

NBP Working Paper No. 257

Early warning models of banking crises applicable to non-crisis countries

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Abstract

We built Early Warning Models (EWM) for determining the optimal moment for build-up phase of the countercyclical capital buffer. For this purpose we estimate a number of early warning models based on the wide panel of countries. We test many potential variables from the early 1970s until 2014, their combinations, and the stability of their signals. Our setting includes country-specific information without using country-specific effects. This allows for direct application of EWM we obtain to any country, including those that have not experienced a banking crisis. Models with three explanatory variables outperform models with smaller number of variates. The probability of extracting a correct signal from best-performing EWM exceeds 0.9. We find that low levels of VIX tend to precede crises, and this was also true before 2006. This corroborates Minsky's hypothesis about periodic underestimation of risk in the financial sector. Other variables that generate signals with the highest accuracy and stability are those associated with credit growth, property prices and growth in the contribution of financial sector to GDP. This last finding suggests that substantial increases in measured value added of the financial sector seem to reflect augmented exposure to systemic risk, rather than welfare improvements.

JEL codes: E44, G01, G21

Keywords: countercyclical capital buffer, early warning models, financial stability.

1. Introduction

Outbreak of the most severe financial crisis in the last decades has increased interest in the tools that would be able to reduce systemic risk. One of them is countercyclical capital buffer, which is designed by the Basel Committee on Banking Supervision (Basel III) and is implemented, among others, within the framework of the Directive of the European Parliament and of the Council 2013/36/ EU of 26 June 2013. (CRD IV). Even though CRD IV obliges the authority responsible for macroprudential supervision to calculate a benchmark for the buffer rate, it allows the final decision to differ from the reference level (this is called guided discretion). Three crucial issues related to the use of countercyclical capital buffer are: (i) when to build up the buffer, (ii) what is the optimal buffer rate level, (iii) when the buffer should be released.

This study focuses on the fundamental, first issue. According to the recommendation of the ESRB (2014) countercyclical capital buffer benchmark rate is calculated as a linear function of only one variable (credit gap) that is obtained under relatively strong assumptions (i.e. the financial cycle is assumed to last over 20 years in all countries). However, rules suggested by the ESRB do not preclude use of other quantitative or qualitative methods since having broader information set should allow for better decisions. In this respect we answer two basic questions: (i) which variables offer best warning signals before the crisis?; (ii) how much does one gain by simultaneously including information from more than one variable?

We analyse early warning properties of many macroeconomic and financial indicators in nearly fifty countries starting (where possible) in the 1970s until

2014. Among the novel variables we include VIX and contribution of the financial sector to GDP and two hypotheses associated with these variables. The VIX, often called a fear index, reflects joint effect of risk perception and attitude toward risk by investors. If financial sector has tendency to be overly optimistic and take excessive risk, which are followed by crises, as suggested by Minsky, low levels of VIX should precede crises. It has also been argued that measurement of contribution of financial sector is flawed (Haldane et al. 2010), and largely reflects risk taken by the sector rather than value added. If that is indeed the case, unusually high share of financial sector in GDP growth is expected to reflect unusually high levels of risk exposure that are bound to sometimes materialise as crisis. We test both these hypotheses.

We evaluate the performance of all indicators using their levels, dynamics and deviations from trend in period ranging from 5 to 16 quarters before the actual crisis. Cyclical components are extracted by adjusting smoothing parameter of the HP filter such that it corresponds to the financial cycle in a given country, instead of assuming that the financial cycle has the same length in all countries. We do not use fixed effects, but include country-specific characteristic by using variables that are standardised using data for each country. Fixed effects improve model performance, but essentially prevent model use in countries that have not experienced crisis (fixed effect would automatically push crisis probability to zero and would likely dominate all explanatory variables also in future). We evaluate individual variables by not only checking accuracy of their signals, but also its stability, i.e. we assess accuracy in sample excluding current crisis, and check for out-of-sample performance during the recent crisis. The best indicators are then included in early warning models of banking crises as explanatory variables. We

subsequently evaluate their statistical properties of models with one, two, three and more explanatory variables. On the basis of the relative costs of missing the crisis and false alarm of a crisis we calculate thresholds of probability which signals crisis risk. We end up with signals that correctly discriminate between tranquil and crisis states in more than 90% of cases, with true positive rate in excess of 0.75 and false positive rate below 0.1.

Study is divided into four parts. Part 2 discusses the results of studies conducted so far. Part 3 contains a description of the data and method, while Part 4 discusses empirical results. Paper concludes with a summary.

2. Literature review

Outbreak of the recent financial crisis intensified research focusing on the usefulness of macroeconomic and financial variables as indicators of early warning of imminent banking and more generally financial crises. One of the first such studies by Borio and Drehmann (2009) uses the signal extraction method (Kaminsky and Reinhart, 1999) and suggests that in the case of the US early warning indicators would have signal significant imbalances in the financial sector already in 2004. According to the study variables connected with credit, real estate prices and equity prices have the highest predictive ability. In addition, authors suggest that the analysis comprising several variables gives better results than in case of one variable. In the following years, a further increase of interest related to this field was observed. As a result, there has been a substantial growth in the number of research papers related to Early Warning Models. For instance Drehmann et al. (2010) used the same methodology as Borio and Drehmann (2009) did. They analysed 7 variables for 36 developed countries. Credit gap, i.e. the deviation of ratio of credit to GDP from the long-term trend, correctly indicates 72% of crises in the sample (overall there are 25 crises) with the ratio of false signals to accurate signals (noise-to-signal ratio - NtS) reaching 20%. Real estate prices are equally useful. This variable correctly indicates crises in 67% of cases which is achieved with NtS of 22%. The value added of their study is the attempt to identify the length of financial cycle. When estimating the cyclical component of analysed variables the authors took into account several different smoothing parameters λ of Hodrick-Prescott filter (1997). They assume that credit cycles are of the same length as the business cycles and that they are respectively: two, three and four times longer. According to the

principle proposed by Ravn and Uhlig (2002) values of smoothing parameters λ are equal to: 1,600; 25,000; 125,000 and 400,000. The most accurate signals were generated by the credit gap under the assumption that credit cycles are four times longer than business cycles. Longer duration of financial cycles relative to the business cycle was confirmed in later studies dedicated to the issue of financial cycle length (see Drehmann et al., 2012; Schüler et al., 2015).

Importance of proper and early signals of imminent banking crisis was highlighted in the study by Babecký et al. (2013) which uses a panel vector autoregression models. Authors confirmed a hypothesis that the currency and debt crises are preceded by banking crises. In the same study, based on the data from 40 developed countries using Bayesian averaging, authors identify variables that should be monitored in order to avoid banking crises. These include credit, the inflow of foreign direct investment and money market interest rates. Drehmann and Juselius (2012) postulate the inclusion of variable called debt service ratio (DSR), which is an aggregate measure of a debt service costs relative to aggregate income. The analysis carried out by Drehmann and Juselius (2014) confirms the usefulness of this indicator, which at shorter horizons, i.e. two years before a crisis, generates more accurate signals than the credit gap. The conclusions regarding the usefulness of credit gap are also confirmed in a study by Behn et al. (2013). That analysis covers 23 EU Member States and uses logistic regression models with fixed effects (country-specific fixed effects). The main caveat of this approach is that due to the inclusion of the country-specific effects, those models have limited usefulness when it comes to the issuing early warning of crises in countries which have never experienced such phenomena. Accuracy of signals generated with those models is high since in over 90% of cases they correctly discriminate between tranquil and crisis periods. It should be noted, however,

that such a high score would not have been achieved had it not taken into account country-specific effects, which increase accuracy¹. Similarly to the studies discussed previously Lainà et al. (2015) estimate a series of logistic regression models for panel data of 11 EU Member States. Authors argue that narrowing the number of countries in the sample (although the reverse trend in the literature is observed) is needed to achieve larger homogeneity of analysed countries. The results support the use of loans to deposits ratio and property prices as those variables that warn about banking crises in the most accurate way. Additionally, the authors analyse the cumulative probability of banking crisis outbreak in the horizon of several quarters that is obtained by multiplying the individual probabilities from a logistic regression model, which implicitly hinges on the assumption that individual probabilities of crisis are independent. Such assumption does not reflect the characteristics of phenomena in question, which in turn means that the resulting cumulative probabilities may differ from the actual ones. Another interesting work is the one by Juks and Melander (2012) that points out that before making a decision about the countercyclical capital buffer one should disaggregate the data by sector (this is possible for the credit gap). Using data for Sweden, authors show that excessive credit growth in the late 80s was driven by the growth in lending to the non-financial corporations, while the credit boom in the years preceding the recent financial crisis was due to the rise in households' debt. Finally, it is worth taking a look at two studies which check the benefits of extending the sample such that it starts in: the beginning of the last century in Finland (Laine et al., 2015) and in 1861 in Italy (Alessandri et al., 2015). The second one calls into question the benefits of extending sample to get more precise estimates of the credit gap.

¹ Catão and Milesi-Ferretti (2014) suggest that the increase of AUROC resulting from country-specific effects totals approximately 20 percentage points. In our sample it artificially "improves" the quality of predictive signals (AUROCs are higher by 20-30 percentage points depending on the variable).

3. Data and method

3.1 Data

Potential leading indicators were analysed based on the data from 47 countries - all EU member states and countries outside the EU, for which the Bank for International Settlements (BIS) publishes data on credit extended to private non-financial sector. Thus it is the largest panel of countries taken into account compared with the studies in the literature. The availability of the data about the credit was the only criterion to include given country to the sample because many studies indicate that the variables connected with the credit cycles (i.e. credit gap and DSR) are the most useful. Our analysis covers the period from the first quarter of 1970 to the second quarter of 2014. However quite often for the initial 10-20 years in the sample the data is not available and it is especially common for the countries of Central and Eastern Europe. Variables were analysed in levels, growth rates (quarterly, annual, two-, three- and four-year) and cyclical deviations from respective long-term trend. In summary, we take into account twelve variables, their ratios and transformations, which results in more than fifty analysed indicators. Description of the data and their sources can be found in Appendix A.

In addition to the variables analysed so far, we included proxies of situation in financial or when possible banking sector. These are contribution of financial sector to GDP growth² (VA hereafter), banking sector index on equity market and VIX. Inclusion of VIX proxies market price of global risk.

² Statistical offices do not publish data on banking sector contribution to GDP, however in majority of countries banking sector plays dominant role in financial system. Thus, financial sector contribution can be still useful in predicting banking crises.

Analysis of this variable has a purpose of checking whether global factors influence probability of banking crisis. Adding VA hinges on the assumption that the value added of this sector is to some extent a measure of risk-taking. According to national accounts VA is calculated as:

$$\text{Revenues-Costs-Amortization} = \text{Remuneration} + \text{Interests} + \text{Dividends} + \text{Taxes} + \text{Retained Earnings}.$$

Equation above shows that high VA (so in particular of banking sector) might not be connected with its contribution to the welfare, but rather with risk-taking, including systemic risk (Haldane et al. 2010; Wang, 2011). Such line of reasoning leads to conclusion that this variable might be useful indicator of imminent banking crises.

Dependent variable is a binary variable from the crisis database which is the result of the work of the ESCB Heads of Research (Babecký et al., 2013). Dating of crises is based on ten other studies which purpose is to identify periods of crisis. Additionally it uses the expertise of ESCB HoR members. Before proceeding to the description of our approach we would like to draw attention to the issue of the type of credit aggregates used in other studies of early warning indicators. There are two types:

- a) Broad measure which covers total indebtedness of private non-financial sector (also issuance of debt by non-financial corporations) – in the financial accounts these are sectors: S.11 (non-financial corporations), S.14 (households) and S.15 (non-profit institutions serving households) and instruments: F.31 (short-term debt), F.32 (long-term debt), F.41 (short-term loans and advances) and F.42 (long-term loans and advances).

- b) Narrow measure which comprises loans extended by domestic banks to the private non-financial sector and banks' holdings of private non-financial sector debt – data from aggregated balance sheet of other monetary financial institutions.

According to the recommendation of the Basel Committee on Banking Supervision (BCBS, 2010) when calculating the value of the CCB rate for banks one should take into account broad measure. The Committee believes that this reflects an attempt to limit the negative consequences of excessive credit growth having its source in a non-bank part of the financial system. Moreover, taking into account the broad measure minimizes the risk of transferring part of the lending outside the banking sector. The use of a broad measure is also proposed by the European Systemic Risk Board (ESRB, 2014, Annex, Part 1). Its recommendation was preceded by analytical work which description can be found in Detken et al. (2014). Other studies based on a broad measure include: Juks and Melander (2012) and Gerdrup et al. (2013). In our opinion, the argument concerning the use of broad measure is definitely justifiable for the construction of early warning model of financial crises, but it is less clear for early warning model designed for the purpose of countercyclical capital buffer. The countercyclical capital buffer is intended to restrict lending in the banking sector. This means that calibration should be linked to the lending in the banking sector and not to the entire financial sector. If it were otherwise, in extreme cases, in which credit is growing rapidly in the non-bank sector and the banking remains unchanged, the imposition of the CCB rate on banks would not be adequate. Lack of action against excessive growth rate of non-bank sector lending (that would still be in the growth phase) could lead to tensions in the financial system. This does not mean, however, that the use of

broad measure is not useful. On the contrary - indicators based on the broad aggregate loan can inform about the situation in the entire financial sector, which can have a spillover effects on the banking sector. Strong growth outside the domestic banking sector, e.g.. through foreign borrowing, might indirectly hit domestic sector through deteriorating creditworthiness of clients and could warrant (countercyclical) capital buffer. This does not change the fact that effective measures must be aimed at the root of the problem. Besides, most of those abovementioned studies use banking crises. Thus it leads to inconsistency because if the broad measure is used then crises caused by non-bank financial institutions should also be taken into account.

3.2 Method

This section describes the approach used to estimate early warning models of banking crises outbursts. Description is divided into three parts and concerns: adjustment of the HP filter smoothing parameter to the length of the financial cycle, choice of the method of extracting information from a set of variables and assessment of the predictive quality of the signals generated by early warning models.

3.2.1 Financial cycle

Estimation of the trend plays a crucial role when it comes to the transformation of variables into deviations from long-term fluctuations. The most commonly used approach is the HP filter with a smoothing parameter $\lambda = 400,000$, which corresponds to the cycles four times longer than the length of the business cycle (see Drehmann et al., 2010). HP filter trend estimates are based on observations in the whole sample. In the literature about early

warning indicators modified version is used and it is called one-sided HP filter, which estimates the trend in period $t-k$ based on the observations from periods $t-k, t-k-1, \dots, 1$. Thus one-sided HP filter reflects the knowledge about the economy in a given period. To determine the actual length of the cycle which corresponds to the value of the smoothing parameter we use the relationship between the smoothing parameter and the frequency (Maravall and Del Rio, 2001) given by:

$$\lambda_{fin} = [2(1 - \cos f_{max})]^{-2} \quad (3.1)$$

Where λ_{fin} is the smoothing parameter and f_{max} is the frequency (in quarters) of financial cycle. Having λ_{fin} we can use rule proposed by Ravn and Uhlig (2002), which based on the λ_{fin} allows to determine the length of financial cycle relative to the business cycle:

$$k = \sqrt[4]{\frac{\lambda_{fin}}{\lambda_{bus}}}$$

It follows that for $\lambda_{fin} = 400.000$ trend corresponds to the fluctuations lasting approximately four times longer than the business cycle. It is intuitive that the length of economic fluctuations differs between countries. Thus it seems reasonable to connect the value of the smoothing parameter with the length of the financial cycle. To this end, we use approach by Comin and Gertler (2006) which consists in extracting the trend from annual growth rates of a given variable (similar methods they used Drehmann et al., 2012, and Schüler et al., 2015). This transformation is necessary, due to the second step of the procedure that relies on the transition from the time domain to the frequency domain.

From the frequency domain perspective each variable can be decomposed into following components: trend, cycle, seasonal and irregular. Such decomposition is carried out using spectral analysis methods (Hamilton 1994). Such methods assign part of the variance of a variable to the given frequency. The greater the variance for a given frequency, the more it affects the whole variable. This allows to determine what is the length of the cycles of a variable in question since it identifies dominant frequency. One of the tools used within spectral analysis is periodogram - estimator of the power spectrum. Periodogram for the variable x_n is given by:

$$\hat{P}(f) = \frac{\Delta t}{N} \left| \sum_{n=0}^{N-1} x_n e^{-i2\pi f n} \right|^2, \quad -\frac{1}{2\Delta t} < f < \frac{1}{2\Delta t} \quad (3.2)$$

where Δt is the interval of the sample (in our case these are quarters), and f is the frequency. The variables for which the power spectrum is estimated should be stationary³. Hence transformation to annual growth rate is needed since it stationarizes variables examined⁴.

Financial cycle is identified as those fluctuations whose variance is the highest in the range from 8 to 30 years. In other words, the frequency for which periodogram attributed the biggest part of the variance is treated as (dominant) length of the fluctuations identified as the financial cycle. Next, using equation 3.1 for each variable we compute the value of smoothing parameter which is consistent with the length of the financial cycle.

³ In the case of non-stationary variables it is not possible to define the power spectrum, because series of autocovariance function do not converge.

⁴ Based on unit root tests in panel data (Im-Pesaran-Shin, ADF, Phillips-Perron) the null hypothesis should be rejected for all variables in annual growth rates.

3.2.2 Non-parametric methods and binary choice models

Based on the literature review in part 2 we conclude that the most common approaches in early warning indicators literature are: signal extraction method (Kaminsky and Reinhart, 1999) and binary choice models. In the next part we briefly present both methods.

Let $Y_{i,t}(0) \in \{0; 1\}$ be a binary variable equal to 1 if in the country i in period t we observe a crisis and 0 otherwise. In order to construct early warning model we have to find a variable $Y_{i,t}(h) \in \{0; 1\}$ which is equal to 1 h periods before the crisis and 0 otherwise. The first way to obtain such a variable is the extraction of a signal, which generate a signal of a crisis when a variable exceeds a predetermined threshold. The description of this method can be presented by:

$$Y_{i,t}(h) = \begin{cases} \mathbf{1}, & X_{i,t}(0) > \theta \\ \mathbf{0}, & X_{i,t}(0) \leq \theta \end{cases} \quad (3.3)$$

Where $X_{i,t}(0)$ is a variable which aim is to issue signals h quarters before the crisis and θ is the threshold for this variable. Output from this method can be stored in a confusion matrix (see Table 1) that summarizes discrimination between tranquil and crisis periods.

Table 1 Confusion matrix

	Crisis period	Tranquil period
Signal	A	B
No signal	C	D

Based on the information given in the table 1 we can calculate various measures that are useful in evaluation of early warning indicators. These are:

noise-to-signal ratio $NtS = \frac{B}{B+D} / \frac{A}{A+C}$, type I error ratio $T1 = \frac{C}{A+C}$, type II error ratio $T2 = \frac{B}{B+D}$.

An alternative to the non-parametric method of signal extraction are models of binary choice - logit and probit models. Davis and Karim (2008) suggest that the use of models gives more accurate signals than non-parametric signal extraction. In their view, the advantage of binary models is greater when one has the intention to design a framework that will be used for many countries without incorporation of country heterogeneity. Due to the small differences between logit and probit models (differing only in the tails of distributions of the error term), interpretation of the estimates from logistic regression model as the odds ratio and due to the common use of logit models in the literature we decided to report the probabilities of the crisis outbreak with logit models⁵:

⁵ We checked robustness of the results (in terms of AUROC) conditional on a distribution we used to estimate the binary choice model. However, neither probit nor scobit models yield significantly higher AUROC than logit model. 3.2.2. Non-parametric method as proposed by Kaminsky and Reinhart also does not produce signals more accurate than those generated with logit.

$$\Pr(Y_{i,t}(h) = 1) = \frac{1}{1+e^{-(\alpha+\beta'X_{i,t})}} \quad (3.4)$$

Where α, β are vectors of parameters, and the $X_{i,t}$ is the matrix of the variables. The next step is to choose the functional form of the model. We need to decide whether the model should include individual effects (for each country), and if so, whether it should be fixed effects or random effects. Approach used most commonly in the literature features fixed effects that do not require the assumption of independence between these effects and the explanatory variables. In this study, we do not use country-specific fixed effects as a mean to account for heterogeneity between countries. It is justifiable by the fact that, according to crises database by ESCB HoR there are six countries in the EU that have never experienced banking crises (Austria, Belgium, Luxembourg, Malta, Poland and Slovakia). For these countries, the probability of banking crises derived from logistic regression model with fixed effects would be of limited use, because fixed effects generate low value of crisis probability throughout whole sample (in fact it is close to zero). To circumvent this problem we use pooled regression model. In addition, the use of pooled regression in case of non-crisis countries in the sample is necessary even if it leads to the omitted variable bias. On the other hand, Bussiere and Fratzscher (2006) show that ignoring the country-specific effects does not always lead to significant changes in the conclusions drawn from models. Finally, the heterogeneity of countries is partially tackled by normalizing the variables (z-score), which is a compromise between country-specific effects and pooled regression on non-normalized variables.

3.2.3 Evaluation of signals

An important requirement in case of early warning model is that it should generate signals with considerable advance. In the case of countercyclical capital buffer lower limit of the horizon is five quarters as the decisions concerning this buffer is effective one year after the announcement. This means that the signal of a crisis in the horizon of two quarters would have limited usefulness for macro-prudential policy makers. The upper limit of the horizon is not established, but in literature the maximum is five years. In this study we decided to shorter upper limit of horizon to four years, which is closer to the duration of the term of macroprudential authority members (results do not change if we set it to either 3 or 5 years). Evaluation of signals accuracy is based on the receiver operating characteristic (ROC) curve, which illustrates the trade-off between the percentage of accurate signals of crises (TPR - true positive rate) and the proportion of false signals of crises (FPR - false positive rate) for all possible threshold values. The information illustrated on the ROC curve is therefore the same as in the case of signal extraction method., though it uses probability obtained from the logit model rather than a variable directly. The area under the ROC curve (AUC) is a measure of the predictive quality of signals. For variables that attain high levels before crisis AUC of 1 means perfect discrimination (i.e. for each threshold early warning model generates only accurate signals $TPR = 1$, $FPR = 0$), while the value of 0.5 means that the signals have no predictive value.

The advantage of the evaluation with the ROC curve is also flexibility in terms of the threshold, because its value depends on the preferences of avoiding the type I error (omitting the crisis) relative to the type II error (false alarm of

crisis). The expected usefulness of particular model can be formalised in the following function, which takes into account both the accuracy of the model and the preferences concerning both types of error (Cohen et al. (2008)):

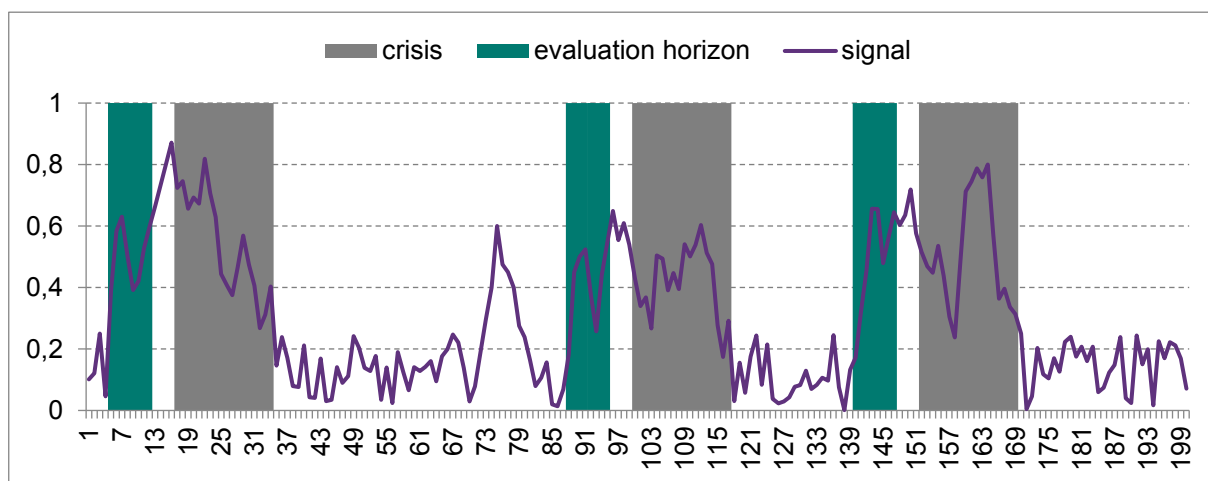
$$E(U) = P(FN \cdot \varphi) + (1 - P)(FP \cdot (1 - \varphi)) \quad (3.5)$$

where P reflects the frequency of the „1“ events, and φ reflects the relative weight of type I (FN) and type II (FP) errors. The more preferable is to avoid the type I errors (or larger the cost associated with committing such error) the lower is the optimal threshold for signalling crisis. To show the impact of changes in preferences on the threshold, FPR and TPR in section 4 we report points on the ROC curves that are associated with optimal thresholds for given preferences (or costs) between the two types of errors. In line with considerations in the literature (ESRB 2014) we assume that type I errors (FN) are more costly than type II errors (relations 2: 1 and 3: 1 are considered). Here again it is worth noting the similarity of the ROC curve to the signal extraction method since relative preferences are the same as weight α in the policy makers' loss function.

Figure 1 shows how we assess the predictive quality of variables. Following Drehmann and Juselius (2014) it is assumed that after the outbreak of the crisis it makes no sense to predict one. This means that we eliminate periods of crisis from the sample (grey boxes in Figure 1), leaving only the information about the outbreak in the particular quarter. However the same authors assumed that every crisis lasted two years, in this paper we use actual duration of crises. This solves the issue of post-crisis bias raised by Bussiere and Fratzscher (2006). Thanks to that we avoid the bias of artificially high ratio of type II errors. This is because the average length of crises is approximately

three years (Cecchetti et al., 2009). In study by Drehmann and Juselius (2014) adoption of lower length means that signals can be only false (type II error), but cannot miss crisis (because it actually occurred). Type I and II errors may be committed only in the assessment window, which was adopted for the period preceding the outbreak of the crisis from sixteen to five quarters (green area in Figure 1).

Figure 1 Evaluation of signals



Source: own source.

4. Empirical results

In this part of the study we show the estimates of pooled logistic regression models, i.e. without country-specific effects, that issued the most accurate signals in the sample of 47 countries in years 1970-2014. We analyse models with one, two, and three variables (adding more variables does not improve performance of the models).

This section is divided into two parts: (i) we examine the quality of the signals for the full sample and check whether their accuracy is sample-dependent (ii) next, we evaluate models with credit gap and three explanatory variables. The first step is considered as the initial phase – preselection of variables that are used in the second stage. Variables that enter the multivariable models issue signals with stable accuracy – i.e. their usefulness is statistically significant in full, pre-crisis and post-crisis sample. The inclusion of the credit gap reflects the desire to create model that is readily applicable in policy making and ESRB recommendation state that such variable should be included. Still, the inclusion (or omission) of the credit gap does not change the performance of the multivariable models.

4.1 Models with one explanatory variable

The results for models with one variable are presented in table 2. Each of these models is estimated in a sample with at least five crisis periods. It is especially important when we want to gauge stability of signals since stability is checked by estimation of models in a pre-crisis sample and evaluation of signals it

issues in a post-crisis sample. In appendix B we report summary of the best models, while in appendix C we show ROC curves for signals they issue.

Five observations stand out. First, VIX appears to be the most informative variable – low levels of VIX precede crises – and 75% of signals from the model correctly identifies the state (the crisis in the horizon of several years or no crisis). In the subsequent section we confirm that this is not necessarily only an artefact of the recent global financial crisis. Overall, such behaviour of VIX is in line with Minsky hypothesis, where financial crises are preceded by undervaluation of risk. Second, and in line with previous studies, we find that the cumulated growth of credit is also a good indicator of crisis, though its predictive power is significantly lower than that of VIX. Third, high growth of value added (VA) of the financial sector also tends to be a harbinger of banking crisis. This is in line with the hypothesis that unusually high VA in the financial sector reflects high risk taken by this sector rather than high value added (Haldane et al. 2010; Wang, 2011). Fourth, we do not find neither Debt Service Ratio nor credit gap – two variables that according to many studies have the highest values of AUC – to be the most accurate. Potential explanation can be twofold. Firstly, we take into account the greatest number of countries analysed so far. Most of the studies from section 2 are related to the euro zone countries or the European Union member states. This fact is likely to facilitate getting high values of AUC (due to the greater homogeneity of countries). The second factor is the specification of models, which does not include country-specific fixed effects which as mentioned earlier, increase AUC. This is confirmed by the AUC level of DSR and credit gap – in the sample that contains only the EU countries and for models including fixed effects – which total respectively 0.929 and 0.818. Finally, it is noteworthy that

threshold of 2:1 yields low or even zero levels of True Positive Rate. It means that the ROC curve is relatively flat near the origin (0,0) and one needs to substantially change preferences or relative costs to reach the tangent point with the non-zero FPR and TPR. In the case of 3:1 preferences we observe a significant drop in the threshold probability in most cases (which generates signal of crisis). In addition, both FPR and TPR increase but due to the fact that the models contain only one variable and have lower AUC than models with several variables, the increase of both ratios is similar. It is worth noting that for most models probability threshold above which alarms is generated ranges from 20 to 40%.

4.2 Stability of signals accuracy

Since models in question are designed to predict banking crises it is not only crucial to achieve high accuracy, but also its stability across the time. Are Early Warning Models able to issue signals correctly throughout the time? Since we have dozen of crises in the sample it is possible that they are not homogenous. So far we discussed results for the full sample. The main disadvantage of full sample is the fact that large fraction of crises is related to the last global financial crisis of 2007-2008. Consequently, this increases significance of global factors (VIX) or variables that have common component related to financial market. Stability of accuracy may be tested by evaluation (via ROC curve) of signals issued in 2007–2014 by models that are estimated in pre-crisis sample (i.e. 1970–2006). If variables have the same predictive quality regardless of type of crisis, their models should generate equally useful signals in pre-crisis sample as well as in out-of-sample exercise. As mentioned

in section 3 of our paper AUC equal to 0.5 means that signals are non-informative. Their accuracy is the same as of signals generated by Bernoulli distribution with probability $p = (1 - p) = \frac{1}{2}$. The upper confidence interval for such AUC value is 0.55. Variables that exceed this value are considered useful. This criterion is used to identify the variables characterized by the stability of accuracy. It is assumed that the accuracy of signals is stable when in full, pre-crisis sample and out-of-sample exercise AUC is significantly higher than 0.5. Thanks to that we filter out variables that are either non-informative or their interpretation changes with time.

Results of stability check can be found in the last two columns of table 2. In column 'AUC before 2006' we report accuracy of signals issued by models that are estimated in pre-crisis sample. High value of AUC means that given variable is useful predictor of banking crises in period 1970–2006. Last column of table 2 informs how accurate are signals that are issued by those models in period 2007–2014.

Even though in shorter, pre-crisis sample models generate equally accurate signals as in full sample, in case of out-of-sample exercise for some variables signals are statistically worse than in case of full of shorter sample. These variables are VIX, level and growth rate of betas, volatility of banking sector index and relative volatility of banking sector index. Thus, usefulness of VIX is to some extent statistical artefact related with the global nature of the last crisis that occurred in more than thirty countries in sample. Nonetheless VIX still issues quite accurate signals. Furthermore VIX meet criteria set before, hence it is considered in the next stage.

Table 2 Models with one variable

Variable	AUC	Conf. interval		2:1	FPR	TPR	3:1	FPR	TPR	Crises	AUC 2006	AUC after 2006
VIX	0.75	0.72	0.77	0.29	0.01	0.04	0.23	0.12	0.35	433	0.75	0.67
Credit (16)	0.73	0.71	0.76	0.51	0	0	0.23	0.07	0.23	406	0.71	0.85
Credit to HH (12)	0.69	0.67	0.72	0.53	0	0	0.19	0.12	0.34	319	0.66	0.77
VA (16)	0.67	0.63	0.71	0.4	0	0	0.21	0.11	0.27	168	0.69	0.63
VA (gap)	0.65	0.61	0.68	0.42	0	0	0.42	0	0	199	0.64	0.7
VA	0.64	0.6	0.68	0.25	0.01	0.05	0.25	0.01	0.05	199	0.67	0.68
PtI (16)	0.64	0.61	0.67	0.22	0.06	0.2	0.21	0.08	0.27	324	0.64	0.64
GDP (12)	0.63	0.6	0.66	0.39	0	0	0.39	0	0	331	0.57	0.78
PtI (gap)	0.63	0.6	0.66	0.28	0	0.02	0.22	0.04	0.12	336	0.62	0.72
Credit gap (Basel III)	0.63	0.59	0.66	0.32	0	0	0.21	0.03	0.09	316	0.64	0.62
DSR (4)	0.61	0.58	0.64	0.36	0	0	0.36	0	0	282	0.59	0.73
Betas (gap)	0.58	0.54	0.61	0.57	0	0	0.32	0	0	244	0.58	0.58
Betas (16)	0.58	0.53	0.61	0.32	0	0	0.22	0.01	0.02	208	0.6	0.45
Rel. volatility (16)	0.57	0.53	0.61	0.28	0	0	0.28	0	0	213	0.6	0.52
Rel. volatility (gap)	0.56	0.52	0.6	0.28	0	0	0.28	0	0	257	0.56	0.59
DSR (gap)	0.54	0.51	0.56	0.13	0	0.01	0.13	0	0.01	300	0.53	0.68
Volatility	0.53	0.49	0.56	0.17	0	0	0.17	0	0	244	0.51	0.32
Volatility (gap)	0.53	0.49	0.56	0.14	0	0	0.14	0	0	244	0.53	0.56
Volatility (12)	0.52	0.48	0.56	0.19	0	0	0.19	0	0	217	0.54	0.45
TED spread (gap)	0.52	0.48	0.56	0.34	0	0.01	0.27	0	0.02	219	0.53	0.51
Betas	0.52	0.48	0.55	0.16	0	0	0.16	0	0	244	0.57	0.35
TED spread (4)	0.52	0.48	0.55	0.22	0	0	0.22	0	0	208	0.51	0.57
Relative volatility	0.51	0.48	0.54	0.16	0	0	0.16	0	0	257	0.54	0.36
TED spread	0.49	0.46	0.53	0.17	0	0	0.17	0	0	224	0.51	0.42

Source: own computations.

Note: Numbers in parentheses indicate growth rate of variable compared with the analogous k -th quarter before. AUC - area under the ROC curve; percentile bootstrap confidence intervals (1,000 repetitions). 2:1 - probability threshold alarming about the crisis and FPR and TPR assuming that the cost of missing a crisis is two times higher than unnecessary alarm of crisis. 3:1 - probability threshold alarming assuming that the cost of missing a crisis is three times higher than unnecessary alarm of crisis. Crises - number of quarters with crises in the sample. AUC 2006 - AUC of signals issued in sample 1970-2006 by models estimated in sample 1970-2006. AUC after 2006 - AUC of signals issued in sample 2007-2014 by models estimated in sample 1970-2006.

4.3 Models with credit gap and three explanatory variables

In this step we estimate models with credit gap and three explanatory variables (table 3). Even though we analysed models with two and three explanatory variables we do not report them, as models with two variables have statistically worse predictive power than models with three variables. The problem with three variables, however, is that the credit gap (computed according to Basel III) very rarely enters most accurate early warning models. However, accordingly to ESRB Recommendation (2014) credit gap has to be incorporated into the model. To comply with this, we included credit gap in each model and then added one, two and three additional explanatory variables. Finally we end up with models of four variables in total, which were statistically better than models comprising of smaller number of variables. Furthermore early warning models with five variables were not statistically more accurate than model with four variables. Below we report results concerning these models.

In case of early warning models with credit gap and three explanatory variables we see that all these models include VIX. Each of these models is statistically more useful than the model based solely on VIX and eight models with the highest AUC do not differ significantly from each other in terms of signals accuracy (all these models are reported in table 3). For given preferences of avoiding type I and type II errors we observe lower variation in the probability thresholds that inform about crises compared with the case of models with just one variable – model thresholds generally range between 20 to 30%. Additionally we do not only observe increase in overall quality of

the models but also there is improvement in terms of lower instances when a crisis is missed – i.e. TPR ranges between 50 to 70%. As a result simultaneous use of more than one variable in the model does not only increase overall accuracy, but crucially substantially increases TPR with only very mild increases in FPR.

Table 3 Models with credit gap and three explanatory variables

Model	AUC	Confidence interval			2:1	FPR	TPR	3:1	FPR	TPR	Crises
Credit gap (Basel III), DSR (4), PFI (16) & VIX	0.92	0.88	0.95	0.3	0.1	0.76	0.3	0.1	0.76	156	
Credit gap (Basel III), Betas (gap), DSR (4) & VIX	0.92	0.88	0.95	0.36	0.07	0.68	0.28	0.11	0.79	121	
Credit gap (Basel III), PFI (gap), DSR (4) & VIX	0.92	0.88	0.95	0.3	0.09	0.76	0.3	0.09	0.76	156	
Credit gap (Basel III), VA (gap), DSR (4) & VIX	0.92	0.88	0.95	0.28	0.1	0.75	0.27	0.11	0.76	96	
Credit gap (Basel III), VA, DSR (4) & VIX	0.91	0.87	0.94	0.37	0.07	0.63	0.22	0.14	0.8	96	
Credit gap (Basel III), VA (16), DSR (4) & VIX	0.91	0.87	0.94	0.34	0.09	0.68	0.24	0.15	0.79	96	
Credit gap (Basel III), Credit to HH (12), DSR (4) & VIX	0.9	0.85	0.93	0.26	0.11	0.72	0.26	0.11	0.72	155	
Credit gap (Basel III), DSR (4), Credit (16) & VIX	0.89	0.85	0.92	0.32	0.06	0.47	0.19	0.14	0.77	178	

Source: own computations.

Note: Numbers in parentheses indicate growth rate of variable compared with the analogous k -th quarter before. AUC - area under the ROC curve; percentile bootstrap confidence intervals (1,000 repetitions). 2:1 - probability threshold alarming about the crisis and FPR and TPR assuming that the cost of missing a crisis is two times higher than unnecessary alarm of crisis. 3:1 - probability threshold alarming assuming that the cost of missing a crisis is three times higher than unnecessary alarm of crisis. Crises– number of quarters with crises in the sample.

Do models including VIX give additional information than models without that variable? In table 4 we report accuracy of signals issued by models that account for domestic factors, hence they do not include VIX. Difference between best model with VIX and two best models without VIX are not statistically significant. Thus, model with variables connected to domestic situation is equally useful as model that additionally incorporates global factors. As before probability threshold is between 20 and 30% for relative preferences 2:1 and between 20 and 25% for preferences 3:1.

Table 4 Models with credit gap domestic explanatory variables (no VIX)

Model	AUC	Confidence interval			2:1	FPR	TPR	3:1	FPR	TPR	Crises
Credit gap (Basel III), PtI (gap), VA (16) & DSR (4)	0,86	0,82	0,89	0,27	0,14	0,75	0,27	0,14	0,75	120	
Credit gap (Basel III), VA (16), DSR (4) & PtI (16)	0,84	0,8	0,87	0,31	0,11	0,64	0,31	0,11	0,65	96	
Credit gap (Basel III), VA, PtI (gap) & Credit (16)	0,83	0,78	0,86	0,32	0,09	0,51	0,22	0,18	0,72	134	
Credit gap (Basel III), VA, PtI (gap) & VA (16)	0,82	0,78	0,86	0,4	0,03	0,4	0,21	0,21	0,75	134	
Credit gap (Basel III), VA, PtI (gap) & GDP (12)	0,82	0,78	0,85	0,26	0,12	0,57	0,23	0,15	0,66	134	
Credit gap (Basel III), VA, PtI (gap) & Credit to HH (12)	0,82	0,77	0,86	0,26	0,14	0,63	0,23	0,17	0,7	134	
Credit gap (Basel III), VA, PtI (gap) & VA (gap)	0,82	0,78	0,85	0,25	0,14	0,61	0,25	0,14	0,61	134	

Source: own computations.

Summing up, our results show that it is possible to obtain Early Warning Models that issue signals with accuracy exceeding 90% without using country-specific fixed effects. Though these effects would further increase AUC they are not useful for countries that have not experienced any crisis,

while models used in this study provide useful policy tools for both crisis and non-crisis countries. Inclusion of VIX in models (a proxy for global factors) is beneficial, however using data that reflects primarily domestic situation still allows for high precision in issuing alarms.

5. Conclusions

The main goal of our study was to choose the variables whose behaviour informs about the imminent banking crises that would be useful for both countries that have experienced crises, and countries that have not. For this purpose, we use early warning models based on logistic regression and evaluate accuracy of signals with the ROC curve. Contrary to previous studies we do not include country-specific fixed effects in model as this would result in relatively low usefulness of models for countries that have not experienced crises, nonetheless we implicitly take into account heterogeneity among countries. To check the robustness of our results we also estimate probit and scobit models as well as non-parametric approach. We analyse dozens of indicators for nearly fifty countries and examine the stability of their signals. We find that VIX, a proxy of price of risk on global financial market, is a leading indicator, though its performance is partly due to global character of the recent crisis. Still, low levels of VIX tended to precede crises even before 2006 and this is in line with Minsky's hypothesis. Credit growth and property prices enjoy among the highest predictive quality of signals, but we also find that high growth in value added of the financial sector consistently predicts crises. This is supportive to the hypothesis that unusually high profits in the financial sector tend to reflect high risk, rather than high value added of its products. Overall we find that using models with three variables exhibit AUC above 90% and True Positive Rate over 70%, which is substantially more compared to any single variable model.

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Appendix A Data description and sources

List of variables and sources:

- Credit extended to non-financial sector; credit extended to households – BIS.
- Nominal GDP – Eurostat.
- Debt service ratio (DSR) – BIS.
- Residential property prices relative to income – OECD.
- VIX - Datastream
- Banking sector index beta – Datastream (Thomson Reuters).
- Volatility of banking sector index – Datastream (Thomson Reuters).
- Contribution of banking sector to GDP growth – Datastream (Thomson Reuters).
- TED spread – Datastream (Thomson Reuters).
- Volatility of banking sector index relative to market volatility – Datastream (Thomson Reuters).

Nominal variables were deflated with CPI (OECD).

Appendix B Logistic regression models

Table 5 Summary of the best models

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-2.594***	-2.324***	-3.094***	-1.382***	-4.135***	-1.351***
	-0.082	(0.063)	(0.135)	(0.141)	(0.293)	(0.170)
VIX	-1.400***		-2.004***		-3.471***	
	-0.103		(0.161)		(0.321)	
Credit (16)		0.774***				
		(0.054)				
DSR (4)			0.675***		0.634***	0.215
			(0.087)		(0.133)	(0.131)
Banks contribution to GDP (16)				0.009***		0.011***
				(0.001)		(0.001)
Property price to income (16)				0.028***	0.035***	0.030***
				(0.004)	(0.004)	(0.005)
Sample	3813	3702	2402	829	1103	576
Model p-value	0.000	0.000	0.000	0.000	0.000	0.000
AUC	0.746	0.729	0.828	0.797	0.912	0.859

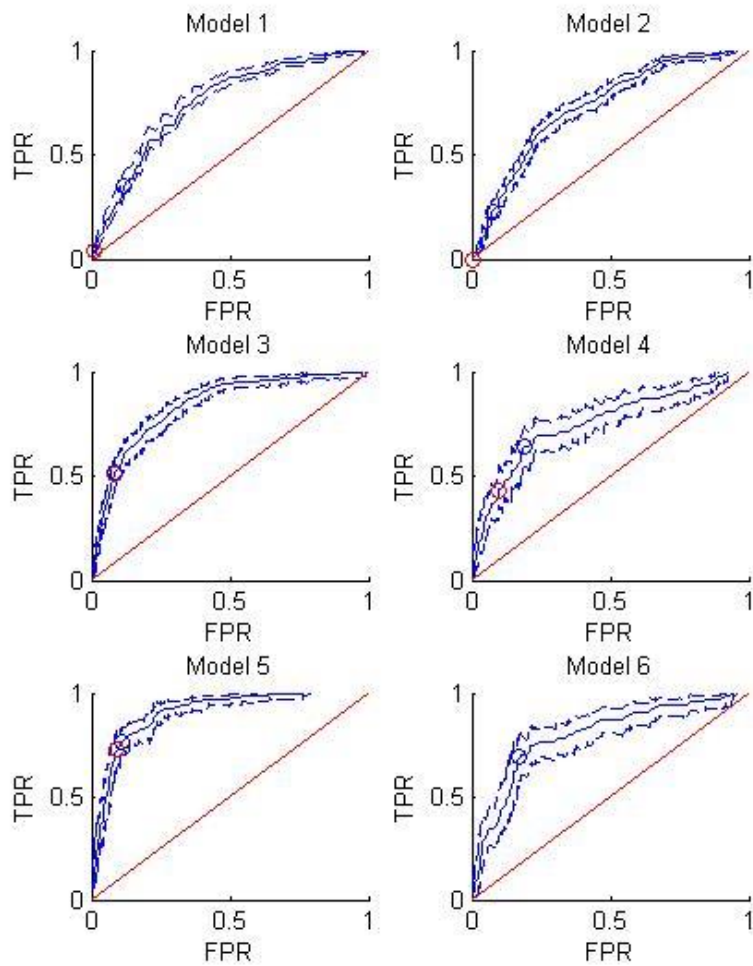
Source: own computations.

Note: *** - variable significant at 1% significance level.; standard errors are reported in parentheses; model p-value– p-value of the test, whose null hypothesis assumes no difference between analyzed model and model without any explanatory variables (only with constant).

Appendix C ROC curves

Figure 3 shows ROC curve for models with the highest AUC analysed in part 4 and percentile bootstrap confidence intervals (1,000 repetitions). Red circle – costs of errors 2:1, blue circle – costs 3:1.

Figure 3 ROC curves



Source: own computations.

Note: Description of models can be found in appendix B.

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