B PREDICTING FINANCIAL VULNERABILITIES TO GUIDE THE SET-UP OF COUNTER-CYCLICAL CAPITAL BUFFERS[1]

The systemic dimension of the financial crisis has underscored the need for an expanded set of policies to contain systemic risk throughout the financial cycle. Counter-cyclical capital buffers (CCBs) form an integral part of the expanded European macro-prudential toolkit in this respect, with a "time series" focus in that they increase the resilience of the banking sector to shocks arising from financial and economic stress over the cycle and thereby provide a means to attenuate pro-cyclicality inherent in the financial system. To guide the setting of CCBs, the Basel Committee on Banking Supervision (BCBS) has proposed a focus on, inter alia, the deviation of the domestic credit-to-GDP ratio from its backward-looking trend (also known as the domestic credit-to-GDP gap), given its track record of signalling financial stress well in advance. The Capital Requirements Directive (CRD) IV specifies that other variables should also be taken into consideration in addition to the credit gap. This special feature assesses the usefulness of private sector credit and other macro-financial and banking sector indicators in guiding the setting of CCBs in a multivariate early warning model framework. The analysis shows that in addition to credit variables, other domestic and global financial factors such as equity and house prices, as well as aggregate banking sector balance sheet indicators, help to predict historical periods of financial vulnerabilities in EU Member States. Consequently, policy-makers deciding on CCB measures could benefit from considering a wide range of indicators.

INTRODUCTION

The CCB aims to increase the resilience of the banking system in case of a financial crisis

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 which has been implemented in the EU's Capital Requirements Directive (CRD) IV is the counter-cyclical capital buffer (CCB).

The CCB aims to increase the resilience of the banking system in case of a financial crisis by ensuring that banks set aside capital in times of "*aggregate growth in credit [...] associated with a build-up of systemic risk*", which can be "*drawn down during stressed periods*".[2] In order to promote international consistency in setting CCB rates, the Basel Committee on Banking Supervision (BCBS) has suggested a methodology giving prominence to the ratio of aggregate private sector credit to GDP.[3] The CRD IV, while acknowledging the importance of credit growth and the credit-to-GDP ratio, specifies that buffer rates could also take into account other variables that can indicate the existence of risks to financial stability.[4] This provides the motivation for this special feature, namely to assess the usefulness of credit and other macro-financial variables for predicting banking sector vulnerabilities in a multivariate framework, thereby enabling a more informed decision on the setting of CCB rates.

1 Prepared by Tuomas Peltonen and Willem Schudel. This special feature is based on Behn, M., Detken, C., Peltonen, T. and Schudel, W., "Setting countercyclical capital buffers based on early warning models: would it work?", *Working Paper Series*, No 1604, ECB, 2013.

2 See Capital Requirements Directive IV (preamble 80), available online at http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2013:176:0338:0436:EN:PDF

3 See Basel Committee on Banking Supervision, "Guidance for national authorities operating the countercyclical capital buffer", December 2010. The BCBS guidelines are based on Drehmann, M., Borio, C., Gambacorta, L., Jiménez, G. and Trucharte, C., "Countercyclical capital buffers: exploring options", *BIS Working Papers*, No 317, BIS, July 2010, as well as on Drehmann, M., Borio, C. and Tsatsaronis, K., "Anchoring countercyclical capital buffers: the role of credit aggregates", *International Journal of Central Banking*, 7(4), 2011.

4 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*".

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 backward-looking long-term trend) represents the best single indicator in terms of signalling a coming financial crisis. However, the evidence presented by the BCBS[5] does not account for the 12-month implementation period needed to raise the capital buffers specified in the CRD IV regulation.[6] In other words, the credit gap may be an early warning indicator that is not *early enough* for policy implementation purposes. Moreover, the guidelines do not directly compare the predictive power of the credit-to-GDP gap with that of other potentially relevant variables related to risks to financial stability (as stated in the CRD IV) in a *multivariate* framework. Furthermore, only seven EU countries were part of the BCBS study. Acknowledging the potentially very large implications that this policy has for the European banking sector, this special feature aims to address these non-trivial issues.

In line with the spirit of the forthcoming legislation for the CCB, the models used in this special feature are calibrated so that they 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. This would, hopefully, allow for a timely build-up of the CCB to increase the resilience of the banking sector.

IDENTIFYING SYSTEMIC BANKING CRISES

Identifying systemic banking crises in the EU

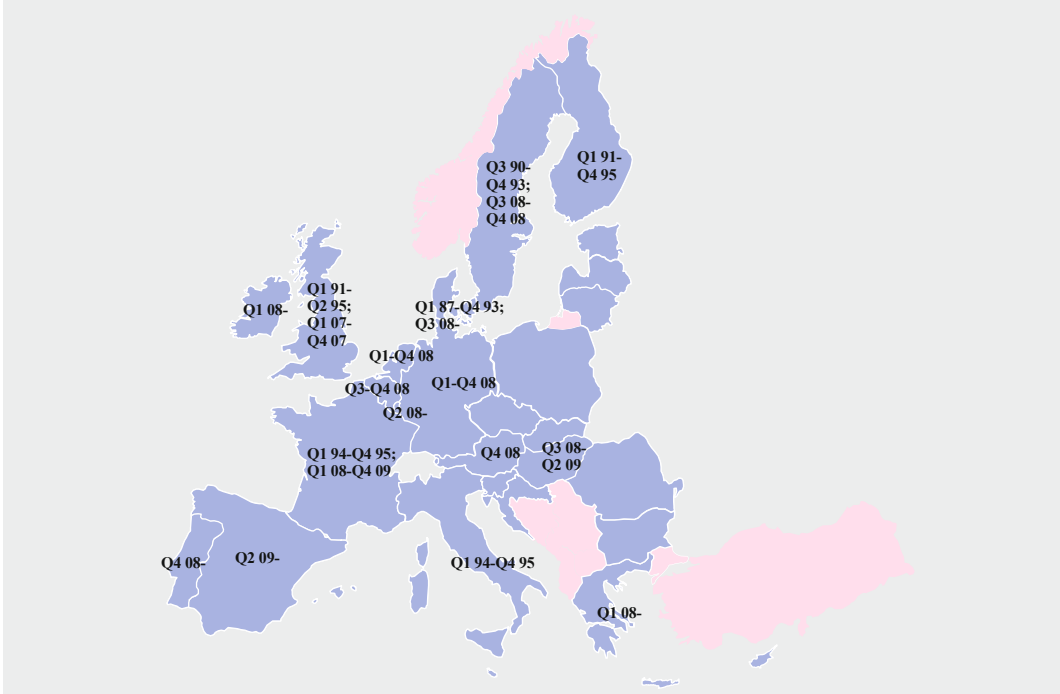
An important element of an early warning model for banking crises is the definition of a *vulnerable state* of the economy from which a banking crisis could emerge, given a suitable trigger. Vulnerable states are defined as the period between twelve and seven quarters before the onset of a banking crisis. This time horizon accounts for the announcement period of twelve months specified in the CRD IV as well as for a time lag required to implement the necessary policies.

The banking crises data is based on a dataset developed by the ESCB Heads of Research Group.[7] This database consists of quarterly data on systemic banking crises in the EU countries between the first quarter of 1970 and the fourth quarter of 2010.[8] 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 database aggregates information about banking crisis occurrences from the academic literature, which is subsequently cross-checked with the ESCB Heads of Research Group before inclusion in the database.

Figure B.1 shows the banking crisis dates for the sample of countries considered in this special feature. The composed dependent variable, a vulnerable state, is equal to 1 between twelve and seven quarters (inclusive) prior to a banking crisis as identified by the banking crises database and 0 for all other quarters in the data.[9]

5 In the BIS working paper forming the background to the BCBS guidelines (Drehmann, M., Borio, C., Gambacorta, L., Jiménez, G. and Trucharte, C., op. cit.), the authors judge a signal of 1 (0) to be correct if a crisis (no crisis) occurs at any time within a three-year horizon.
6 See Article 126(6) of the CRD IV.
7 The data was collected by a team at Česká národní banka and was published in Babecky, J., Havranek, T., Mateju, J., Rusnak, M., Smidkova, K. and Vasicek, B., "Banking, debt, and currency crises: early warning indicators for developed countries", *Working Paper Series,* No 1485, ECB, October 2012.
8 Croatia, which joined the EU on 1 July 2013, has not yet been included in the database.
9 In order to overcome crisis and post-crisis bias, all country quarter observations which are in, or within six quarters of, a banking crisis are omitted from the analysis. See, for example, Bussiere, M. and Fratzscher, M., "Towards a new early warning system of financial crises", *Journal of International Money and Finance*, 25(6), 2006.

Figure B.1 Banking crisis dates for the sample countries



Sources: ESCB Heads of Research database, Česká národní banka and ECB.
Note: The data was first published in Babecky, J., Havranek, T., Mateju, J., Rusnak, M., Smidkova, K. and Vasicek, B., "Banking, debt, and currency crises: early warning indicators for developed countries", *Working Paper Series*, No 1485, ECB, October 2012.

MACRO-FINANCIAL AND BANKING SECTOR INDICATORS

Country-specific indicators: credit variables…

The panel dataset used in the analysis contains quarterly macro-financial and banking sector data from the second quarter of 1982 onwards, for 23 EU Member States. The data is sourced through Haver Analytics and originally comes from the Bank for International Settlements (BIS), the ECB, Eurostat, the International Monetary Fund (IMF) and the Organisation for Economic Cooperation and Development (OECD).[10]

Given the importance of credit in the BCBS proposal and the CRD IV, several measures of credit to the private sector are taken into account. The source of the credit data is the BIS, whose credit series appears to be based on the broadest definition of credit provision to the private sector, while having been adjusted for data gaps and structural breaks.[11] The model framework includes four different measurements of credit, accounting for credit growth and leverage at the domestic and at the global level. *Credit growth* is entered as a percentage (annual growth), while leverage is

10 In particular, the individual series stem from the following original sources: data on total credit to the private non-financial sector are obtained from the BIS and from Eurostat for those countries where BIS data are not available; information on nominal GDP growth and inflation rates comes from the IMF's International Financial Statistics; data on stock prices are obtained from the OECD, while data on house prices are provided by the BIS; and interest rate and banking sector variables are obtained from the OECD.

11 The BIS' long series on total credit and domestic bank credit to the private non-financial sector includes "[c]redit [that] is provided by domestic banks, all other sectors of the economy and non-residents". The "private non-financial sector" includes non-financial corporations (both privately owned and publicly owned), households and non-profit institutions serving households. In terms of financial instruments, credit covers loans and debt securities. A description of the database can be found in Dembiermont, C., Drehmann, M. and Muksakunratana, S., "How much does the private sector really borrow? A new database for total credit to the private non-financial sector", *Bank for International Settlements*, 2013.

measured by the deviation of the *credit-to-GDP ratio* (using nominal GDP data) from its long-term backward-looking trend as proposed in the BCBS 2010 Consultative Document.[12]

In an increasingly integrated global economy, vulnerabilities that develop in one country or at a global level can potentially rapidly transmit to other countries around the world. In fact, earlier studies have stressed the importance of global variables and their interactions with domestic variables in predicting domestic banking and financial crises.[13] Moreover, the CRD IV regulation stipulates that the institution-specific CCB rates are to be calculated using a weighted average of the CCB rates in countries to which the respective institution is exposed. Therefore, it is important to analyse developments of credit (and other variables) beyond national boundaries.

Global credit variables have been computed using a GDP-weighted average of the variable in question for several countries, including the United States, Japan, Canada, and all European countries which are part of this study. In addition, four sets of *interaction terms* are included, namely the product of the domestic variables (to account, for example, for circumstances in which fast domestic credit growth is combined with a high level of leverage of the domestic economy), the product of the global variables (to account, for example, for fast global credit growth combined with a high level of global leverage) and the product of domestic and global credit variables (to account, for example, for fast domestic credit growth coinciding with fast global credit growth).

… macro-financial and banking sector indicators

In order to test the importance of credit variables in a comparative fashion as well as to analyse the potential importance of other factors, a number of additional variables are also added to the models. These are selected based on the existing literature and on data availability and include *nominal GDP growth* (domestic and global), *consumer price inflation rates*, *equity prices, residential house prices* (domestic and global), *bank capitalisation* (calculated as the ratio of total banking sector equity over total banking sector assets) and *aggregate banking sector profitability* (defined as net income before tax as a percentage of total assets).

MACRO DEVELOPMENTS IN THE RUN-UP TO BANKING CRISES

Chart B.1 presents the average developments of the six main explanatory variables of interest over time before and after the onset of a banking crisis. For the purpose of predicting banking crises based on simple descriptive statistics, one would hope to find an indicator variable that displays a typical pattern in the run-up to a crisis so that it can be used as a signal. In the current case of predicting vulnerable states of the economy that precede future banking crises, variables that signal a crisis way ahead of time (i.e. two to three years before the crisis) would be of interest, so that policy-makers can use this time to increase the resilience of banks.

Indicator developments before and after a crisis

On average, the credit gap increases slowly prior to a banking crisis and starts falling about one year into the crisis. The BCBS concedes that the credit-to-GDP gap may not capture turning points well.[14] Consequently, the ratio will not fall unless credit falls faster than GDP, something which is not at all certain during a banking crisis. Still, it shows that from a purely descriptive perspective, any signal to be derived from the credit gap will come from the level of this variable breaching a threshold value, not from turning points in its development.

12 See Basel Committee on Banking Supervision, "Guidance for national authorities operating the countercyclical capital buffer", *Bank for International Settlements*, 2010. The backward-looking trend is calculated using a Hodrick-Prescott filter with a smoothing parameter λ of 400,000.

13 See, for example, Lo Duca, M. and Peltonen, T., "Assessing systemic risks and predicting systemic events", *Journal of Banking & Finance*, 37(7), 2013.

14 See Basel Committee on Banking Supervision, op. cit.

Chart B.1 Properties of macro variables before and during banking crises

(x axis: quarters around the crisis; y axis: percentages)

Sources: BIS, Eurostat, IMF, OECD and ECB calculations.
Notes: The figure depicts the development of key variables around banking crises (16 quarters before and after the start of a crisis) within the sample. The first crisis quarter is indicated by the vertical line, while the vulnerability state of twelve to seven quarters preceding a banking crisis is depicted by the grey window. The solid curve shows the development in the median country and the dashed lines represent the countries at the 25th and 75th percentile, respectively.

Unlike the credit gap, credit growth (as depicted in annual percentage changes) does appear to hit a peak about two years before the onset of banking crises, even though its fall only becomes clear during the last pre-crisis year. A similar development can be observed for nominal GDP growth and equity price growth figures. These variables do (on average) peak before the start of a crisis.

In the sample, the growth rate of residential house prices tends to peak on average about three years before a crisis happens, starting a clear descent (although prices are still rising) that lasts into the crisis, when house price growth stalls. To sum up, several macro-financial variables seem to possess potentially useful pre-crisis properties which may guide decisions on the set-up of CCBs. Yet, an early warning system analysis can provide a more formal framework to assess the usefulness of variables.

EVALUATING EARLY WARNING SIGNALS

Evaluating the predictive performance of individual indicators…

Banking crises are quite rare events and over the past two decades most EU countries have encountered no more than one, if any at all. Still, when banking crises occur, they tend to be very costly for societies, both in a direct sense (bailouts and fiscal interventions) and indirectly, owing to the associated loss of economic output and welfare following these crises.[15] Thus, policy-makers have a clear incentive to be able to detect potential signs of vulnerabilities that might precede banking crises early enough in order to take measures to prevent the further build-up of imbalances and to strengthen the resilience of the banking sector. Yet, at the same time, policy-makers do not want to signal crises which then do not in fact materialise. Doing so may: (a) reduce the credibility of their warnings, weaken decision-making and damage their reputation; and (b) needlessly incur costs on the part of the banking sector, endangering credit supply to the private sector. 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 suggested by some studies,[16] 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).

As the CRD IV regulation emphasises the role of credit variables in setting the CCB rate – in particular the role of credit growth and the credit-to-GDP gap – the usefulness of these variables for the identification of vulnerable states (recall that vulnerable states are defined as the period between twelve and seven quarters before the onset of a systemic banking crisis) within the EU banking sector is assessed first. The analysis is conducted as much as possible in a *real-time* fashion, meaning that only 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 available up to that point.

Table B.1 reports the signalling performance of several credit variable indicators, assuming a strong preference for the detection of crises by the policy-maker.[17] The table also shows the percentage of type I and type II errors, as well as the absolute and the relative usefulness, the adjusted noise-to-signal

15 It is acknowledged that these losses may seem larger when crises are preceded by a credit boom which inflates GDP growth figures. Moreover, there is increasing evidence that so-called "credit-less recoveries" which occur after a credit bust can be as fast as credit-fuelled recoveries. For a recent discussion, see Takáts, E. and Upper, C., "Credit and growth after financial crises", *BIS Working Papers*, No 416, July 2013.

16 See, for example, Alessi, L. and Detken, C., "Quasi real time early warning indicators for costly asset price boom/bust cycles: a role for global liquidity", *European Journal of Political Economy*, 27(3), 2011. For technical details on the evaluation method followed in this special feature, see Sarlin, P., "On policymakers' loss functions and the evaluation of early warning systems", *Economics Letters*, 119(1), 2013.

17 For a detailed discussion of the various evaluation metrics, see Behn, M., Detken, C., Peltonen, T. and Schudel, W., op. cit.

Table B.1 Evaluation of individual credit variables

	T1	T2	Absolute usefulness	Relative usefulness	aNtS ratio	% predicted	Cond prob	Diff prob
Domestic credit to GDP gap	0.187	0.552	0.023	0.256	0.678	0.813	0.168	0.047
Domestic credit growth (yoy)	0.309	0.443	0.022	0.240	0.641	0.691	0.176	0.056
Domestic credit to GDP ratio	0.585	0.118	0.019	0.211	0.452	0.415	0.232	0.112
Domestic credit gap	0.154	0.640	0.018	0.201	0.757	0.846	0.153	0.033
Domestic credit growth (4q ma)	0.244	0.555	0.017	0.194	0.734	0.756	0.157	0.037
Domestic credit growth (6q ma)	0.415	0.404	0.015	0.170	0.690	0.585	0.165	0.045
Domestic credit growth (qoq)	0.252	0.588	0.014	0.153	0.786	0.748	0.148	0.028
Domestic credit growth – GDP growth	0.431	0.454	0.009	0.103	0.798	0.569	0.146	0.026
Domestic credit growth (8q ma)	0.537	0.349	0.009	0.100	0.752	0.463	0.154	0.034
Global credit to GDP gap	0.081	0.474	0.040	0.443	0.516	0.919	0.209	0.089
Global credit growth (yoy)	0.187	0.396	0.037	0.412	0.487	0.813	0.219	0.099
Global credit to GDP ratio	0.179	0.405	0.037	0.411	0.493	0.821	0.217	0.097
Global credit gap	0.114	0.497	0.035	0.386	0.561	0.886	0.196	0.076
Global credit growth (4q ma)	0.106	0.518	0.033	0.373	0.580	0.894	0.191	0.071
Global credit growth (6q ma)	0.114	0.565	0.029	0.318	0.637	0.886	0.176	0.056
Global credit growth (qoq)	0.642	0.111	0.021	0.229	0.310	0.358	0.306	0.185
Global credit growth – GDP growth	0.146	0.634	0.019	0.216	0.742	0.854	0.155	0.035
Global credit growth (8q ma)	0.626	0.179	0.016	0.178	0.478	0.374	0.222	0.102

Sources: BIS, Eurostat and ECB calculations.
Note: "yoy" stands for "year on year"; "ma" stands for "moving average"; "qoq" stands for "quarter on quarter".

ratio (aNtS),[18] 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 sense that it generates the highest relative usefulness. This 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 the sample used. Other variables that perform relatively well are annual credit growth, the credit-to-GDP ratio and the credit gap.

Interestingly, global variables seem to outperform domestic variables in terms of usefulness. 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 the sample. This suggests that focusing on the development of domestic credit variables alone might not be sufficient. In an increasingly integrated global economy, vulnerabilities that develop at a global level potentially transmit to countries around the world. Therefore, policy-makers would benefit from taking these developments into account when deciding on CCB rates.

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 were subject to 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 the sample countries. To a certain extent, this puts the higher usefulness of global variables relative to domestic variables in perspective. However, the current crisis is certainly one

18 The adjusted noise-to-signal 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. A lower adjusted noise-to-signal ratio indicates better predictive abilities of the model.

of the best examples of a non-domestic vulnerability spreading to banking systems around the world. Thus, if the aim of the CCB is to increase the resilience of the banking system, developments both at the domestic and at the global level can provide useful information to the policy-maker.

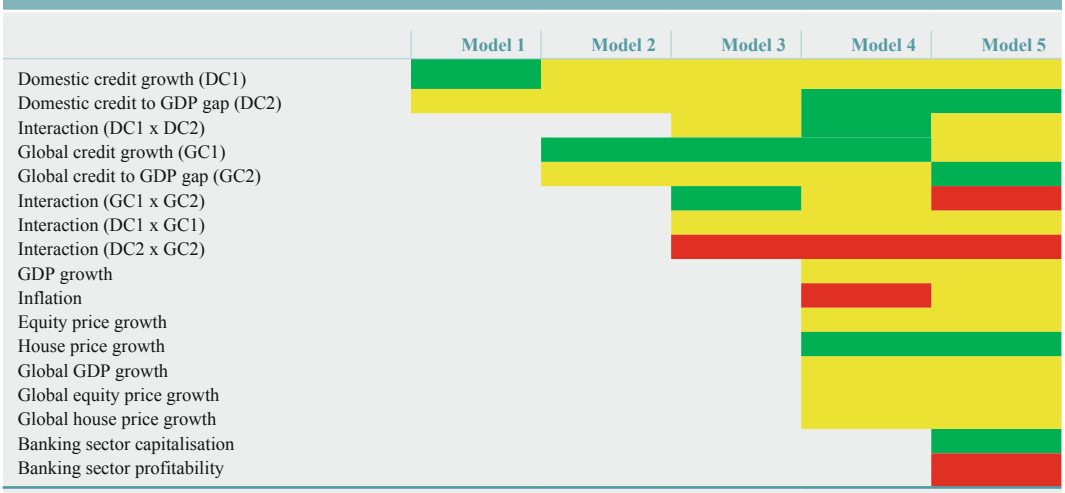
DEVELOPING AN EMPIRICAL MODEL TO PREDICT VULNERABILITIES

… and of multivariate logit models

While the signalling approach presented above 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. Therefore, as is common in the literature,[19] a multivariate logistic regression model is used in order to assess the predictive abilities of a combination of credit, macro-financial and banking sector variables. In addition to the dependent variable and the independent variables mentioned earlier, the estimations also include a set of country dummy variables in order to account for unobserved time-invariant heterogeneity at the country level (country fixed effects). Robust standard errors clustered at the quarterly level are used 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. Furthermore, all explanatory variables have been lagged by one quarter to account for lags in data availability.[20]

Table B.2 depicts the main results of the model estimations, while Table B.3 shows some model evaluation metrics. Starting by considering a model which takes into account the domestic credit gap and domestic credit growth (with the relative usefulness of Model 1 measuring 0.24), it is, surprisingly, found that the model performance is slightly weaker than the one of the domestic credit gap alone (with a relative usefulness of 0.26). Next, the global credit variables are included

Table B.2 Model results



Sources: BIS, Eurostat, IMF, OECD and ECB calculations.
Notes: The colour coding serves to get a quick overview of the main estimation results. A green colour corresponds to a significant (at the 5% level) positive effect on the probability of observing a future banking crisis (over a horizon of twelve to seven quarters), while a red colour implies a significant (at the 5% level) negative effect on the same probability. All effects (coefficients) which are not significant at the 5 % level of statistical significance are depicted in yellow.

19 See, for example, Davis, E. and Karim, D., "Comparing early warning systems for banking crises", *Journal of Financial Stability*, 4(2), 2008.
20 Lagging the explanatory variables also helps to account for endogeneity bias through simultaneity. This simple procedure cannot crowd out all endogeneity-related bias, but the fact that the dependent variable itself is an early warning variable could be considered to be a mitigating factor. Moreover, the time horizon for which this variable is equal to one has been chosen in the context of the exercise and has not been exogenously determined.

Table B.3 Evaluation of the models

	T1	T2	Absolute usefulness	Relative usefulness	aNtS ratio	% Predicted	Cond Prob	Diff Prob
Model 1	0.224	0.534	0.021	0.236	0.688	0.776	0.166	0.045
Model 2	0.088	0.573	0.030	0.336	0.628	0.912	0.178	0.058
Model 3	0.136	0.364	0.045	0.497	0.421	0.864	0.245	0.125
Model 4	0.052	0.342	0.054	0.603	0.361	0.948	0.285	0.159
Model 5	0.111	0.278	0.051	0.596	0.312	0.889	0.282	0.173

Sources: BIS, Eurostat, IMF, OECD and ECB calculations.

with the result that the predictive power of the model improves (the relative usefulness of Model 2 rises to 0.34). As also shown in Behn et al. (2013),[21] the inclusion of domestic and global interaction terms further improves the model performance, with Model 3's relative usefulness measuring 0.50. Moreover, by including further variables that could potentially be useful in measuring the stability of the banking sector, the model performance increases further (the relative usefulness of Model 4 rises to 0.60) and the model issues a warning in 94.8% of the quarters in the sample where a banking crisis occurs, seven to twelve quarters ahead. Finally, the performance of Model 5, which includes banking sector variables, is similar to that of Model 4. However, Model 5 includes controls for banking sector profitability and level of capitalisation, which are important factors to take into account when setting CCBs.[22]

In sum, it seems that 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 other variables are included. For example, the positive coefficient for house price growth in Model 4 indicates that asset price booms promote the build-up of vulnerabilities in the financial sector. Moreover, Model 5 shows that banking sector variables exert a significant influence on the build-up of financial vulnerabilities: a country is more likely to be in a vulnerable state when the aggregate bank capitalisation within the country is relatively low. In addition, it seems that future banking crises are more likely when profits in the banking sector are relatively high. This could well be related to the fact that periods of high bank profitability are typically associated with increased risk-taking and the build-up of vulnerabilities, which could explain the positive coefficient for the profitability variable preceding banking crises. As such, the multivariate analysis confirms the pattern illustrated in Chart B.2, namely that several macro-financial variables contain useful information which can be used to predict or signal future banking crises.

Simulating the effects of the CCB while accounting for macro-financial feedback effects

Higher banking sector capitalisation is expected not only to strengthen the resilience of the banking sector, but also to a certain degree to dampen the financial cycle and reduce financial imbalances by slowing credit, GDP and asset price growth. The multivariate logistic regression model combined with a global vector auto regression (GVAR) model could be one of the tools to guide policy-makers in calibrating CCBs. The main advantage of this simple approach is that it makes it possible to analyse the potential effects of higher capital levels on financial vulnerabilities across countries, while controlling for macro-financial feedback effects.[23]

21 See Behn, M., Detken, C., Peltonen, T. and Schudel, W., op. cit.
22 The availability of long time series of banking sector variables limits the use of Model 5 for the out-of-sample analysis.
23 See Behn, M. Groß, M., Peltonen, T. and Schudel, W., "Calibrating countercyclical capital buffers with an integrated early warning GVAR model", ECB, mimeo.

Assessing the out-of-sample predictive performance

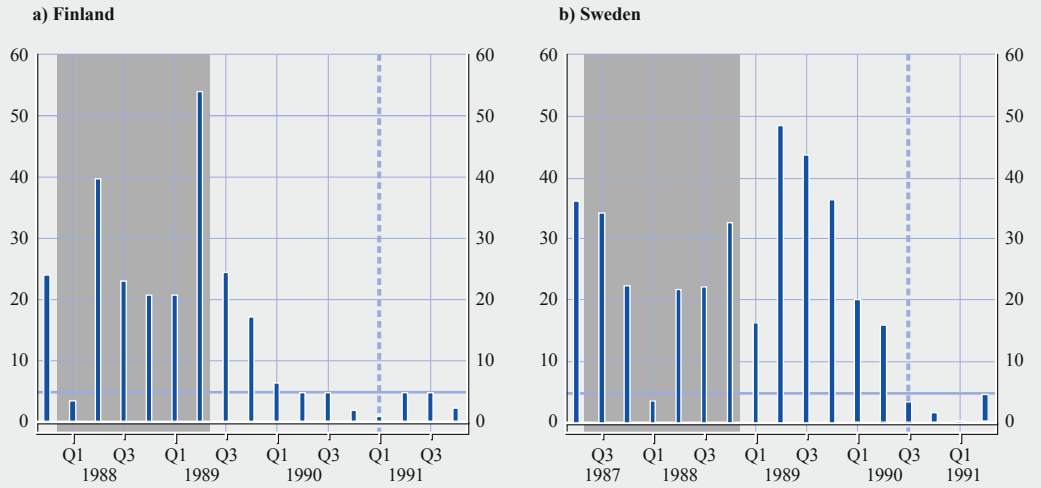
OUT-OF-SAMPLE PREDICTIONS

Given the objective of the early warning systems, any assessment of the indicators and models should focus on the out-of-sample performance. Moreover, successful in-sample predictions are much easier to achieve than successful out-of-sample predictions.[24] The out-of-sample usefulness of the model is assessed as follows. First, countries that had a banking crisis prior to 2007 are consecutively excluded from the estimation of the model. Then, the ability of the model based on the remaining countries to predict the crises in the excluded ones is assessed.[25]

Two examples of this out-of-sample forecasting exercise are presented in Chart B.2 using Model 4 from Table B.2. As is visible from the chart, the model signals the banking crises in the Nordic countries well before their onset in the early 1990s. In both Finland and Sweden, the indicator consistently exceeds the threshold from the second quarter of 1988 onwards, which is 11 quarters ahead of the crisis for Finland and nine quarters ahead for Sweden. In both cases, banks would have had enough time to build up capital before the crisis if the CCB had been activated. In other words, the model seems to exhibit overall good out-of-sample properties, while information from the current crisis seems to be useful for the out-of-sample prediction of other systemic banking crises in the EU.

Chart B.2 Out-of-sample model performance for selected countries

(y-axis: percentage probability)



Sources: BIS, Eurostat, IMF, OECD and ECB calculations.
Notes: The chart shows the model prediction for the respective country excluded from the estimation sample. The dashed vertical line corresponds to the first banking crisis quarter, while the vulnerability stage of twelve to seven quarters preceding a crisis (which the models try to predict) is depicted by the grey area.

24 See Berg, A., Borensztein, E. and Patillo, C., "Assessing early warning systems: how have they worked in practice?", *IMF Staff Papers*, Vol. 53, No 3, 2005.

25 Of course, one could try 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 the sample occur after 2007, and as it would be useful to learn something from these episodes, the approach described above has been chosen, i.e. using the information from the current crisis and checking whether it would have been useful for the prediction of past crises. Model 4 is used as the benchmark specification here.

CONCLUDING REMARKS

As a response to recent financial crises, the Basel III and CRD IV regulatory frameworks include the implementation of CCBs to increase the resilience of the banking sector and its ability to absorb shocks arising from financial and economic stress.

This special feature finds 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 in EU Member States. Consequently, the main policy implication of this study is that in the context of setting up CCB measures, policy-makers could benefit from considering a wide range of macro-financial and banking sector indicators. Multivariate models, such as the one introduced here, are found to be more useful in this respect as they include the combined behaviour of several indicators.