for different values of the covariates. Moreover, the statistical significance of these effects cannot be evaluated with a simple t-test, but should be evaluated for each observation separately. Doing so allows us to conclude that for most observations only the Interaction(GC1×GC2) is significantly positive, while the other interactions are insignificant (although e.g. the Interaction(DC2×GC2) has a significantly negative sign in the regression itself).

cators we once more apply the signalling approach by translating the predicted probabilities into country specific percentiles and determining the optimal threshold for the issuance of warnings as the one that maximizes the relative usefulness of the model (see Section 4.2). Table 5 shows that the relative usefulness of the domestic models is around 0.24, which is lower than the one of the best individual indicators. However, the stepwise inclusion of the remaining variables improves the usefulness, so that Model and Model 8 surpass the best domestic as well as the best global indicators in terms of relative usefulness. This indicates the benefits of a multivariate framework as compared to single indicators. In the next section, we will elaborate more on these benefits by taking into account not only credit variables, but also other variables that might affect the stability of the banking sector.[26]

5.2. Extended models

Although the CRD IV emphasises the importance of the credit-to-GDP ratio, it also states that when setting the rate for the CCB, the designated authority should take into account "other variables that it considers relevant for addressing cyclical systemic risk" (EU [19], Article 126(3c)). However, the regulation remains silent about which variables should be included, hence granting the designated authorities a considerable amount of discretion for their buffer decisions. In order to assess the usefulness of several indicators for this purpose, we will now extend the multivariate framework from the previous section by including macro-financial and banking sector variables into the credit models.

Table 6 provides the estimation results for the extended models. The sample size is somewhat smaller than in the credit models as the data is not available for all variables across the whole period (see Table 1). From now on, we include country fixed effects in each regression in order to account for unobserved heterogeneity.[27] In order to make results comparable, we first re-estimate the credit models from Table 4 on the reduced sample (columns 1, 3, 5 and 7) and then include the other variables (columns 2, 4, 6 and 8). In each

[26] Again, results for other values of the preference parameter μ are provided in the Appendix.

[27] Another way to account for unobserved heterogeneity is to transform all variables into country-specific percentiles before entering them into the regression (see e.g. Lo Duca and Peltonen [30]). As shown in the robustness section, using this approach does not alter our main results.

case, the inclusion of macro-financial and banking sector variables significantly improves the fit as well as the usefulness of the model (see Table 7).

The predictive abilities of the models are quite impressive. For example, Model 16, to which we refer as our *benchmark model*, achieves 60.3 % of the usefulness of a perfectly performing model and thus outperforms any individual indicator. The model issues a warning whenever the predicted probability is above its 63^{rd} percentile within the respective country. In this way, a warning is issued in 94.8 % of the quarters in our sample where a banking crisis occurs seven to twelve quarters ahead. The probability of a crisis conditional on a signal being issued is 28.5 %, which is 15.9 % higher than the unconditional probability of a crisis. Finally, the area under the ROC curve for this model is equal to 0.865, indicating a good predictive ability of the model for a wide range of policy maker's preference parameters (see Figure 2 for an illustration of the ROC curve for our benchmark model).[28]

Several other things are noteworthy about these models. First, we find that the credit variables are indeed among the most important predictors of vulnerable states of the economy. However, as stated above, both model fit and model performance increase significantly when we include the other variables. For example, the consistently positive coefficient for house price growth indicates that asset price booms promote the build-up of vulnerabilities in the financial sector. This suggests that regulators should keep an eye on these developments instead of focusing exclusively on the development of credit variables. Second, the inclusion of the global as well as the credit interaction variables significantly improves the performance of the model, which is consistent with the evidence from the previous section. Again, this highlights the importance of international spillovers and the benefits of a multivariate framework in this context, and cautions policy makers against focusing only on domestic developments. Finally, columns 10-12 of Table 6 show that banking sector variables exert a significant influence on the build-up of financial vulnerabilities.[29] We make

[28] In contrast to the individual indicators and most of the credit models, the extended models perform well also for lower values of the preference parameter μ, which we see as another advantage of these models (see Tables A.1, A.2 and A.3 in the appendix).

[29] As banking sector variables are not available for all our sample countries the sample size for Model 18 differs from the sample size for the other estimations. In order to make estimation and model evaluation results comparable we therefore re-estimate Model 16 on the reduced sample (see Model 17).

the following observations: First, a country is more likely to be in a vulnerable state, when aggregate bank capitalisation within the country is relatively low. This is a particularly important finding in the context of countercyclical capital buffers as it indicates that indeed regulators could improve the resilience of the banking system by requiring banks to hold more capital when vulnerabilities build up. In Section 6, we will illustrate in how far an activation of the CCB based on signals from our model would have reduced the estimated probability of a country being in a vulnerable state in our sample countries. Second, we find that future banking crises are more likely when profits in the banking sector are relatively high. As Borio et al. [7] point out, periods of high bank profitability are typically associated with rapid credit growth, increased risk-taking and building up of vulnerabilities, which could explain the positive coefficient for the profitability variable preciding banking crises.

5.3. Out-of-sample performance of the models

Given the objective of the early warning systems, any assessment should focus on the out-of-sample performance. Moreover, as shown by e.g. Berg et al. [6], successful in-sample predictions are much easier to achieve than successful out-of-sample predictions. In order to assess the out-of-sample usefulness of the model we proceed as follows: First, we consecutively exclude countries that had a banking crisis prior to 2007 from the estimation of the benchmark model. Then, we test whether the model based on the remaining countries is able to predict the crises in the excluded ones.[30]

The results of this exercise are presented in Figure 3. The benchmark model signals the banking crises in the Nordic countries well before their onset in the early 1990s.[31] In both Finland and Sweden, the indicator is consistently above the threshold from 1988Q2 onwards, which is 11 quarters ahead of the crisis for Finland and 9 quarters ahead for Swe-

[30]In principle we could have tried to fit a model to the observations prior to 2007 in order to see whether this model would be able to predict the current crisis. However, as most of the crisis episodes in our sample occur after 2007, and as we particularly want to learn something from these episodes, we prefer the approach described above, i.e., we use the information from the current crisis and check whether it would have been useful for the prediction of past crises.

[31]The model issues a warning whenever the predicted probability is higher than the optimal threshold within the country (indicated by the dashed horizontal line in the figure).

den. In both cases, banks would have had enough time to build up capital before the crisis if the countercyclical capital buffer had been activated. Similarly, the model issues a warning signal for Italy from 1991Q2 onwards, 11 quarters ahead of the crisis in 1994. In the United Kingdom, the crisis is relatively close to the beginning of the sample period. Yet, in those quarters preceding the crisis of 1991, the benchmark model consistently issues a warning signal. Overall, the benchmark model exhibits strong out-of-sample properties. Information from the current crisis seems to be useful for the prediction of other systemic banking crises in the European Union.

5.4. Robustness checks—forecast horizon

This section analyses model performance across different forecast horizons (see also Schudel [37]). Specifically, we check how the performance of the benchmark model and the indicator properties of variables change if the time window of the vulnerable state preceding a systemic banking crisis is altered. Table 8 depicts the benchmark model from Table 6 for three alternative pre-crisis time horizons: 1-6 quarters (Model R1) and 1-12 quarters (Model R2) preceding a crisis in order to properly take into account potential late signals of the model; and 13-20 quarters (Model R3), so as to analyse potential early crisis signals.

The overall fit (as given by the Pseudo R-squared and the AUROC metrics) of the alternative models is in most cases superior to that of the benchmark model in column 1. Comparing the estimated coefficients of the alternative models to the benchmark model, three main differences can be observed, namely with regards to the estimated coefficients of the credit variables, inflation rate and asset price growth. First, domestic and global credit growth are negatively associated to the early vulnerable state as depicted in Model R3, whereas these variables are either statistically not significant (domestic credit) or positively (global credit) related to vulnerable states in the other specifications, including the benchmark model. The global credit gap is estimated to have a statistically significant effect in the early time horizon only. Second, the inflation rate is estimated to have a positive coefficient in the alternative specifications, while it is negative in the benchmark model. Third, house price growth is estimated to have a positive sign in the benchmark model (domestic house prices) and Model R3 (global house prices), but a negative sign (domestic and global) in Model R1, confirming the visual observation that house prices seem to peak a number of quarters before the onset systemic banking crises. Global equity price growth is not statistically significant in the benchmark model, but is estimated to be positive in the alternative specifications.

Table 9 presents the evaluation of the models estimated in Table 8. As expected, the Models R2 (0.321) and R3 (0.332) make less type II errors compared to the benchmark model (0.342). However, they also give fewer correct signals, and thus make more type I errors (0.165 and 0.292, respectively, compared to 0.052 of the benchmark model). Therefore, both the absolute and the relative usefulness measures of the benchmark model are slightly higher than those of Models R2 and R3. Model R1 makes significantly more type II errors (0.533), and thus has lower absolute and relative usefulness measures than the benchmark model.

To sum up, while the benchmark model seems to be broadly robust to an alteration of the forecasting horizon, the relative importance and the estimated signs of the coefficients seem to vary somewhat depending on the forecast horizon. Particularly important are the different signs for global credit variables in the model R3 (13-20 quarters) as well as global asset prices in the alternative forecasting horizons. The benchmark model with a forecast horizon of 7-12 quarters seems to provide the highest absolute and relative usefulness measures, followed by the model with forecast horizon 1-12 quarters. The performances of the models with the early (1-6 quarters) and late (13-20 quarters) pre-crisis time horizons in terms of absolute and relative usefulness are broadly similar, but markedly lower than that of the the benchmark model.

5.5. Further robustness checks

In this section we modify the benchmark model (Model 16 of Table 6) in several ways in order to further assess the robustness of our results. The results from the robustness analysis are presented in Table 10, where also the benchmark model is reproduced in column 1.

First, we check whether our results depend on the definition of the dependent variable. Apart from the ESCB Heads of Research database used in our analysis, the most common definitions of systemic banking crises are provided by Reinhart and Rogoff [34] and Laeven and Valencia [28]. Although the various databases are broadly consistent with each other, there are some deviations in the timing of crises as the definition of a systemic event in the banking sector requires a considerable amount of judgment. Columns 2 and 3 show that overall results are relatively similar for all three crisis definitions. Moreover, the area under the ROC curve is also greater than 0.8 for the other two models with the alternative crisis definitions, indicating good predictive abilities of the models.

Second, we include a dummy variable that is equal to one for each quarter in which the respective country is a member of the European Monetary Union (EMU). As expected, the coefficient for this dummy variable is positive and significant as most crises in our sample occur after the establishment of the EMU in 1999 (see column 4). However, the coefficients of the other variables remain largely unaffected by the inclusion of this dummy variable. Furthermore, the results are robust if we restrict the sample to include only countries from the EU-15 (column 5) or only countries that are part of the EMU (column 6).

Third, we augment the model with a money market rate (column 7). The estimated negative coefficient is potentially related to the 'great moderation', i.e., the general decline of inflation and money market rates over the sample period. The high R-squared and AUROC indicate that the fit of the model is superior compared to the other models. Despite this, we do not select this model as our benchmark model as its out-of-sample forecast abilities are inferior to the benchmark model, potentially due to an overfitting problem.

Finally, following Lo Duca and Peltonen [30], we transform all variables into country-specific percentiles before using them in the regression. This method can be seen as an alternative way to account for heterogeneity across countries as differences in levels of indicators between countries vanish for the transformed variables. Columns 8 and 9 show that most of the estimated coefficients have the same sign as in the benchmark model if we use this alternative method.

6. Applying the model for the activation of CCBs

So far, we have documented the usefulness of several indicator variables for the decision on activating the countercyclical capital buffer. Moreover, we have shown that policy makers should take a broad approach when making their decision on the CCB as we have shown that a multivariate framework outperforms individual indicators in the prediction of future banking crises. In this section, we try to go a step further and evaluate whether an activation of the CCB prior to the crises in our sample would have achieved its goal, i.e., whether it would have reduced vulnerabilities and increased the resilience of the banking system. The analysis is done in a *ceteris paribus* fashion, which means that we do, e.g., not account for the effects of higher buffers on bank lending and its feedback effects to the real economy as well as on all other variables in the model, which might in turn affect the probability of a future crisis.[32] Moreover, we do not account for potential positive or negative signalling effects of the announcement of the activation of the CCB.

6.1. Model prediction and actual bank capitalisation

We start by documenting the relationship between the probabilities of the vulnerable states generated by the benchmark model (Model 16 in Table 6) and the actual banking sector capitalisation in our sample countries. Figure 4 plots these two variables for those sample countries that had a banking crisis in 2007/2008. As visible from the figures, most countries exerted declining or constantly low levels of bank capitalisation prior to the crisis, which is consistent with the evidence presented in Section 5.2.[33] At the same time, the benchmark model issues a warning already in late-2004/early-2005 in most cases.[34] Hence—even if we account for an announcement period of twelve months—regulators would have had enough

[32]To the extent that an activation is effective in reducing excessive credit growth and hence the probability of a future crisis, our results might be seen as conservative estimates of the effect of higher bank capitalisation on crisis probabilities. However, assessing the impact of countercyclical capital buffers on lending and other economic variables is beyond the scope of this paper.

[33]A notable exception is Austria (and to some extent Denmark), where aggregate banking sector capitalisation actually increased prior to the crisis.

[34]Again, the model issues a warning whenever the predicted probability is higher than the optimal threshold within the country (indicated by the dashed horizontal line in the figure).

time for the activation of the CCB prior to the crisis. By activating it, the regulator could have stopped the decline in aggregate bank capital ratios (e.g. in France, Hungary, Ireland, Sweden or the United Kingdom) or raised the ratio in countries with low aggregate banking sector capitalisation (e.g. Belgium, Germany, Luxembourg, or the Netherlands). In the next section, we investigate how this would have affected the probability of a country entering into a vulnerable state with a potential for a future banking crisis in our sample countries.

6.2. Effect of higher banking sector capitalisation

Figure 5 plots the predicted probability of a vulnerable state, using the benchmark model whilst adding the banking sector variables (Model 18 in Table 6). The figure includes all sample countries that had a crisis in 2007/2008 (indicated by the dashed vertical line) and for which information on aggregate banking sector variables is available.[35] In order to investigate how higher banking sector capitalisation would have affected the stability of the system we proceed as follows. First, we estimate the model using the actual numbers for banking sector capitalisation (Model 18). Second, we calculate hypothetical series reflecting the activation of CCBs by adding 0.5 % [1 %; 2 %] to the actual banking sector capitalisation from the fourth quarter after the first signal issued by our model onwards.[36] The percentages correspond to CCB rates of 1.25 %, 2.5 % and 5 %, respectively.[37] Third, we use the coefficient estimates from step one in order to calculate simulated probabilities of vulnerable states by using the simulated instead of the actual numbers for banking sector capitalisation. As the coefficient for banking sector capitalisation is negative, higher numbers for banking sector capitalisation should correspond to lower predicted probabilities. We now proceed by assessing the size of this effect.

The blue bars in Figure 5 depict the actual predicted probabilities from Model 18,

[35]As Model 18 includes banking sector variables and is based on a different sample than Model 16, predicted probabilities in Figure 5 are slightly different from those in Figure 4.

[36]According to the CRD IV, regulators have to announce increases in CCB rates four quarters in advance in order to give banks a sufficient amount of time for raising the required equity.

[37]Our measure of banking sector capitalisation is defined as equity over total assets, whereas the CCB is defined in terms of risk-weighted assets (RWA). As RWA for banks in the EU are roughly 40 % of total assets, an increase of 1.25 % in the ratio of equity to RWA corresponds to an increase of 0.5 % in the ratio of equity to total assets ($0.4 \cdot 1.25$ %, equivalent transformation for the other percentages).

whereas the green bars correspond to predicted probabilities with a CCB of 1.25 %, the red bars to those with a CCB of 2.5 % and the yellow bars to those with a CCB of 5 %. Once more, based on our analysis, the countercyclical capital buffer would have been activated relatively early in our sample countries.[38] In most countries, it would have been activated in 2004 or 2005, and all countries would have activated it by 2006Q2. As expected, higher banking sector capitalisation reduces the probability of a country entering into a vulnerable state that could be followed by a banking crisis, by strengthening the resilience of the system. However, the magnitude of the effect critically depends on the the size of the CCB. The reduction in simulated probabilities is relatively modest for a CCB of 1.25 %, implying that the model would continue to predict the economy to be in a vulnerable state. The impact is, however, more pronounced for a CCB of 2.5 %, which would correspond to the maximum regular rate recommended in the CRD IV.[39] In this case, the predicted probabilities are reduced to approximately half of their size in most countries. This illustrates that the resilience of the banking sector can, in principle, be reduced by increasing the countercyclical capital buffer or by higher banking sector capitalisation in general. However, predicted probabilities for vulnerable states remain elevated in many cases (i.e., above the model threshold), hence raising concerns that a CCB rate of 2.5 % might not be sufficient to achieve the aim of the buffer. In a final step, the yellow bars depict predicted probabilities for a CCB rate of 5 %, a rate that is well in excess of the CRD IV recommendation of 2.5 %. Crisis probabilities go down significantly and reduce to values close to zero in many sample countries. In our view, this provides a strong argument in favour of higher capital buffer rates and a higher level of banking sector capitalisation in general.

[38] As long as the buffer is not activated, the actual and the hypothetical series of banking sector capitalisation and therefore also the predicted probabilities are identical (see Figure 5).

[39] §126 of the CRD IV specifies that the CCB rate should be between 0 % and 2.5 %. However, the same paragraph also states that with an appropriate justification "a designated authority may set a countercyclical buffer rate in excess of 2.5 %."

7. Conclusion

As a response to recent financial crises, the Basel III / CRD IV regulatory framework includes a countercyclical capital buffer (CCB) to increase the resilience of the banking sector and its ability to absorb shocks arising from financial and economic stress. In this context, this paper seeks to provide an early warning model, which can be used to guide the build-up and release of capital in the banking sector. Given the prominence of private credit variables in the upcoming regulations, the paper first examines the evolution of credit variables preceding banking crises in the EU Member States, and assesses their usefulness in guiding the setting of the CCB. Furthermore, the paper examines the potential benefits of complementing private credit variables with other macro-financial and banking sector indicators in a multivariate logit framework. The evaluation of the policy usefulness of the credit indicators and models follows the methodology applied in Alessi and Detken [2], Lo Duca and Peltonen [30] and Sarlin [36].

The paper finds that, in addition to credit variables, other domestic and global financial factors such as equity and house prices and banking sector variables help to predict macro-financial vulnerabilities in EU Member States. We therefore suggest that policy makers take a broad approach in their analytical models supporting CCB policy measures. The models demonstrate good out-of-sample predictive power, signalling the Swedish and Finnish banking crises of the early 1990s at least 6 quarters in advance. Finally, a simple *ceteris paribus* simulation analysis of the model reveals that in order to effectively reduce the probability of banking crises for the historical examples considered, the CCB should have been set at the upper end or even above the 0-2.5 % range specified in the CRD IV.

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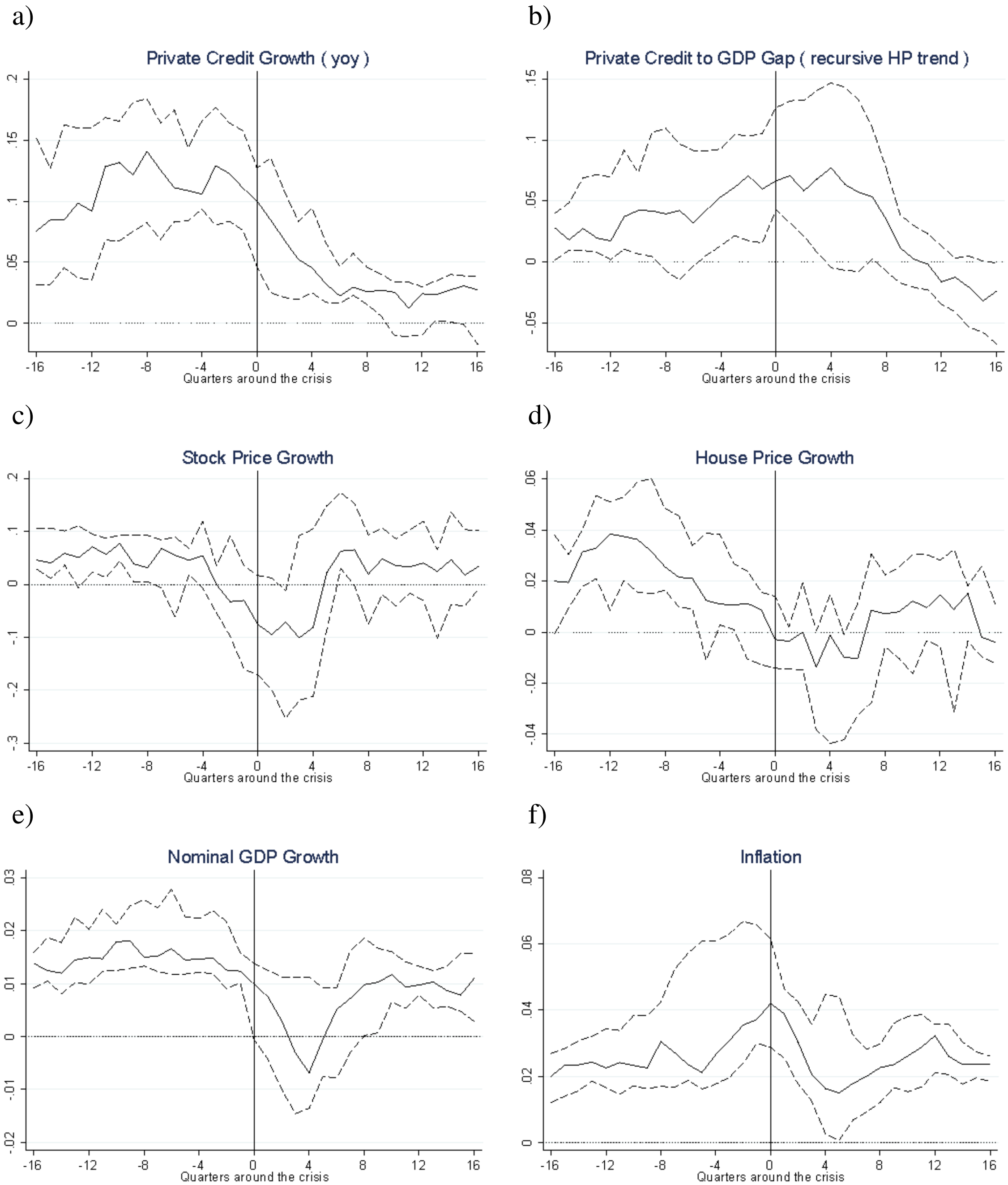


Figure 1: Development of key variables around banking crises

The figure depicts the development of selected key variables around banking crises within the sample countries. The start date of a banking crisis is indicated by the vertical line, while the solid line shows the development in the median country and the dashed lines represent the countries at the 25th and the 75th percentile, respectively.

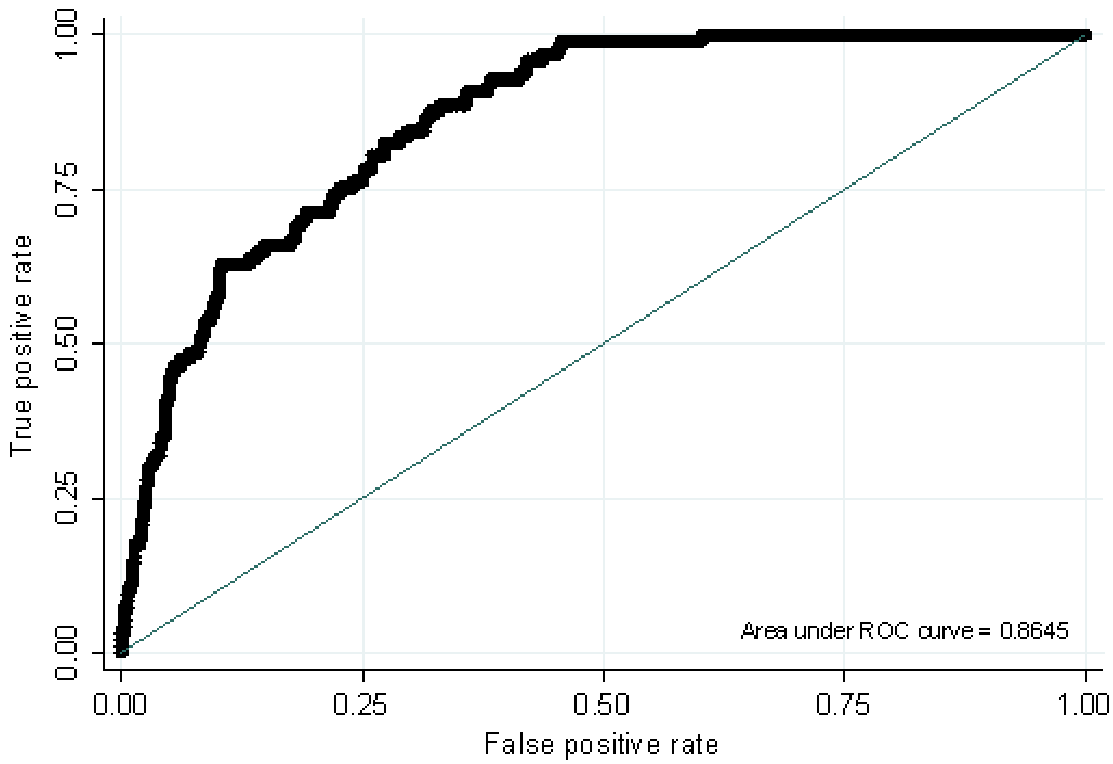


Figure 2: ROC Curve for benchmark model (Model 8)

The figure shows the Receiver Operating Characteristic (ROC) curve for our benchmark model (Model 16 in Table 6). The area under the ROC curve (AUROC) is equal to 0.8645.

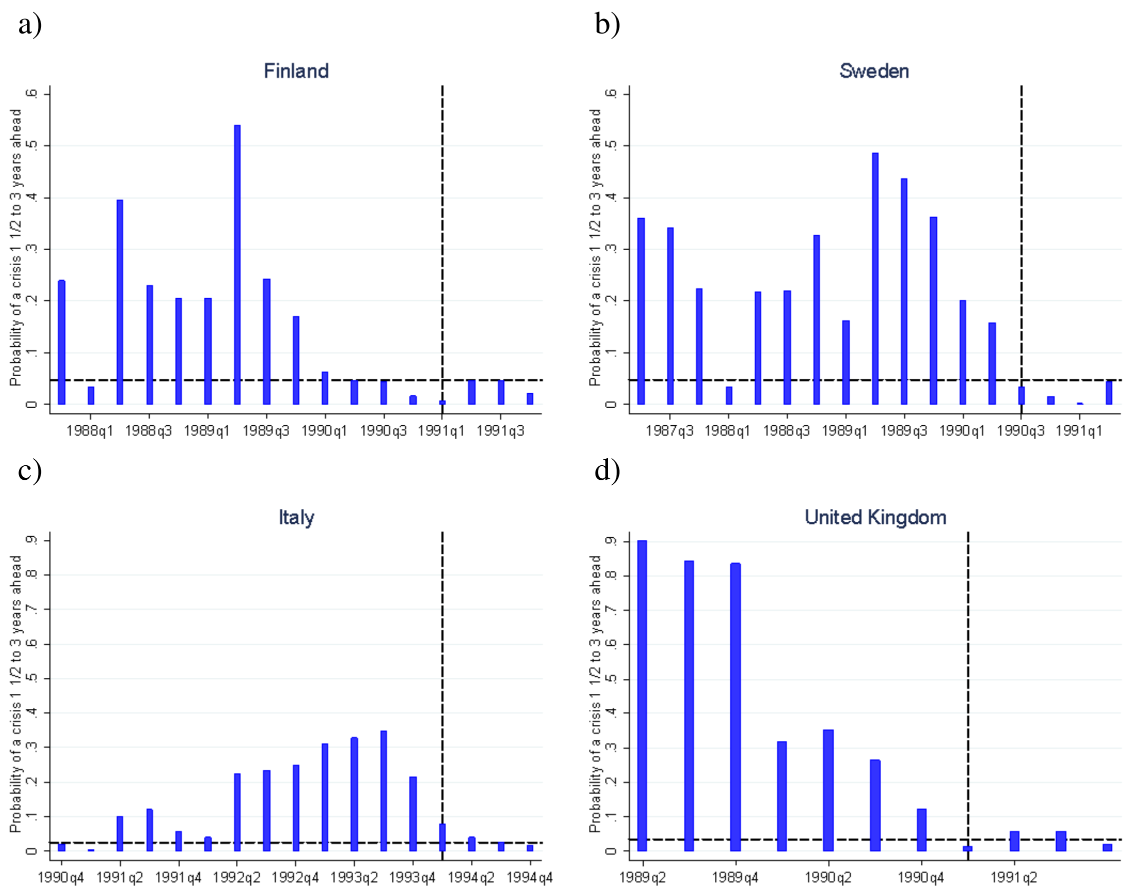
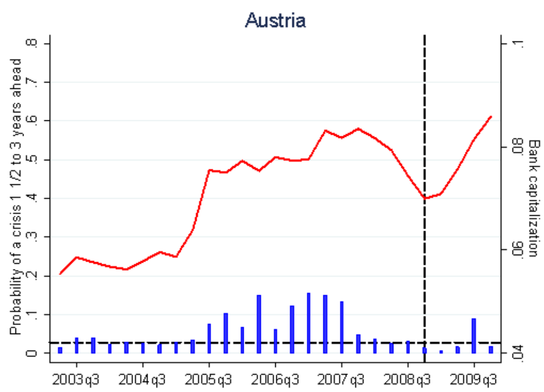


Figure 3: Out-of-sample performance of the model

The figure shows results for an out-of-sample evaluation of our benchmark model (Model 16 in Table 6). We exclude the respective country from the estimation and depict the predicted probabilities from a model based on the remaining countries around the crisis in the excluded country (dashed vertical line).

a)



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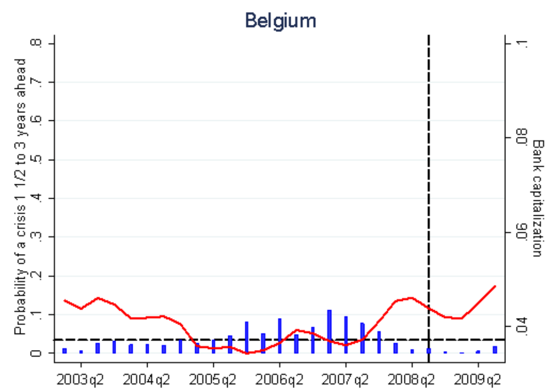

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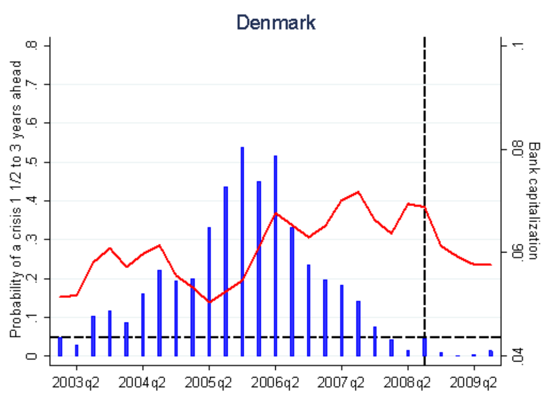

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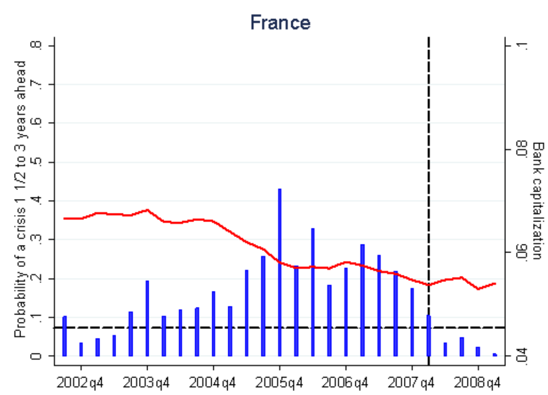

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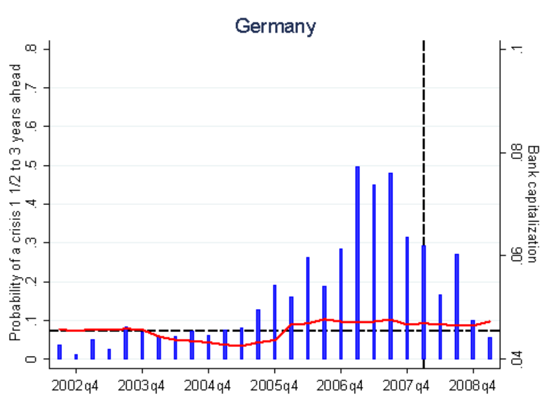

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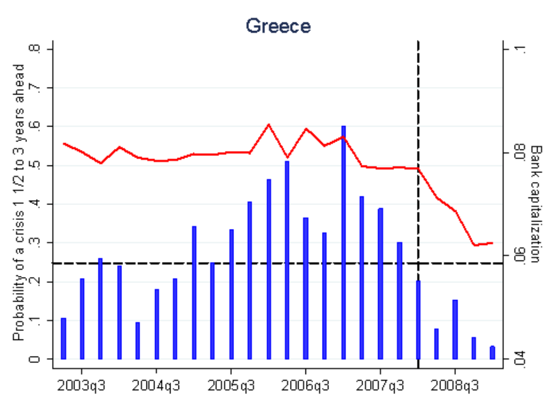
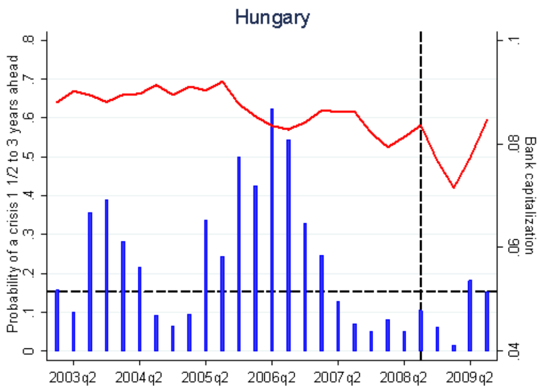


Figure 4: Predicted crisis probabilities and banking sector capitalisation

a)



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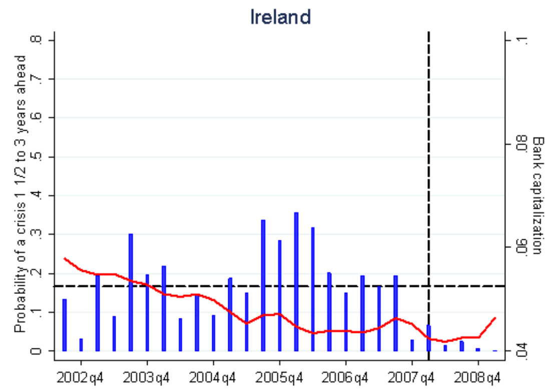

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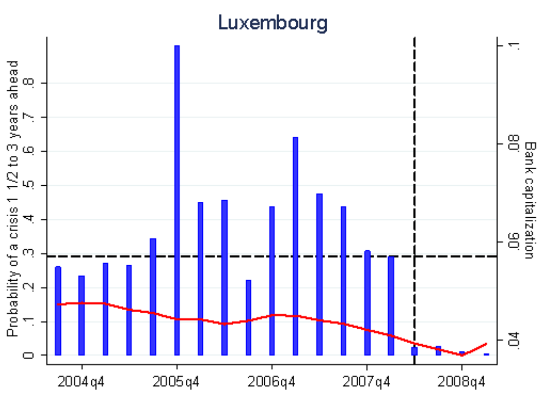

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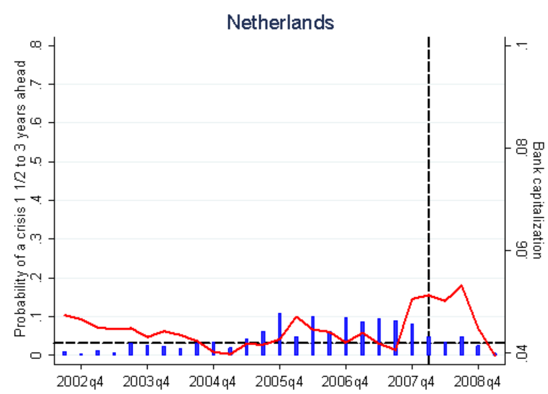

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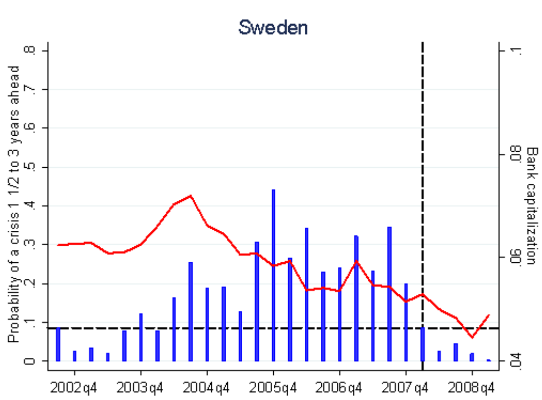

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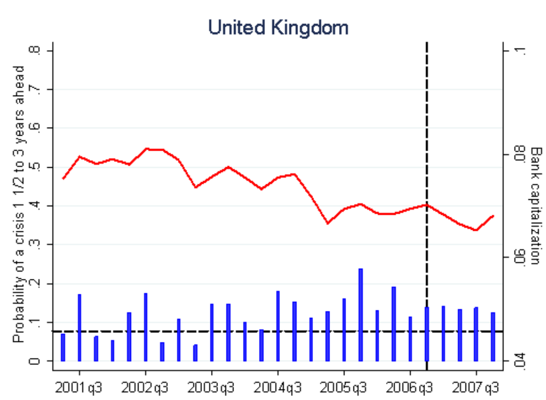


Figure 4 continued...

The figure plots the predicted probabilities from our benchmark model (Model 16 in Table 6) around the crises of 2008 in our sample countries (depicted by the dashed vertical lines). The optimal threshold for each country is depicted by the dashed horizontal line. The model issues a warning whenever the predicted probability is above this threshold. The red line shows the development of aggregate capitalisation in the banking sector.

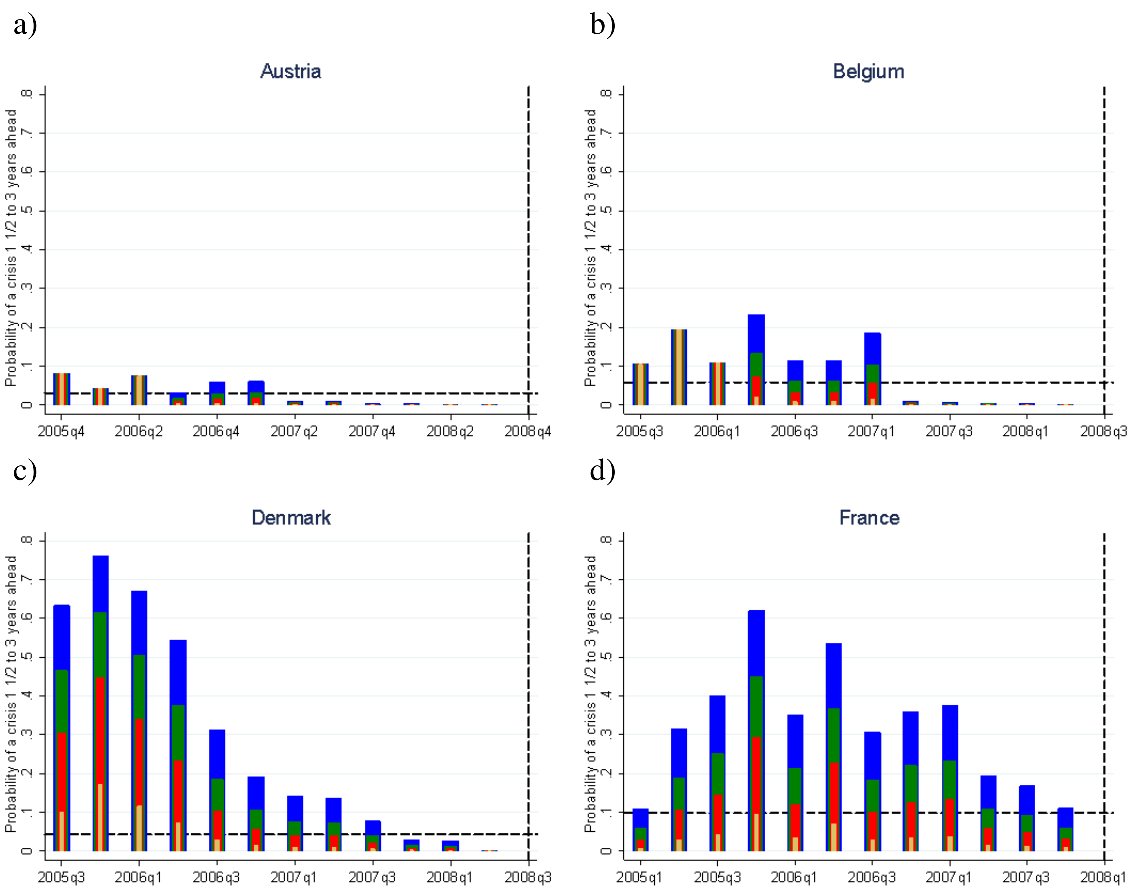
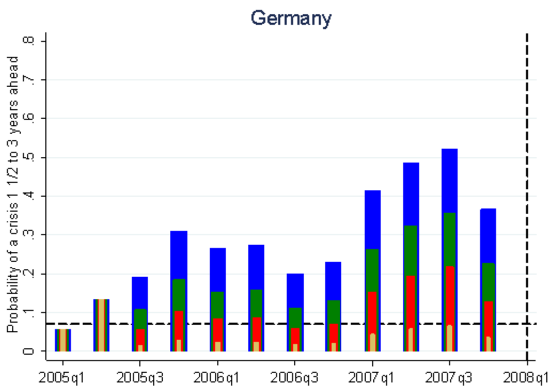


Figure 5: Effect of higher banking sector capitalisation

e)



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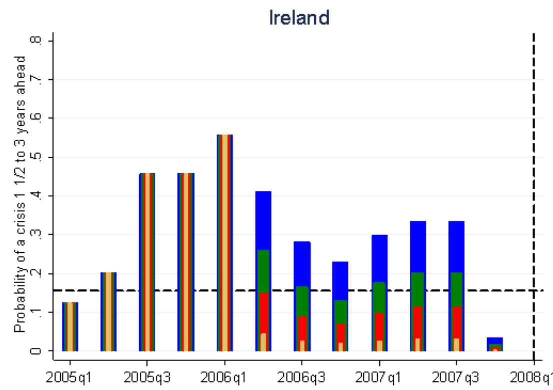

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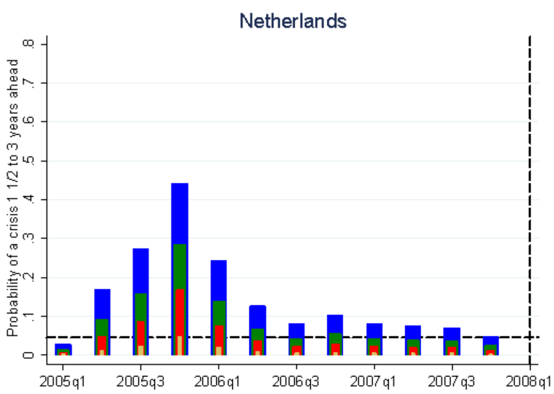

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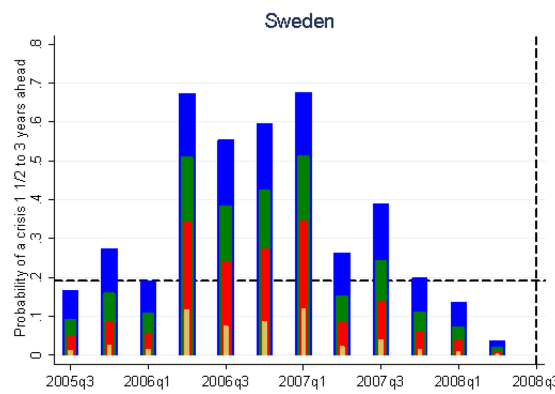

Figure 5 continued

The figure shows how higher banking sector capitalisation would have affected predicted crisis probabilities in our sample countries before the crises of 2008 (depicted by the dashed vertical lines). Blue bars correspond to the predicted probabilities from the model that includes banking sector variables (Model 18 in Table 6). Green [red; yellow] bars show how predicted probabilities would change if banking sector capitalisation was 0.5 % [1 %; 2 %] higher starting from four quarters after the first signal from our model onwards.

Table 1: Data availability and descriptive statistics

Panel A: Data availability	Credit Variables	Other Variables	HoR Banking Crises
Austria	1982Q1-2012Q3	1986Q4-2012Q3	2008Q4
Belgium	1982Q2-2012Q3	1982Q1-2012Q3	2008Q3-2008Q4
Czech Republic	1994q2-2012Q2	—	1998Q1-2002Q2
Denmark	1982Q2-2012Q3	1992Q2-2012Q3	1987Q1-1993Q4, 2008Q3-ongoing
Estonia	2005Q1-2012Q2	2005Q2-2012Q2	–
Finland	1982Q2-2012Q3	1987Q2-2012Q3	1991Q1-1995Q4
France	1982Q2-2012Q3	1992Q2-2012Q3	1994Q1-1995Q4, 2008Q1-2009Q4
Germany	1982Q2-2012Q2	1991Q2-2011Q4	2008Q1-2008Q4
Greece	2003Q1-2012Q2	2003Q1-2012Q2	2008Q1-ongoing
Hungary	1997Q1-2012Q3	2002Q1-2012Q2	2008Q3-2009Q2
Ireland	1999Q1-2012Q3	1999Q1-2010Q4	2008Q1-ongoing
Italy	1982Q2-2012Q3	1990Q3-2012Q2	1994Q1-1995Q4
Lithuania	2005Q1-2012Q2	2005Q1-2012Q2	2009Q1-2009Q4
Luxembourg	2004Q2-2012Q3	2004Q2-2010Q4	2008Q2-ongoing
Malta	2006Q2-2012Q2	—	–
Netherlands	1982Q2-2012Q2	1982Q1-2011Q4	2008Q1-2008Q4
Poland	1997Q1-2012Q3	2003Q1-2012Q3	–
Portugal	1982Q2-2011Q4	1998Q2-2011Q4	–
Slovakia	2005Q2-2012Q2	—	–
Slovenia	2005Q3-2012Q2	—	–
Spain	1982Q2-2012Q3	1995Q2-2012Q3	1982Q2-1985Q3
Sweden	1982Q2-2012Q3	1986Q2-2012Q3	1990Q3-1993Q4, 2008Q3-2008Q4
United Kingdom	1982Q2-2012Q3	1988Q2-2012Q2	1991Q1-1995Q2, 2007Q1-2007Q4

Panel B: Descriptives	Obs	Mean	Std. Dev.	Min	Max
Dom. Credit Growth (qoq)	1220	0.0228	0.0196	-0.0318	0.0989
Dom. Credit Growth (yoy)	1220	0.0926	0.0662	-0.0690	0.3579
Dom. Credit Gap	1220	0.1149	0.1186	-0.1570	0.4550
Dom. Credit Growth (4q MA)	1220	0.0232	0.0166	-0.0173	0.0897
Dom. Credit Growth (6q MA)	1220	0.0232	0.0154	-0.0122	0.0813
Dom. Credit Growth (8q MA)	1220	0.0233	0.0150	-0.0099	0.0805
Dom. Credit to GDP Ratio	1220	1.2756	0.4259	0.4426	2.4829
Dom. Credit to GDP Gap	1220	0.0346	0.0796	-0.1788	0.3249
Dom. Credit Growth - GDP Growth	1220	0.0081	0.0171	-0.0508	0.0715
Glo. Credit Growth (qoq)	1220	0.0152	0.0086	-0.0048	0.0335
Glo. Credit Growth (yoy)	1220	0.0614	0.0289	-0.0113	0.1095
Glo. Credit Gap	1220	0.0597	0.0431	-0.0101	0.1593
Glo. Credit Growth (4q MA)	1220	0.0154	0.0071	-0.0028	0.0274
Glo. Credit Growth (6q MA)	1220	0.0156	0.0069	-0.0021	0.0280
Glo. Credit Growth (8q MA)	1220	0.0158	0.0065	0.0005	0.0274
Glo. Credit to GDP Ratio	1220	0.7557	0.1193	0.5778	0.9933
Glo. Credit to GDP Gap	1220	0.0158	0.0285	-0.0420	0.0676
Glo. Credit Growth - Glo. GDP Growth	1220	0.0022	0.0235	-0.0492	0.0671
GDP Growth	919	0.0123	0.0088	-0.0232	0.0437
Inflation	919	0.0242	0.0166	-0.0108	0.1078
Equity Price Growth	919	0.0240	0.1199	-0.3759	0.3051
House Price Growth	919	0.0172	0.0289	-0.0735	0.1204
Banking Sector Capitalization	756	0.0507	0.0161	0.0238	0.1088
Banking Sector Profitability	756	0.0066	0.0040	-0.0142	0.0292
Gov. Bond Yield	862	0.0575	0.0237	0.0220	0.1385
Money Market Rate	862	0.0460	0.0292	0.0010	0.1643
Global GDP Growth	919	0.0117	0.0229	-0.0585	0.0616
Global Equity Price Growth	919	0.0135	0.0675	-0.3344	0.1122
Global House Price Growth	919	0.0066	0.0162	-0.0389	0.0539

Panel A shows the availability of credit and other variables as well as the crisis dates for the 23 countries in our sample. Credit variables are obtained from the BIS database for total credit to the private non-financial sector (see Dembiermont et al. [13]) and from Eurostat for those countries where the BIS data is not available. Other macro-financial and banking sector variables are obtained from various sources, including the BIS, the IMF, and the OECD. The crisis definitions are from the ESCB Heads of Research database described in the paper by Babecky et al. [3]. Panel B shows descriptive statistics for the credit as well as the other variables. Credit variables are available for a longer period of time in most countries, which is why the number of observations is larger for them.

Table 2: Contingency matrix

		Actual class C_j	
		1	0
Predicted class P_j	1	*True positive (TP)*	*False positive (FP)*
	0	*False negative (FN)*	*True negative (TN)*

The table shows the relationship between model prediction and actual outcomes. Observations are classified into those where the indicator issues a warning that is indeed followed by a banking crises seven to twelve quarters ahead (TP), those where the indicator issues a warning that is not followed by a crisis (FP), those where the indicator issues no warning and there is no crises seven to twelve quarters ahead (TN), and those where the indicator issues no warning although there is a crisis coming (FN).

Table 3: Evaluation of individual indicators

	μ	Threshold	TP	FP	TN	FN	T_1	T_2	Absolute Usefulness	Relative Usefulness	aNtS Ratio	% Predicted	Cond Prob	Diff Prob
Panel A: Domestic Variables														
Dom. Credit to GDP Gap	0.9	40	100	497	404	23	0.187	0.552	0.023	0.256	0.678	0.813	0.168	0.047
Dom. Credit Growth (yoy)	0.9	58	85	399	502	38	0.309	0.443	0.022	0.240	0.641	0.691	0.176	0.056
Dom. Credit to GDP Ratio	0.9	69	51	169	732	72	0.585	0.188	0.019	0.211	0.452	0.415	0.232	0.112
Dom. Credit Gap	0.9	37	104	577	324	19	0.154	0.640	0.018	0.201	0.757	0.846	0.153	0.033
Dom. Credit Growth (4q MA)	0.9	48	93	500	401	30	0.244	0.555	0.017	0.194	0.734	0.756	0.157	0.037
Dom. Credit Growth (6q MA)	0.9	61	72	364	537	51	0.415	0.404	0.015	0.170	0.690	0.585	0.165	0.045
Dom. Credit Growth (qoq)	0.9	46	92	530	371	31	0.252	0.588	0.014	0.153	0.786	0.748	0.148	0.028
Dom. Credit Growth - GDP Growth	0.9	54	70	409	492	53	0.431	0.454	0.009	0.103	0.798	0.569	0.146	0.026
Dom. Credit Growth (8q MA)	0.9	66	57	314	587	66	0.537	0.349	0.009	0.100	0.752	0.463	0.154	0.034
Panel B: Global Variables														
Glo. Credit Gap	0.9	45	113	427	474	10	0.081	0.474	0.040	0.443	0.516	0.919	0.209	0.089
Glo. Credit Growth (qoq)	0.9	60	100	357	544	23	0.187	0.396	0.037	0.412	0.487	0.813	0.219	0.099
Glo. Credit Growth (yoy)	0.9	57	101	365	536	22	0.179	0.405	0.037	0.411	0.493	0.821	0.217	0.097
Glo. Credit Growth (4q MA)	0.9	49	109	448	453	14	0.114	0.497	0.035	0.386	0.561	0.886	0.196	0.076
Glo. Credit Growth (6q MA)	0.9	46	110	467	434	13	0.106	0.518	0.033	0.373	0.580	0.894	0.191	0.071
Glo. Credit Growth (8q MA)	0.9	41	109	509	392	14	0.114	0.565	0.029	0.318	0.637	0.886	0.176	0.056
Glo. Credit to GDP Ratio	0.9	75	44	100	801	79	0.642	0.111	0.021	0.229	0.310	0.358	0.306	0.185
Glo. Credit to GDP Gap	0.9	37	105	571	330	18	0.146	0.634	0.019	0.216	0.742	0.854	0.155	0.035
Glo. Credit Growth - Glo. GDP Growth	0.9	83	46	161	740	77	0.626	0.179	0.016	0.178	0.478	0.374	0.222	0.102

The table shows results for the evaluation of individual indicator variables using the signalling approach (see Section 3.5 for a detailed description). The preference parameter of $\mu = 0.9$ indicates that policy makers have a strong preference for the detection of crises (i.e. avoiding type I errors) as compared to the avoidance of false alarms (i.e. type II errors). The optimal threshold is calculated as the one that maximises the relative usefulness and gives the percentile of the country-specific distribution at which the respective indicator issues a warning. The columns of the table report the number of observations: where the indicator issues a warning that is indeed followed by a banking crises seven to twelve quarters ahead (TP); where the indicator issues a warning that is not followed by a crisis (FP); where the indicator issues no warning and there is no crises seven to twelve quarters ahead (TN); and where the indicator issues no warning although there is a crisis coming (FN). Furthermore, the table reports the fraction of type I errors $T_1 = FN/(TP+FN)$, the fraction of type II errors $T_2 = FP/(FP+TN)$, the absolute and the relative usefulness (see Section 3.5 for details), the adjusted noise-to-signal ratio (i.e. the ratio of false signals measured as a proportion of months where false signals could have been issued to good signals as a proportion of months where good signals could have been issued, or $(FP/(FP+TN))/(TP/(TP+FN)))$, the probability of a crisis conditional on a signal being issued (Cond Prob) and the difference between the conditional and the unconditional probability of a crisis (Diff Prob). The domestic and the global variables are ranked in terms of relative usefulness, respectively.

Table 4: Credit models

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7	(8) Model 8
Dom. Credit Growth (DC1)	7.93***	6.38**	6.89***	2.66	6.55***	1.96	5.30***	1.61
	(1.34)	(2.59)	(1.34)	(2.95)	(1.36)	(2.98)	(1.31)	(2.75)
Dom. Credit to GDP Gap (DC2)	1.04	3.01	-0.02	2.71	-0.14	3.01	0.92	3.70
	(1.50)	(1.93)	(1.92)	(2.80)	(2.03)	(2.76)	(1.69)	(2.66)
Interaction(DC1 × DC2)					11.75	11.68	26.99	26.42
					(17.18)	(17.70)	(19.15)	(21.83)
Glo. Credit Growth (GC1)			12.59***	16.71***	13.27***	17.72***	10.77***	16.07***
			(4.04)	(4.26)	(4.50)	(4.85)	(4.05)	(4.80)
Glo. Credit to GDP Gap (GC2)			8.01	1.96	5.81	-0.83	2.68	-2.74
			(6.88)	(7.67)	(6.94)	(7.55)	(6.06)	(6.57)
Interaction(GC1 × GC2)					242.42	255.75	352.84*	391.54**
					(173.31)	(170.38)	(183.77)	(188.05)
Interaction(DC1 × GC1)							73.47	45.98
							(66.46)	(75.98)
Interaction(DC2 × GC2)							-209.75***	-239.65***
							(46.48)	(49.73)
Constant	-3.07***		-3.91***		-3.88***		-3.64***	
	(0.31)		(0.43)		(0.45)		(0.36)	
Country dummies	NO	YES	NO	YES	NO	YES	NO	YES
Observations	1,220	1,220	1,220	1,220	1,220	1,220	1,220	1,220
Pseudo R-Squared	0.0535	0.0894	0.0712	0.108	0.0748	0.111	0.0945	0.133
AUROC	0.678	0.710	0.689	0.733	0.706	0.746	0.740	0.780
Standard error	0.0263	0.0266	0.0238	0.0232	0.0220	0.0218	0.0207	0.0185

The table shows estimation results for multivariate logit models, where the dependent variable is set to one, seven to twelve quarters preceding a banking crisis in a respective country. Observations for banking crises and six quarters following banking crises are omitted, while other dependent variable observations are set to zero. The focus in this table is on credit growth and the credit-to-GDP gap, both on the domestic and on the global level. In columns 2, 4, 6 and 8 country-specific dummy variables account for unobserved heterogeneity across countries. Robust standard errors adjusted for clustering at the quarterly level are reported in parentheses. * indicates statistical significance at the 10 %-level, ** at the 5 %-level, and *** at the 1 %-level.

Table 5: Credit model evaluation

	μ	Threshold	TP	FP	TN	FN	T_1	T_2	Absolute Usefulness	Relative Usefulness	aNtS Ratio	% Predicted	Cond Prob	Diff Prob
Model 1	0.9	49	100	501	415	25	0.200	0.547	0.022	0.248	0.684	0.800	0.166	0.046
Model 2	0.9	48	97	489	427	28	0.224	0.534	0.021	0.236	0.688	0.776	0.166	0.045
Model 3	0.9	39	118	587	329	7	0.056	0.641	0.027	0.302	0.679	0.944	0.167	0.047
Model 4	0.9	43	114	525	391	11	0.088	0.573	0.030	0.336	0.628	0.912	0.178	0.058
Model 5	0.9	46	111	498	418	14	0.112	0.544	0.031	0.341	0.612	0.888	0.182	0.062
Model 6	0.9	46	112	479	437	13	0.104	0.523	0.033	0.370	0.584	0.896	0.190	0.069
Model 7	0.9	57	105	341	575	20	0.160	0.372	0.042	0.463	0.443	0.840	0.235	0.115
Model 8	0.9	56	108	333	583	17	0.136	0.364	0.045	0.497	0.421	0.864	0.245	0.125

The table shows results for the evaluation of the credit models presented in Table 4. As for the individual indicators, we apply the signalling approach by transforming predicted probabilities into country-specific percentiles. The preference parameter of $\mu = 0.9$ indicates that a policy maker has a strong preference for the detection of crises (i.e. avoiding type I errors) as compared to the avoidance of false alarms (i.e. type II errors). The optimal threshold is calculated as the one that maximizes the relative usefulness and gives the percentile of the country-specific distribution at which the respective indicator issues a warning. The columns of the table report the number of observations: where the indicator issues a warning that is indeed followed by a banking crises seven to twelve quarters ahead (TP); where the indicator issues a warning that is not followed by a crisis (FP); where the indicator issues no warning and there is no crises seven to twelve quarters ahead (TN); and where the indicator issues no warning although there is a crisis coming (FN). Furthermore, the table reports the fraction of type I errors $T_1 = FN/(TP+FN)$, the fraction of type II errors $T_2 = FP/(FP+TN)$, the absolute and the relative usefulness (see Section 4.2 for details), the adjusted noise-to-signal ratio (i.e. the ratio of false signals measured as a proportion of months where false signals could have been issued to good signals as a proportion of months where good signals could have been issued, or $(FP/(FP+TN))/(TP/(TP+FN))$), the probability of a crisis conditional on a signal being issued (Cond Prob) and the difference between the conditional and the unconditional probability of a crisis (Diff Prob).

Table 6: Extended models

	(1) Model 9	(2) Model 10	(3) Model 11	(4) Model 12	(5) Model 13	(6) Model 14	(7) Model 15	(8) Model 16	(9) Model 17	(10) Model 18	(11) Model 19	(12) Model 20
Dom. Credit Growth (DC1)	7.38**	1.82	1.42	-2.92	2.00	-2.72	3.93	1.54	-0.16	-5.40	-4.77	0.70
	(3.01)	(3.30)	(3.41)	(3.83)	(3.15)	(3.75)	(3.27)	(3.73)	(4.78)	(3.56)	(3.66)	(3.60)
Dom. Credit to GDP Gap (DC2)	5.18***	9.27***	5.05**	9.03***	4.02	8.22***	8.55***	12.98***	13.24***	14.46***	14.68***	20.04***
	(1.70)	(1.99)	(2.55)	(3.34)	(2.50)	(3.06)	(2.27)	(2.27)	(3.19)	(1.90)	(2.02)	(2.68)
Interaction(DC1 × DC2)					28.57	36.11*	55.68**	55.12**	83.05**		37.55	53.94
					(23.58)	(21.88)	(22.77)	(22.35)	(38.97)		(27.49)	(35.03)
GDP Growth		60.24***		37.87*		43.77**		19.64	41.84	78.37***	74.45***	30.80
		(18.01)		(19.83)		(20.76)		(18.97)	(26.08)	(23.01)	(23.23)	(27.05)
Inflation		-18.55*		-25.28***		-26.70***		-29.04**	-10.04	9.95	8.43	14.19
		(10.39)		(9.74)		(9.89)		(11.73)	(12.23)	(9.55)	(9.55)	(12.18)
Equity Price Growth		1.12		-1.15		-0.88		-1.01	-0.38	2.00	2.14	-0.15
		(1.09)		(1.02)		(1.02)		(1.10)	(1.14)	(1.38)	(1.42)	(1.35)
House Price Growth		18.64***		19.17***		18.68***		16.73***	19.80***	19.95***	19.89***	18.05***
		(4.97)		(5.72)		(5.56)		(5.40)	(5.56)	(4.57)	(4.54)	(5.35)
Banking Sector Capitalization										-106.96***	-105.48***	-136.85***
										(36.69)	(36.86)	(39.63)
Banking Sector Profitability										246.31***	235.93***	324.89***
										(66.70)	(69.91)	(76.45)
Glo. Credit Growth (GC1)			30.54***	29.25***	28.51***	28.02***	29.01***	25.99***	19.72*			6.72
			(5.72)	(8.70)	(5.55)	(8.55)	(5.61)	(8.88)	(11.12)			(12.82)
Glo. Credit to GDP Gap (GC2)			1.46	7.24	8.32	12.28	6.74	12.19	26.84**			41.15***
			(7.83)	(10.46)	(7.02)	(8.80)	(6.67)	(8.89)	(11.72)			(15.31)
Interaction(GC1 × GC2)					-430.18*	-270.49	-486.53*	-324.72	-472.64			-973.05***
					(240.41)	(276.63)	(258.07)	(305.59)	(312.51)			(317.56)
Global GDP Growth				-10.07		-10.09		-10.24	-10.58			-9.88
				(13.29)		(12.76)		(12.62)	(13.68)			(13.79)
Global Equity Price Growth				8.00*		7.26		7.39	7.61			7.78
				(4.85)		(4.82)		(4.80)	(5.42)			(6.12)
Global House Price Growth				8.02		6.02		16.29	14.97			30.09
				(18.16)		(18.36)		(18.34)	(20.67)			(22.55)
Interaction(DC1 × GC1)							-56.67	-28.48	-129.64			34.59
							(56.65)	(68.99)	(124.41)			(128.36)
Interaction(DC2 × GC2)							-417.35***	-472.20***	-410.73***			-582.20***
							(67.99)	(91.07)	(100.92)			(109.21)
Country dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	919	919	919	919	919	919	919	919	756	756	756	756
Pseudo R-Squared	0.108	0.160	0.160	0.233	0.168	0.237	0.210	0.278	0.272	0.210	0.213	0.336
AUROC	0.728	0.771	0.793	0.841	0.792	0.841	0.824	0.865	0.846	0.811	0.812	0.892
Standard error	0.0303	0.0273	0.0226	0.0182	0.0239	0.0182	0.0195	0.0160	0.0165	0.0253	0.0250	0.0157

The table shows estimation results for the extended multivariate logit models. As with the credit models, the dependent variable is set to one, seven to twelve quarters preceding a banking crisis in a respective country. Observations for banking crises and six quarters following banking crises are omitted, while other dependent variable observations are set to zero. Besides the credit variables, regressions in columns 2, 4, 6 and 8-12 include other macro-financial and banking-sector variables. All regressions include country-specific dummy variables to account for unobserved heterogeneity across countries. Robust standard errors adjusted for clustering at the quarterly level are reported in parentheses. * indicates statistical significance at the 10 %-level, ** at the 5 %-level, and *** at the 1 %-level.

Table 7: Extended model evaluation

	μ	Threshold	TP	FP	TN	FN	T_1	T_2	Absolute Usefulness	Relative Usefulness	aNtS Ratio	% Predicted	Cond Prob	Diff Prob
Model 9	0.9	57	70	278	397	27	0.278	0.412	0.026	0.291	0.571	0.722	0.201	0.076
Model 10	0.9	50	81	355	320	16	0.165	0.526	0.027	0.298	0.630	0.835	0.186	0.060
Model 11	0.9	49	90	321	354	7	0.072	0.476	0.040	0.447	0.513	0.928	0.219	0.093
Model 12	0.9	62	93	247	428	4	0.041	0.366	0.053	0.590	0.382	0.959	0.274	0.148
Model 13	0.9	48	92	329	346	5	0.052	0.487	0.041	0.458	0.514	0.948	0.219	0.093
Model 14	0.9	62	92	249	426	5	0.052	0.369	0.051	0.576	0.389	0.948	0.270	0.144
Model 15	0.9	67	71	174	501	26	0.268	0.258	0.041	0.456	0.352	0.732	0.290	0.164
Model 16	0.9	63	92	231	444	5	0.052	0.342	0.054	0.603	0.361	0.948	0.285	0.159
Model 17	0.9	63	66	179	408	6	0.083	0.305	0.051	0.595	0.333	0.917	0.269	0.160
Model 18	0.9	83	36	87	500	36	0.500	0.148	0.029	0.344	0.296	0.500	0.293	0.183
Model 19	0.9	91	28	43	544	44	0.611	0.073	0.027	0.312	0.188	0.389	0.394	0.285
Model 20	0.9	67	64	163	424	8	0.111	0.278	0.051	0.596	0.312	0.889	0.282	0.173

The table shows results for the evaluation of the extended models presented in Table 6. As before, we apply the signalling approach by transforming predicted probabilities into country-specific percentiles. The preference parameter of $\mu = 0.9$ indicates that policy makers have a strong preference for the detection of crises (i.e. avoiding type I errors) as compared to the avoidance of false alarms (i.e. type II errors). The optimal threshold is calculated as the one that maximizes the relative usefulness and gives the percentile of the country-specific distribution at which the respective indicator issues a warning. The columns of the table report the number of observations: where the indicator issues a warning that is indeed followed by a banking crises seven to twelve quarters ahead (TP); where the indicator issues a warning that is not followed by a crisis (FP); where the indicator issues no warning and there is no crises seven to twelve quarters ahead (TN); and where the indicator issues no warning although there is a crisis coming (FN). Furthermore, the table reports the fraction of type I errors $T_1 = FN/(TP+FN)$, the fraction of type II errors $T_2 = FP/(FP+TN)$, the absolute and the relative usefulness (see Section 4.2 for details), the adjusted noise-to-signal ratio (i.e. the ratio of false signals measured as a proportion of months where false signals could have been issued to good signals as a proportion of months where good signals could have been issued, or $(FP/(FP+TN))/(TP/(TP+FN))$), the probability of a crisis conditional on a signal being issued (Cond Prob) and the difference between the conditional and the unconditional probability of a crisis (Diff Prob).

Table 8: Robustness—Forecast horizon

	(1) Benchmark 7-12 quarters	(2) Model R1 1-6 quarters	(3) Model R2 1-12 quarters	(4) Model R3 13-20 quarters
Dom. Credit Growth (DC1)	1.54	-11.63	-3.06	-11.77***
	(3.73)	(8.06)	(4.28)	(4.07)
Dom. Credit to GDP Gap (DC2)	12.98***	61.69***	33.92***	16.03***
	(2.27)	(20.72)	(3.91)	(4.08)
Interaction(DC1 × DC2)	55.12**	-18.61	139.78***	-1.36
	(22.35)	(82.99)	(36.95)	(32.76)
GDP Growth	19.64	-28.92	-14.58	35.03
	(18.97)	(48.51)	(20.64)	(40.03)
Inflation	-29.04**	77.15***	22.54*	24.42**
	(11.73)	(24.02)	(13.25)	(10.59)
Equity Price Growth	-1.01	2.14	-0.45	-1.14
	(1.10)	(2.34)	(1.40)	(1.98)
House Price Growth	16.73***	-22.60**	7.29	8.62
	(5.40)	(9.98)	(6.19)	(5.91)
Glo. Credit Growth (GC1)	25.99***	113.85***	93.09***	-50.73***
	(8.88)	(18.75)	(12.10)	(14.10)
Glo. Credit to GDP Gap (GC2)	12.19	17.90	2.08	28.57**
	(8.89)	(21.61)	(10.95)	(13.06)
Interaction(GC1 × GC2)	-324.72	6,895.95***	2,763.43***	-52.28
	(305.59)	(1,067.10)	(502.18)	(449.06)
Global GDP Growth	-10.24	-0.39	-2.07	12.86
	(12.62)	(12.63)	(13.10)	(9.72)
Global Equity Price Growth	7.39	14.15***	15.06***	12.53***
	(4.80)	(5.08)	(4.91)	(4.76)
Global House Price Growth	16.29	-60.67**	-32.74	116.13***
	(18.34)	(30.62)	(23.07)	(21.94)
Interaction(DC1 × GC1)	-28.48	453.38	223.97**	-606.47***
	(68.99)	(322.98)	(99.32)	(111.78)
Interaction(DC2 × GC2)	-472.20***	-1,947.93***	-1,193.54***	-458.57***
	(91.07)	(565.00)	(151.01)	(79.88)
Observations	919	919	919	919
Pseudo R-Squared	0.278	0.781	0.617	0.340
AUROC	0.865	0.726	0.960	0.895
Standard error	0.0160	0.0179	0.0063	0.0134

The table assesses the robustness of our findings to the forecast horizon. Column 1 re-estimates Model 16 from Table 6, which we call our benchmark model. The dependent variable in this regression is set to one 7 to 12 quarters preceding a banking crisis in a respective country. In column 2, we replace the dependent variable with a dummy that is equal to one, 1 to 6 quarters before a banking crisis. Similarly, the dependent variable in column 3 equals one 1 to 12 quarters before a banking crisis in the respective country. Finally, the dependent variable in column 4 is equal to one 13 to 20 quarters before the onset of a banking crisis in a respective country. Robust standard errors adjusted for clustering at the quarterly level are reported in parentheses. * indicates statistical significance at the 10 %-level, ** at the 5 %-level, and *** at the 1 %-level.

Table 9: Robustness—Model evaluation

	μ	Threshold	TP	FP	TN	FN	T_1	T_2	Absolute Usefulness	Relative Usefulness	aNtS Ratio	% Predicted	Cond Prob	Diff Prob
Benchmark	0.9	63	92	231	444	5	0.052	0.342	0.054	0.603	0.361	0.948	0.285	0.159
Model R1	0.9	42	91	417	366	6	0.062	0.533	0.036	0.401	0.568	0.938	0.179	0.069
Model R2	0.9	65	81	251	532	16	0.165	0.321	0.045	0.503	0.384	0.835	0.244	0.134
Model R3	0.9	69	34	224	451	14	0.292	0.332	0.032	0.357	0.468	0.708	0.132	0.065

The table shows results for the evaluation of the models presented in Table 8. As before, we apply the signalling approach by transforming predicted probabilities into country-specific percentiles. The preference parameter of $\mu = 0.9$ indicates that policy makers have a strong preference for the detection of crises (i.e. avoiding type I errors) as compared to the avoidance of false alarms (i.e. type II errors). The optimal threshold is calculated as the one that maximizes the relative usefulness and gives the percentile of the country-specific distribution at which the respective indicator issues a warning. The columns of the table report the number of observations: where the indicator issues a warning that is indeed followed by a banking crises seven to twelve quarters ahead (TP); where the indicator issues a warning that is not followed by a crisis (FP); where the indicator issues no warning and there is no crises seven to twelve quarters ahead (TN); and where the indicator issues no warning although there is a crisis coming (FN). Furthermore, the table reports the fraction of type I errors $T_1 = FN/(TP+FN)$, the fraction of type II errors $T_2 = FP/(FP+TN)$, the absolute and the relative usefulness (see Section 4.2 for details), the adjusted noise-to-signal ratio (i.e. the ratio of false signals measured as a proportion of months where false signals could have been issued to good signals as a proportion of months where good signals could have been issued, or $(FP/(FP+TN))/(TP/(TP+FN)))$, the probability of a crisis conditional on a signal being issued (Cond Prob) and the difference between the conditional and the unconditional probability of a crisis (Diff Prob).

Table 10: Further robustness checks

	(1) Benchmark	(2) RR	(3) LV	(4) EMU	(5) EU-15	(6) Euro	(7) Interest Rates	(8) Percentiles	(9) Percentiles
Dom. Credit Growth (DC1)	1.54	-10.01**	-0.58	-1.08	1.01	-4.23	2.83	-0.009	-0.000
	(3.73)	(4.71)	(3.28)	(4.29)	(4.57)	(6.77)	(5.86)	(0.008)	(0.010)
Dom. Credit to GDP Gap (DC2)	12.98***	23.91***	4.09	15.68***	12.46***	14.70***	37.86***	0.039***	0.050***
	(2.27)	(4.32)	(2.60)	(2.51)	(2.64)	(4.73)	(4.67)	(0.007)	(0.009)
Interaction(DC1 × DC2)	55.12**	35.24	26.75	57.40**	55.10*	138.12*	83.42*	0.018***	0.026***
	(22.35)	(36.30)	(26.96)	(26.67)	(31.69)	(71.79)	(46.34)	(0.005)	(0.005)
GDP Growth	19.64	2.67	11.35	12.95	18.29	14.00	35.04	0.003	0.001
	(18.97)	(20.61)	(25.41)	(20.57)	(20.65)	(21.40)	(24.89)	(0.006)	(0.006)
Inflation	-29.04**	-3.98	-25.31*	-29.70**	-3.65	15.29	68.72***	-0.001	-0.004
	(11.73)	(11.60)	(15.21)	(12.35)	(10.79)	(10.41)	(20.10)	(0.005)	(0.006)
Equity Price Growth	-1.01	-0.20	-1.46	-1.57	-0.43	-0.14	-1.77	-0.008	-0.009
	(1.10)	(1.49)	(2.11)	(1.16)	(1.26)	(1.51)	(1.91)	(0.006)	(0.006)
House Price Growth	16.73***	14.03***	6.73	21.02***	23.45***	20.71***	20.73**	0.019***	0.015**
	(5.40)	(4.81)	(8.52)	(6.20)	(5.33)	(5.50)	(9.37)	(0.005)	(0.006)
Gov. Bond Yield							-28.69		
							(45.08)		
Money Market Rate							-125.08***		
							(38.55)		
Glo. Credit Growth (GC1)	25.99***	32.12***	39.40***	49.67***	18.57**	13.00	108.66***	0.024**	0.018
	(8.88)	(10.77)	(15.26)	(10.14)	(9.42)	(10.23)	(16.80)	(0.010)	(0.011)
Glo. Credit to GDP Gap (GC2)	12.19	-8.68	42.49***	-4.67	20.22*	18.52*	-37.62**	-0.033***	0.004
	(8.89)	(10.83)	(15.62)	(12.87)	(11.24)	(10.52)	(17.82)	(0.008)	(0.013)
Interaction(GC1 × GC2)	-324.72	-255.97	1,718.19***	-806.86**	-390.66	-121.35	-1,941.20***	0.011	-0.005
	(305.59)	(320.49)	(587.11)	(345.60)	(296.43)	(301.21)	(527.98)	(0.009)	(0.010)
Global GDP Growth	-10.24	-4.87	-40.28*	-8.78	-7.63	-10.67	0.08	-0.004	-0.004
	(12.62)	(12.25)	(20.80)	(12.60)	(12.95)	(15.21)	(11.66)	(0.009)	(0.009)
Global Equity Price Growth	7.39	7.11	21.31***	6.86	8.58*	10.72*	6.47	0.016	0.018*
	(4.80)	(4.56)	(7.62)	(4.99)	(5.07)	(6.14)	(4.61)	(0.010)	(0.010)
Global House Price Growth	16.29	8.29	51.73**	11.56	20.92	27.87	27.49	0.046***	0.054***
	(18.34)	(17.54)	(23.01)	(20.00)	(18.53)	(21.34)	(19.84)	(0.014)	(0.013)
Interaction(DC1 × GC1)	-28.48	77.07	12.25	-17.42	-240.77**	-134.60	208.01	-0.001	-0.004
	(68.99)	(88.37)	(104.67)	(89.52)	(102.03)	(101.30)	(139.13)	(0.005)	(0.006)
Interaction(DC2 × GC2)	-472.20***	-754.19***	-339.87***	-617.47***	-436.37***	-276.74**	-1,466.07***	-0.042***	-0.062***
	(91.07)	(102.92)	(66.07)	(133.84)	(96.37)	(109.19)	(182.09)	(0.006)	(0.010)
D(EMU)				2.83***					
				(0.62)					
Country dummies	YES	YES	YES	YES	YES	YES	YES	NO	YES
Observations	919	835	893	919	869	664	862	919	919
Pseudo R-Squared	0.278	0.286	0.442	0.314	0.269	0.270	0.477	0.324	0.372
AUROC	0.865	0.827	0.807	0.887	0.847	0.836	0.942	0.892	0.909
Standard error	0.0160	0.0207	0.0223	0.0136	0.0172	0.0184	0.0091	0.0126	0.0117

The table shows several robustness checks for our benchmark model (Model 16 in Table 6). In column 2 we use the Reinhart and Rogoff [33] crisis definition instead of the Babecky et al. [3] definition, while in column 3, we use the definition by Laeven and Valencia [26]. Column 4 includes a dummy that is equal to one for each quarter in which the respective country is a member of the European Monetary Union (EMU) and column 5 restricts the sample to include only EU-15 countries for which data availability is better than for the rest of our sample countries. Column 6 restricts the sample to include only the countries that are a part of the EMU. In column 7 we include two interest rate variables, the 10-year government bond yield and the 3-months interbank lending rate. Finally, in columns 8 and 9 we transform all variables into country-specific percentiles before using them in the regression. All specifications (except column 8) include country-specific dummy variables to account for unobserved heterogeneity across countries. Robust standard erros adjusted for clustering at the quarterly level are reported in parantheses. * indicates statistical significance at the 10 %-level, ** at the 5 %-level, and *** at the 1 %-level.

Appendix

Table A.1: Evaluation of individual indicators—alternative μ values

	μ	Threshold	TP	FP	TN	FN	T_1	T2	Absolute Usefulness	Relative Usefulness	aNtS Ratio	% Predicted	Cond Prob	Diff Prob
Dom. Credit Growth (qoq)	0.8	99	5	14	887	118	0.959	0.016	0.001	0.007	0.382	0.041	0.263	0.143
Dom. Credit Growth (yoy)	0.8	99	2	15	886	121	0.984	0.017	-0.002	-0.020	1.024	0.016	0.118	-0.002
Dom. Credit Gap	0.8	99	3	11	890	120	0.976	0.012	0.000	-0.002	0.501	0.024	0.214	0.094
Dom. Credit Growth (4q MA)	0.8	99	1	15	886	122	0.992	0.017	-0.002	-0.028	2.048	0.008	0.063	-0.058
Dom. Credit Growth (6q MA)	0.8	99	0	15	886	123	1.000	0.017	-0.003	-0.036		0.000	0.000	-0.120
Dom. Credit Growth (8q MA)	0.8	99	0	16	885	123	1.000	0.018	-0.003	-0.039		0.000	0.000	-0.120
Dom. Credit to GDP Ratio	0.8	75	38	114	787	85	0.691	0.127	0.003	0.032	0.410	0.309	0.250	0.130
Dom. Credit to GDP Gap	0.8	96	8	25	876	115	0.935	0.028	0.000	0.004	0.427	0.065	0.242	0.122
Dom. Credit Growth - GDP Growth	0.8	99	5	13	888	118	0.959	0.014	0.001	0.009	0.355	0.041	0.278	0.158
Glo. Credit Growth (qoq)	0.8	99	5	16	885	118	0.959	0.018	0.000	0.002	0.437	0.041	0.238	0.118
Glo. Credit Growth (yoy)	0.8	99	1	13	888	122	0.992	0.014	-0.002	-0.023	1.775	0.008	0.071	-0.049
Glo. Credit Gap	0.8	98	2	18	883	121	0.984	0.020	-0.002	-0.027	1.229	0.016	0.100	-0.020
Glo. Credit Growth (4q MA)	0.8	99	1	13	888	122	0.992	0.014	-0.002	-0.023	1.775	0.008	0.071	-0.049
Glo. Credit Growth (6q MA)	0.8	99	0	13	888	123	1.000	0.014	-0.003	-0.032		0.000	0.000	-0.120
Glo. Credit Growth (8q MA)	0.8	99	0	13	888	123	1.000	0.014	-0.003	-0.032		0.000	0.000	-0.120
Glo. Credit to GDP Ratio	0.8	75	44	100	801	79	0.642	0.111	0.009	0.115	0.310	0.358	0.306	0.185
Glo. Credit to GDP Gap	0.8	99	0	7	894	123	1.000	0.008	-0.001	-0.017		0.000	0.000	-0.120
Glo. Credit Growth - Glo. GDP Growth	0.8	98	5	16	885	118	0.959	0.018	0.000	0.002	0.437	0.041	0.238	0.118
Dom. Credit Growth (qoq)	0.85	88	28	121	780	95	0.772	0.134	0.002	0.020	0.590	0.228	0.188	0.068
Dom. Credit Growth (yoy)	0.85	78	48	204	697	75	0.610	0.226	0.004	0.040	0.580	0.390	0.190	0.070
Dom. Credit Gap	0.85	86	27	109	792	96	0.780	0.121	0.003	0.032	0.551	0.220	0.199	0.078
Dom. Credit Growth (4q MA)	0.85	70	58	278	623	65	0.528	0.309	0.000	-0.005	0.654	0.472	0.173	0.053
Dom. Credit Growth (6q MA)	0.85	99	0	15	886	123	1.000	0.017	-0.002	-0.026		0.000	0.000	-0.120
Dom. Credit Growth (8q MA)	0.85	99	0	16	885	123	1.000	0.018	-0.002	-0.027		0.000	0.000	-0.120
Dom. Credit to GDP Ratio	0.85	70	49	159	742	74	0.602	0.176	0.011	0.126	0.443	0.398	0.236	0.115
Dom. Credit to GDP Gap	0.85	93	15	50	851	108	0.878	0.055	0.003	0.036	0.455	0.122	0.231	0.111
Dom. Credit Growth - GDP Growth	0.85	99	5	13	888	118	0.959	0.014	0.002	0.018	0.355	0.041	0.278	0.158

Table A.1 continued...

	μ	Threshold	TP	FP	TN	FN	T_1	T2	Absolute Usefulness	Relative Usefulness	aNtS Ratio	% Predicted	Cond Prob	Diff Prob
Glo. Credit Growth (qoq)	0.85	65	91	304	597	32	0.260	0.337	0.019	0.218	0.456	0.740	0.230	0.110
Glo. Credit Growth (yoy)	0.85	57	101	365	536	22	0.179	0.405	0.017	0.195	0.493	0.821	0.217	0.097
Glo. Credit Gap	0.85	45	113	427	474	10	0.081	0.474	0.016	0.186	0.516	0.919	0.209	0.089
Glo. Credit Growth (4q MA)	0.85	56	94	368	533	29	0.236	0.408	0.012	0.133	0.534	0.764	0.203	0.083
Glo. Credit Growth (6q MA)	0.85	47	108	456	445	15	0.122	0.506	0.008	0.096	0.576	0.878	0.191	0.071
Glo. Credit Growth (8q MA)	0.85	48	97	438	463	26	0.211	0.486	0.003	0.037	0.616	0.789	0.181	0.061
Glo. Credit to GDP Ratio	0.85	75	44	100	801	79	0.642	0.111	0.016	0.186	0.310	0.358	0.306	0.185
Glo. Credit to GDP Gap	0.85	99	0	7	894	123	1.000	0.008	-0.001	-0.012		0.000	0.000	-0.120
Glo. Credit Growth - Glo. GDP Growth	0.85	83	46	161	740	77	0.626	0.179	0.009	0.098	0.478	0.374	0.222	0.102
Dom. Credit Growth (qoq)	0.95	5	122	868	33	1	0.008	0.963	0.001	0.019	0.971	0.992	0.123	0.003
Dom. Credit Growth (yoy)	0.95	39	109	604	297	14	0.114	0.670	0.004	0.083	0.756	0.886	0.153	0.033
Dom. Credit Gap	0.95	23	117	694	207	6	0.049	0.770	0.006	0.124	0.810	0.951	0.144	0.024
Dom. Credit Growth (4q MA)	0.95	33	108	654	247	15	0.122	0.726	0.000	0.010	0.827	0.878	0.142	0.022
Dom. Credit Growth (6q MA)	0.95	1	120	900	1	3	0.024	0.999	-0.002	-0.052	1.024	0.976	0.118	-0.002
Dom. Credit Growth (8q MA)	0.95	1	120	901	0	3	0.024	1.000	-0.002	-0.053	1.025	0.976	0.118	-0.003
Dom. Credit to GDP Ratio	0.95	3	123	869	32	0	0.000	0.964	0.002	0.036	0.964	1.000	0.124	0.004
Dom. Credit to GDP Gap	0.95	33	107	570	331	16	0.130	0.633	0.004	0.085	0.727	0.870	0.158	0.038
Dom. Credit Growth - GDP Growth	0.95	1	123	894	7	0	0.000	0.992	0.000	0.008	0.992	1.000	0.121	0.001
Glo. Credit Growth (qoq)	0.95	34	118	639	262	5	0.041	0.709	0.009	0.203	0.739	0.959	0.156	0.036
Glo. Credit Growth (yoy)	0.95	50	111	445	456	12	0.098	0.494	0.013	0.294	0.547	0.902	0.200	0.080
Glo. Credit Gap	0.95	39	119	504	397	4	0.033	0.559	0.017	0.370	0.578	0.967	0.191	0.071
Glo. Credit Growth (4q MA)	0.95	45	113	493	408	10	0.081	0.547	0.012	0.276	0.596	0.919	0.186	0.066
Glo. Credit Growth (6q MA)	0.95	42	114	515	386	9	0.073	0.572	0.012	0.270	0.617	0.927	0.181	0.061
Glo. Credit Growth (8q MA)	0.95	38	113	551	350	10	0.081	0.612	0.010	0.212	0.666	0.919	0.170	0.050
Glo. Credit to GDP Ratio	0.95	1	123	892	9	0	0.000	0.990	0.000	0.010	0.990	1.000	0.121	0.001
Glo. Credit to GDP Gap	0.95	24	115	695	206	8	0.065	0.771	0.004	0.088	0.825	0.935	0.142	0.022
Glo. Credit Growth - Glo. GDP Growth	0.95	16	115	745	156	8	0.065	0.827	0.001	0.032	0.884	0.935	0.134	0.014

Table A.2: Credit model evaluation—alternative μ parameters

	μ	Threshold	TP	FP	TN	FN	T_1	T2	Absolute Usefulness	Relative Usefulness	aNtS Ratio	% Predicted	Cond Prob	Diff Prob
Model 1	0.8	99	3	14	902	122	0.976	0.015	-0.001	-0.009	0.637	0.024	0.176	0.056
Model 2	0.8	92	20	67	849	105	0.840	0.073	0.000	0.000	0.457	0.160	0.230	0.110
Model 3	0.8	99	1	15	901	124	0.992	0.016	-0.002	-0.028	2.047	0.008	0.063	-0.058
Model 4	0.8	99	1	14	902	124	0.992	0.015	-0.002	-0.025	1.910	0.008	0.067	-0.053
Model 5	0.8	79	46	151	765	79	0.632	0.165	0.001	0.007	0.448	0.368	0.234	0.113
Model 6	0.8	70	66	230	686	59	0.472	0.251	-0.002	-0.022	0.476	0.528	0.223	0.103
Model 7	0.8	78	59	128	788	66	0.528	0.140	0.014	0.166	0.296	0.472	0.316	0.195
Model 8	0.8	72	77	170	746	48	0.384	0.186	0.017	0.210	0.301	0.616	0.312	0.192
Model 1	0.85	81	45	175	741	80	0.640	0.191	0.006	0.065	0.531	0.360	0.205	0.084
Model 2	0.85	74	58	233	683	67	0.536	0.254	0.006	0.071	0.548	0.464	0.199	0.079
Model 3	0.85	69	64	256	660	61	0.488	0.279	0.007	0.080	0.546	0.512	0.200	0.080
Model 4	0.85	54	94	411	505	31	0.248	0.449	0.005	0.058	0.597	0.752	0.186	0.066
Model 5	0.85	72	61	215	701	64	0.512	0.235	0.011	0.125	0.481	0.488	0.221	0.101
Model 6	0.85	62	85	310	606	40	0.320	0.338	0.014	0.157	0.498	0.680	0.215	0.095
Model 7	0.85	70	80	201	715	45	0.360	0.219	0.026	0.301	0.343	0.640	0.285	0.165
Model 8	0.85	64	95	243	673	30	0.240	0.265	0.030	0.350	0.349	0.760	0.281	0.161
Model 1	0.95	41	109	580	336	16	0.128	0.633	0.004	0.089	0.726	0.872	0.158	0.038
Model 2	0.95	31	112	669	247	13	0.104	0.730	0.002	0.044	0.815	0.896	0.143	0.023
Model 3	0.95	35	122	634	282	3	0.024	0.692	0.011	0.256	0.709	0.976	0.161	0.041
Model 4	0.95	43	114	525	391	11	0.088	0.573	0.011	0.236	0.628	0.912	0.178	0.058
Model 5	0.95	35	124	634	282	1	0.008	0.692	0.013	0.291	0.698	0.992	0.164	0.044
Model 6	0.95	36	121	599	317	4	0.032	0.654	0.012	0.277	0.676	0.968	0.168	0.048
Model 7	0.95	49	113	433	483	12	0.096	0.473	0.014	0.319	0.523	0.904	0.207	0.087
Model 8	0.95	52	112	378	538	13	0.104	0.413	0.016	0.362	0.461	0.896	0.229	0.108

Table A.3: Extended model evaluation—alternative μ parameters

	μ	Threshold	TP	FP	TN	FN	T_1	T2	Absolute Usefulness	Relative Usefulness	aNtS Ratio	% Predicted	Cond Prob	Diff Prob
Model 9	0.8	90	22	54	621	75	0.773	0.080	0.005	0.058	0.353	0.227	0.289	0.164
Model 10	0.8	92	30	52	623	67	0.691	0.077	0.012	0.147	0.249	0.309	0.366	0.240
Model 11	0.8	70	62	159	516	35	0.361	0.236	0.012	0.143	0.369	0.639	0.281	0.155
Model 12	0.8	85	52	85	590	45	0.464	0.126	0.023	0.271	0.235	0.536	0.380	0.254
Model 13	0.8	75	53	135	540	44	0.454	0.200	0.011	0.125	0.366	0.546	0.282	0.156
Model 14	0.8	82	57	105	570	40	0.412	0.156	0.022	0.260	0.265	0.588	0.352	0.226
Model 15	0.8	78	53	107	568	44	0.454	0.159	0.018	0.213	0.290	0.546	0.331	0.206
Model 16	0.8	84	59	81	594	38	0.392	0.120	0.030	0.356	0.197	0.608	0.421	0.296
Model 17	0.8	81	45	77	510	27	0.375	0.131	0.024	0.313	0.210	0.625	0.369	0.260
Model 18	0.8	92	26	38	549	46	0.639	0.065	0.016	0.207	0.179	0.361	0.406	0.297
Model 19	0.8	91	28	43	544	44	0.611	0.073	0.016	0.215	0.188	0.389	0.394	0.285
Model 20	0.8	85	44	56	531	28	0.389	0.095	0.029	0.385	0.156	0.611	0.440	0.331
Model 9	0.85	78	41	133	542	56	0.577	0.197	0.012	0.130	0.466	0.423	0.236	0.110
Model 10	0.85	82	47	123	552	50	0.515	0.182	0.019	0.214	0.376	0.485	0.276	0.151
Model 11	0.85	65	70	194	481	27	0.278	0.287	0.027	0.294	0.398	0.722	0.265	0.140
Model 12	0.85	65	89	222	453	8	0.082	0.329	0.039	0.429	0.358	0.918	0.286	0.161
Model 13	0.85	70	61	172	503	36	0.371	0.255	0.023	0.250	0.405	0.629	0.262	0.136
Model 14	0.85	66	86	218	457	11	0.113	0.323	0.037	0.406	0.364	0.887	0.283	0.157
Model 15	0.85	67	71	174	501	26	0.268	0.258	0.031	0.349	0.352	0.732	0.290	0.164
Model 16	0.85	72	81	162	513	16	0.165	0.240	0.043	0.478	0.287	0.835	0.333	0.208
Model 17	0.85	72	58	125	462	14	0.194	0.213	0.036	0.449	0.264	0.806	0.317	0.208
Model 18	0.85	90	29	51	536	43	0.597	0.087	0.021	0.257	0.216	0.403	0.363	0.253
Model 19	0.85	91	28	43	544	44	0.611	0.073	0.022	0.266	0.188	0.389	0.394	0.285
Model 20	0.85	79	51	89	498	21	0.292	0.152	0.037	0.454	0.214	0.708	0.364	0.255
Model 9	0.95	18	93	562	113	4	0.041	0.833	0.003	0.074	0.868	0.959	0.142	0.016
Model 10	0.95	40	87	428	247	10	0.103	0.634	0.006	0.133	0.707	0.897	0.169	0.043
Model 11	0.95	45	94	354	321	3	0.031	0.524	0.018	0.406	0.541	0.969	0.210	0.084
Model 12	0.95	60	94	261	414	3	0.031	0.387	0.024	0.544	0.399	0.969	0.265	0.139
Model 13	0.95	45	94	350	325	3	0.031	0.519	0.018	0.412	0.535	0.969	0.212	0.086
Model 14	0.95	62	92	249	426	5	0.052	0.369	0.023	0.515	0.389	0.948	0.270	0.144
Model 15	0.95	42	94	374	301	3	0.031	0.554	0.017	0.376	0.572	0.969	0.201	0.075
Model 16	0.95	63	92	231	444	5	0.052	0.342	0.024	0.542	0.361	0.948	0.285	0.159
Model 17	0.95	63	66	179	408	6	0.083	0.305	0.024	0.528	0.333	0.917	0.269	0.160
Model 18	0.95	27	71	449	138	1	0.014	0.765	0.009	0.207	0.776	0.986	0.137	0.027
Model 19	0.95	33	69	413	174	3	0.042	0.704	0.010	0.213	0.734	0.958	0.143	0.034
Model 20	0.95	56	69	242	345	3	0.042	0.412	0.023	0.504	0.430	0.958	0.222	0.113