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Early Warning Models of Banking Crises: VIX and High Profits

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Abstract

We built a logistic regression Early Warning Models (EWM) for banking crises in a panel of 47 countries based on data from 1970–2014 using candidate variables that cover macro and financial market indicators. We find that VIX, a proxy of global risk-premium, has a strong signalling properties and that low VIX (low price of risk) increases likelihood of crisis. It does not only mean that stability leads to instability, but that this tends to be a global rather than a domestic phenomenon. We also find that particularly high contribution of financial sector to GDP growth often precedes crises, suggesting that such instances are primarily driven by excessive risk taking by financial sector and may not necessarily be sustainable. Other variables that feature prominently include credit and residential prices. Models using multiple variable clearly outperform single variable models, with probability of correct signal extraction exceeding 0.9. Our setting includes country-specific information without using country-specific effects in a regression, which allows for direct application of EWM we obtain to any country, including these that have not experienced a banking crisis.

Keywords: early warning models, financial stability

JEL Classification: E44, G01, G21

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1 Introduction

Global Financial Crisis (GFC) of 2007–2009 has created a renewed interest in financial cycles and crises, as well as in contribution of the financial sector to growth. It has also resulted in the creation of new policy – macroprudential policy – and new tools to either decrease the probability of crises or dampen their consequences. Following the GFC there was increased interest, both in academia and in bodies responsible for conduct of macroprudential policy, in understanding and predicting banking crises.
Outbreak of the most severe financial crisis in the last few 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 based on credit gap (i.e. deviation of credit-to-GDP from its long-term trend), it allows the final decision to differ from the reference level and to use other information as well. This is where EWM have been primarily applied. It has been shown that crises can indeed be predicted, often many years in advance, and that early warning model can be a useful tool for macroprudential policy (Lang et al., 2018).
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. However, rules suggested by the ESRB does not preclude using other quantitative or qualitative methods since having broader information set should allow for (at least ex ante) higher-quality decisions. Many studies show that this is indeed the case (Alessi et al., 2015). Still, it is often challenging to apply the results from EWM literature to the countries that have not experienced crises in the past. A pooled regression approach that allows such application has a drawback of abstracting from country-specific effects. However, by transforming variables for individual countries into their Z-scores we are able to account for country specificities and make models directly applicable to non-crisis countries. We do so using logistic regression in a panel of 47 countries covering period of 1970–2014 using candidate variables that cover macro and financial market indicators. We verify accuracy of signals from various variables and their combinations, as well as their stability by assessing the accuracy in the full, pre-crisis and post-crisis sample. Among the candidate signalling variables we include the ones that have been earlier shown to provide valuable signals – inter alia credit and residential prices – but we also add new variables, that have not been used before. These variables allow us to test two important hypotheses.
It is perhaps no coincidence that the Global Recession followed the Great Moderation. This is the hypothesis put forward by Minsky (1977) – that stability leads to instability, as over-optimism creates too much risk taking and results in crisis. Recent empirical studies suggests that this is indeed the case, and prolong low volatility of

stock returns is conducive to future crises (Danielsson et al., 2018). We complement this line of research by asking whether low price of risk on a global financial market, as proxied by VIX, can signal future crises in individual countries.

There is also a long debate in economics, dating back to Schumpeter (1911), concerning the impact of financial sector on growth. The pre-crisis empirical status quo, of largely positive impact of financial deepening on growth (see Levine (2005) for a review), has been challenged and ultimately altered (Arcand et al., 2012). Following GFC it has been suggested that what we often measure as financial sector's contribution to GDP (value added) may not always reflect contribution to welfare, but profits from excessive risk taking (Wang, 2011). We test this hypothesis by including value added of the financial sector as one of potential explanatory variables.

We find that VIX, our proxy of global risk-premium, has a strong signalling properties concerning crises in individual countries and that low VIX (low price of risk) increases likelihood of crisis. It does not only mean that stability leads to instability (as is stated in Minsky's hypothesis and was empirically verified by Danielsson et al. (2018)), but that this tends to be a global rather than a local (domestic) phenomenon. Second, we indeed find that particularly high contribution of financial sector to GDP growth signals crises, suggesting that such instances are primarily driven by systemic risk taking rather than contribution to welfare. We confirm that credit gap, indeed has early warning properties, but other variables fare better. Finally, models including multiple variables clearly outclass models with single variables. Augmenting models from one to four explanatory variables allows to drastically improve true positive rate of crisis prediction, and reach probability of correct signal extraction in excess of 0.9, but adding more variables does not improves signals further.

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

While there is no universal definition of a banking crisis, review of the literature in Babecký et al. (2014) helps to distinguish some often shared qualitative characteristics. Banking crises are identified as events where there are significant losses in the banking sector, leading to closure, merging, takeover, or large-scale government assistance of an important financial institution, followed by similar interventions in other institutions. Banking crises have severe consequences for welfare. Bordo et al. (2001) and Babecký et al. (2014) report an average decrease in output of 6–7% related to banking crisis, while Laeven and Valencia (2012), find even larger losses – an output loss of 26% for emerging countries and 33% for developed countries.

Outbreak of the GFC 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 related to credit, real estate prices and equity prices have the highest predictive ability and using multiple variables improves signalling properties of models. In the following years, there has been a substantial growth in the number of research papers related to Early Warning Models (EWM), which was partly driven by its direct applicability to macroprudential policy. This includes Drehmann et al. (2010), Alessi and Detken (2011), Drehmann and Juselius (2012), Lo Duca and Peltonen (2013), Babecký et al. (2013), Betz et al. (2014), Alessi and Detken (2014), Alessandri et al. (2015), Lainà et al. (2015), Holopainen and Sarlin (2015), Alessi et al. (2015), Lang et al. (2018) and Danielsson et al. (2018).

A comprehensive review of modelling choices and results in the literature is provided by Alessi et al. (2015) and Lang et al. (2018). Empirical studies strongly suggest that banking crises can be predicted often many years in advance. Variables that help in identifying crises in advance are usually related to level of credit and its growth, real estate prices and their dynamics, as well as market valuations and market price of risk. There are various approaches concerning modeling choice for the binary problem of crisis prediction, but no model has been found as clearly outperforming others. As a results there is a wide range of possibilities concerning modelling choice and variables used.

Studies most relevant for our research are Alessi et al. (2015) and Danielsson et al. (2018). In Alessi et al. (2015) there is a line of research followed by Bush et al. (2013) who study the predictive properties of credit-to-GDP gap, leverage ratio, liquid asset ratios, and price of risk for 15 EU countries over the course of 1980–2010. They find that these variable help in identifying crisis periods as early as 5 years in advance. They do not include VIX as a variable, but a proxy for VIX for each country, which they calibrate based on individual stock market indices. They do find that low price of risk is related to future higher of crisis.

Investigation by Danielsson et. (2018) is conducted over much longer horizon. They study the effects of stock market volatility on risk-taking and financial crises by constructing a cross-country database spanning up to 211 years and 60 countries. They find that periods of low volatility of stock market returns lead to excessive credit build-ups and balance sheet leverage in the financial system, indicating that agents take more risk in periods of low risk. They thus conclude, in line with Minsky hypothesis, that "stability is destabilizing."

Our study complements this research in the following dimensions. First, by using VIX rather than measures of volatility of stock market returns for individual countries, we are able to identify to what extent global, external factors play a role, and to what extent low volatility may be therefore a common phenomenon. A study by Jorda et al. (2015) which covers data over 130 years across many economics strongly suggests that stock market returns have been increasingly dependent over last decades – the average correlation increased from approx. 0.4. in late 80's to approx. 0.8 in 2010. This means that there is increasingly common component in the market price of risk, which we aim to capture with the VIX.

Second, Borio et al. (2010) point out that periods of high bank profitability are typically associated with rapid credit growth, increased risk-taking. As a result high profits might come at a price of heightened vulnerabilities. There only few studies that analyse the of profits of banks as a potential leading indicators. This is a hypothesis tested by Behn et al. (2014), who conduct a study over 1982–2012 for 23 EU countries, and find that high profitability of the banking sectors helps in predicting crises. Still, profits of the sector do not include remuneration of the employees. Incentives to employees in terms of bonuses can have a major impact on the risk-taking. It has been shown that excess renumeration in the financial sector tends to peak before the crises (Philippon and Reshef, 2012). A variable that encompasses broadly understood profits in the sector – distributed to shareholders, paid as taxes and distributed to employees – is a value added of the sector to GDP. In principle, it is associated with contribution to welfare, but it can also reflect high profits from sectoral booms. This is a reason why Ferrari et al. (2015) include value-added to GDP of the construction sector as potential predictor, as housing booms have been often associated with crisis. We complement these results and test whether period of increasing contribution of the financial sector to GDP growth provides a signal of future crisis.

3 Data and method

3.1 Data

Our analysis covers the period from the first quarter of 1970 to the second quarter of 2014. We use two types of indicators – macroeconomic and market-based. This is to account for the findings from the literature that both macroeconomic data and market data have useful information concerning future crises events. The list of variables, their description and sources is presented in Table 1.

Coding of crisis and non-crisis periods is taken from Babecký et al. (2014), who construct a quarterly dataset covering banking crisis (as well as debt and currency crisis, which are not the focus of this study) episodes in 40 developed countries over 1970–2010. Their taxonomy and dating of crises is based on 10 other studies in the literature and surveys with country experts. This dual approach is motivated, inter alia, by lack of universal definition of crisis (some studies identify crisis episodes with the help of a certain variable and its threshold value, other studies employ expert judgment or use systematic literature and media reviews) and selective coverage of countries in some studies. This lack of a universal definition made authors validate the coding of crisis episodes with the help of country experts, who cross-check and correct, if needed, the coding of crises. In this study we focus exclusively on banking

Table 1: Indicators used in the analysis of early warning properties

Variable name	Description	Source
Credit to PNFS	Credit from banks to private non-financial sector (PNFS), billions of national currency	BIS
Credit to HH	Credit from banks to households, billions of national currency	BIS
DSR	Ratio of interest payments plus amortisations to gross disposable income in the private non-financial sector (PNFS: households and enterprises); for detailed methodology see: https://www.bis.org/statistics/dsr/dsr_doc.pdf	BIS
GDP	Gross domestic product, nominal, national currency	Eurostat, OECD, FRED
Credit gap (Basel III and country-specific)	Deviation of ratio of credit to GDP from a long-term trend set with a one-sided Hodrick-Prescott filter with $\lambda = 400,000$ (Basel III) or country-specific λ (set at a frequency for which periodogram attributed the biggest part of the variance, i.e. dominant frequency of the credit cycle)	BIS, Eurostat, OECD, FRED
RRE	Nominal house prices, index based in 2010	OECD
RRE PtI	Residential Real Estate Price to Income, nominal house prices divided by nominal disposable income per head, index based in 2010	OECD
VA	Value added of the financial sector in the GDP growth	Eurostat, OECD, FRED
Volatility banks	Volatility of banking sector index, standard deviation of daily returns in a given quarter	Datastream (Thomson Reuters)
Relative volatility banks to market	Ratio of volatility of banking sector index to market (broad stock market index) volatility, relative standard deviation of daily returns in a given quarter	Datastream (Thomson Reuters)
Beta banks	CAPM beta of the banking sector index, daily returns in a given quarter	Datastream (Thomson Reuters)
TED spread	Spread of 3M interbank rate over 3M government bills, average of daily data over a quarter	Bloomberg, Datastream (Thomson Reuters)
VIX	Chicago Board Options Exchange's CBOE Volatility Index, average over a quarter	Datastream (Thomson Reuters)

crises. We also extend the coding of crises to 2014 using the updated version of the survey among the experts done by the ESRB, as well as an updated version of Laeven and Valencia (2013, 2020) database, which has also been used by Babecký et al. (2014).

Concerning the explanatory (i.e. signalling) variables, we follow the literature on early warning models against banking crises and we include various types of credit to non-financial sector, debt service and real estate prices as potential leading macroeconomic indicators, as well as value added of the financial sector in the GDP growth. Adding the VA to the analysis stems from the hypothesis that the value added of this sector can be a measure of risk-taking by the financial industry. According to national accounts VA is calculated as: Revenues-Costs-Amortization = Renumeration + Interests + Dividends + Taxes + Retained Earnings. This formula shows that high VA might not be related with contribution of the financial sector to welfare, but instead with profits from excessive risk-taking, including systemic risk (Haldane et al. 2010; Wang, 2011). If that would be the case, high VA could be expected to signal an impending crisis. If on the other hand high value added indeed reflects contribution to welfare one would not expect any significant signalling properties concerning future crises. This is one of the hypotheses we investigate.

Concerning market-based indicators, we use VIX, volatility of the stock returns of the banking sector, relative volatility of returns of banks to market volatility, and the CAPM Beta of the banking sector. All market variables are either taken as an average over a given quarter (VIX), or estimated using daily data over quarterly interval (volatilities, Beta). Inclusion of VIX proxies market price of risk on international financial market and gauges to what extent global factors affect crisis probability in individual countries. It should be noted that while the VIX reflects the implied volatility of short-term options it likely reflects the relative level of the implied volatility with longer maturities. This is due to the fact that the term structure of implied volatility has an important common component (Cont, Da Fonseca, 2002), which implies that shifts of the structure of the implied volatility are predominantly parallel. Thus level and changes of VIX are likely to reflect changes not only in expectations and prices of short term-options, but also of options with longer maturities, which could be more relevant for thinking about crises.

We use available data for 47 countries – all EU member states (as of 2014) and countries outside the EU, for which the Bank for International Settlements (BIS) publishes data on credit extended to private non-financial sector (Australia, Brazil, Canada, China, Hong-Kong, India, Indonesia, Iceland, Japan, Malesia, Mexico, Norway, Russia, South Africa, South Korea, Switzerland, Thailand, Turkey, USA). The criterion of credit as a variable was used to account for the fact that many studies indicate that the variables related to the credit cycles (i.e. credit gap and DSR) are useful early warning indicators, and credit gap is the recommended variable by the BIS and the ESRB to guide the countercyclical capital buffer. It is therefore a natural

benchmark to assess the usefulness of other variables, as well as models that use multiple variables relative to the ones that use only single variable.
As there may be many hypotheses concerning whether it is the level of the variable, its growth or deviation from some equilibrium value that are important predictors of crises, we analyse candidate variable under various transformations: in levels, growth rates (quarterly, annual, two-, three- and four-year) and cyclical deviations from long-term trend. The most commonly used approach in the literature on financial cycles to account for trend is the HP filter with a smoothing parameter $\lambda = 400{,}000$, which corresponds to the cycles of approximately 25 years, i.e. four times longer than the length of the business cycle (see Drehmann et al., 2010). However, we also include deviations from a trend assuming idiosyncratic length of the financial cycle for each country. To this end, we first use an approach by Comin and Gertler (2006), which consists in extracting the trend from annual growth rates of a given variable (similar methods was used by Drehmann et al., 2012, and Schüler et al., 2015), and second, using the periodogram we identify the dominant frequency of the credit cycle. Financial cycle is identified as those fluctuations whose variance is the highest in the range from 8 to 30 years. Next, using relationship between the smoothing parameter in the one-sided HP filter and the frequency (Maravall and Del Río, 2001) we compute the value of smoothing parameter in the HP filter which is consistent with the length of the financial cycle for each variable. The use of one-sided filter, is motivated by the use information available at a given date.

3.2 Method

This section describes the approach used to estimate early warning models of banking crises outbursts. Description is divided into two parts and concerns method of extracting information from a set of variables and assessment of the predictive quality of the signals generated by early warning models.

Early warning model
Early-warning model is an example of two-class classification. Holopainen and Sarlin (2015) provide a review of various early-warning modelling techniques and categorize them into four subgroups: (i) linear discriminant analysis and logistic regression, (ii) relying directly on contingency matrix, (iii) similarity functions, (iv) other approaches. They find that, notwithstanding differences in complexity, there is no single best modelling technique. We apply logistic regression, which has been one of the most prominent methods used.
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. Early warning model is to generate signals $Y_{i,t}(h) \in \{0,1\}$ with "ones" h periods before the crisis and "zeros" 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:

$$Y_{i,t}\left(h\right)=\begin{cases}1, & X_{i,t}\left(0\right)>\theta,\\ 0, & X_{i,t}\left(0\right)\leq\theta,\end{cases} \tag{1}$$

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 2) that summarizes discrimination between tranquil and crisis periods.

Table 2: Confusion matrix

	Crisis period	Tranquil period
Signal	A (True Positive)	B (False Positive)
No signal	C (False Negative)	D (True Negative)

Based on the information given in the Table 2 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 $T2=\frac{B}{B+D}$. Additionally Alessi and Detken (2011) suggests using policy makers' loss function $L(\alpha)=\alpha\frac{C}{A+C}+(1-\alpha)\frac{B}{B+D}$, where $0\leq\alpha\leq1$ and indicator's usefulness $U=\min_{\alpha}\{(1-\alpha);\alpha\}-L(\alpha)$. This can be directly applied to logistic regression models via cost of type I and type II errors, which effectively changes the level of signalling threshold (see Equation (3)).
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 models:

$$\Pr\left(Y_{i,t}\left(h\right)=1\right)=\frac{1}{1+e^{-\left(\alpha+\beta' X_{i,t}\right)}}, \tag{2}$$

where α,β are vectors of parameters, and the $X_{i,t}$ is the matrix of the variables (we checked robustness of the results (in terms of AUROC) conditional on a distribution we used to estimate the binary choice model. However, probit model yield significantly higher AUROC than logit model. Non-parametric method as proposed by Kaminsky and Reinhart (1999) also does not produce signals more accurate than those generated with logit). 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.

Evaluation of signals

An important requirement in case of early warning model is that it should generate signals with considerable advance. Given the fact that EWM could be used by macroprudential authorities to deal with cyclical risk of banking crisis, by setting a countercyclical capital buffer (CCyB), the signal must be generated at least one year in advance. This is because CCyB is made effective one year after the announcement. As a result a lower limit of the signalling horizon is five quarters, so that CCyB can be build in the banking sector prior to crisis. 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.

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. The difference is that in the second of these methods given variable is used, rather than the probability obtained from the logit model. Note that lowering the threshold means moving up and to the right-hand side along the ROC curve as exceeding the lower limit is more frequent, causing an increase in both FPR and TPR. The area under the ROC curve (AUROC) is a measure of the predictive quality of signals. For variables that attain high levels before crisis AUROC 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):

$$E(U) = P(\mathrm{FN} \cdot \varphi) + (1 - P)(\mathrm{FP} \cdot (1 - \varphi)), \tag{3}$$

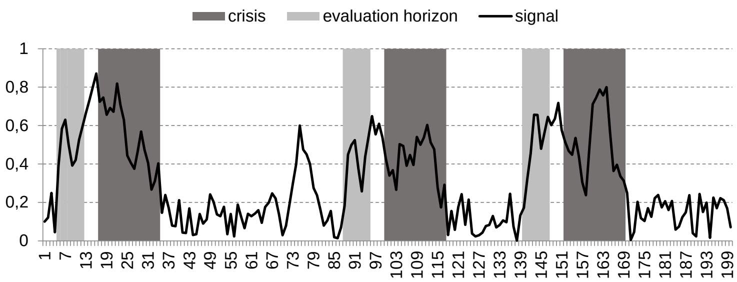
where P reflects the frequency of the „1" events, and φ reflects the relative weight of type I (FN) and type II (FP) errors. The more preferable is to avoid the type I errors (or larger the cost associated with committing such error) the lower is the optimal threshold for signalling crisis. To show the 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. Like in Drehmann and Juselius (2014) it is assumed that after the outbreak of the crisis it makes no sense to predict one. We are therefore not interested in the behaviour of EWM during the crisis periods. This means that the sample ignores periods of crisis, which are essentially excluded from the data (dark grey boxes in Figure 1). However the same authors assumed that every crisis lasted two years, while 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). The window in which we want to get a signal is marked as light grey area in Figure 1. It reflects period stretching from 5 to 16 quarters before the actual crisis.

4 Empirical results

In this part of the study we show the estimates of pooled logistic regression models, i.e. without country-specific effects in the sample of 47 countries between 1970–2014. We start with models with one explanatory variable, testing the hypotheses concerning the impact of price of risk (i.e. VIX), the impact of value added attributed to the financial sector on crisis probability, as well as other variables in predicting crises, including the credit gap postulated by the Basel Committee. Subsequently we expand

Figure 1: Evaluation of signals



Note: Vertical axis shows hypothetical probability of crisis extracted from EWM, horizontal axis depicts timeline. Dark grey areas reflect crisis periods. Light grey bars show evaluation periods, where EWM should generate signal of crisis, i.e. in advance of crisis. The gap between the two reflects the fact that signal are expected to be generated not just before the crisis, but at least 6 quarters ahead.

the number of explanatory variables and analyse how the augmented information set impacts the performance of early warning models.

4.1 Models with one explanatory variable – VIX, value added of the financial sector and other

The results for models with one variable are presented in Table 3. 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-GFC sample and evaluation of signals it issues in a post-GFC sample. In Appendix A we report summary of the best models.

The greatest usefulness in terms of accurate signals of crises is featured by VIX, whose AUROC is 0.75. This means that 75% of signals from the model correctly identify future state (crisis or no crisis). Importantly, the lower the VIX, the higher the probability of crisis 6–16 quarters ahead. It may be surprising that the VIX, which reflects the implied volatility of short-term options, does contain information on crisis probabilities many quarters ahead. To understand this, it should be noted that the term structure of option prices, i.e. the implied volatility of short- and long-term options, has an important common component, which implies that shifts of the structure of the implied volatility are predominantly parallel (Cont, Da Fonseca, 2002). This explains why VIX, i.e. a variable related to short-term future, can have an information concerning more distant one, as implied volatility of longer-term option can be expected to move largely together with short-term implied volatility reflected in VIX. Moreover, the autocorrelation of this common factor is substantial, which further implies that VIX has a tendency to remain in regions of low and high volatility – a phenomenon well-known in financial markets literature. Low volatility periods tend to be persistent, as well as high-volatility ones. This and the fact the low readings of VIX tend to proceed crises is therefore in line with the hypothesis that stability (i.e. low volatility) leads to instability.

Particularly high growth in the value added of the financial sector over the 4-year period also has high signalling properties – similar to the growth of credit over the same horizon. This is in line with proposition that what we measure as value added may at time reflect excessive risk-taking in the financial sector. It turns out that high growth in this indicator and deviations from long-term averages are a harbinger of trouble.

Similarly good signal are generated by growth in credit, i.e. 4-year credit growth rate. Debt Service Ratio and credit gap, which according to the previous studies have the highest values of AUROC. While these variables are still among the most useful, contrary to the results in the literature, they are no longer the most accurate. Explanation of these results is 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 AUROC (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 AUROC. This is confirmed by the AUROC level of DSR and credit gap – in the sample that contains only the EU countries and for models including fixed effects – which amounts respectively to 0.929 and 0.818.

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 in most cases we observe a significant drop in the threshold probability (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 AUROC 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. Since we have dozen of crises in the sample it is intuitive that they are not homogenous – this is because they have different origins. Are EWM able to issue signals correctly throughout the time? So far we discussed results for the full sample however such approach has pros and cons. With regard to the latter the main disadvantage is that the biggest fraction of crises is connected with the last financial crisis. Consequently, this results in bias of model towards correct identification of crises that have similar origins like the last one. This, in turn, 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 AUROC equal to 0.5 means that signals are non-informative. Their accuracy is the same as of signals generated by Bernoulli distribution with probability $p = (1 - p) = 1/2$. The upper confidence interval for such AUROC value is 0.55. Variables that exceed this value are considered as useful, that is, as those that give additional information. 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 AUROC is significantly higher than 0.5. Thanks to that we filter out variables that are either non-informative or their interpretation changes with time. Criteria set out above are met by fourteen variables. If we use more stringent criterion – AUROC significantly higher than 0.5 in both full and pre-crisis sample – we end up with only five variables generating stable signals.

Results of stability check can be found in the last two columns of Table 3. In column 'AUROC after 2006' we report accuracy of signals issued by models that are estimated in pre-crisis sample. High value of AUROC means that given variable is useful predictor of banking crises in period 1970–2006. Last column of Table 3 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 connected 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.

4.3 Models with credit gap and three explanatory variables

In this step we estimate models with credit gap and three explanatory variables (see Table 4). Even though we analysed models with two and three explanatory variables we do not report them. Justification for that is following: models with two variables are better than models with one variable, however their signals are less accurate than signals that are produced by models with three variables. The problem with three variables, however, is that the credit gap (computed according to Basel III) very rarely

Table 3: 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
Rel. 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

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 (i.e. 6 quarters before the start of GFC). AUC after 2006 – AUC of signals issued in sample 2007–2014 by models estimated in sample 1970–2006.

Table 4: Models with credit gap and three explanatory variables

Model	AUC	Conf. interval		2:1	FPR	TPR	3:1	FPR	TPR	Crises
Credit gap (Basel III), DSR (4), PtI (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), PtI (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

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.

Table 5: Models with credit gap domestic explanatory variables (no VIX)

Model	AUC	Conf. 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

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 lower 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 AUROC do not differ significantly from each other in terms of signals accuracy (all these models are reported in Table 4). 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.

Do models containing only domestic variables performed worse than models containing both domestic and global variables, i.e. VIX? We test this proposition by comparing the quality of the signals extracted from best-performing models across two approaches. In Table 5 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 presented in Table 5 are not statistically significant. Thus, much of the information concerning crisis probability can be extracted from the combination of domestic factors, even though VIX tends to have best accuracy on its own.

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 threefold. First, we wanted to assess whether stability (i.e. low volatility) leads to instability and if this is a global, rather than a local phenomenon. We confirm that this is indeed the case. Previous studies have shown that low volatility of the stock market returns have strong signalling properties concerning future crisis. We extend these result, by showing that this is not necessarily a domestic factor at play, but a global risk premia, which we proxy with VIX. Second, following the debate on the impact of finance on growth, we tested the hypothesis whether high contribution of the financial sector to the value added may reflect too much finance and too much risk taking, rather than genuine improvements to welfare. It turns out that high growth in the contribution of the financial sector to GDP over 4-year horizon has strong signalling properties, comparable with credit growth and better than the credit gap. We also analysed dozens of indicators for nearly fifty countries and examined the stability of signals they issue. As in previous studies credit and property prices feature the highest predictive quality of signals. We did not include country-specific fixed effects in model, nonetheless we implicitly took into account heterogeneity among countries. The results prove that it is possible to calibrate the build-up phase fairly reliably and such signals turn out to be quite stable. We document that models including multiple variables outclass models with single variables. Augmenting models from one to four explanatory variables allows to greatly improve the quality of signals, and reach probability of correct signal extraction in excess of 0.9. Adding more variables does not improves signals further.

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Appendix A Logistic regression models

Table A.1: Summary of the best models

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-2.594*** (0.082)	-2.324*** (0.063)	-3.094*** (0.135)	-1.382*** (0.141)	-4.135*** (0.293)	-1.351*** (0.170)
VIX	-1.400*** (0.103)		-2.004*** (0.161)		-3.471*** (0.321)	
Credit (16)		0.774*** (0.054)				
DSR (4)			0.675*** (0.087)		0.634*** (0.133)	0.215 (0.131)
Banks contribution to GDP (16)				0.009*** (0.001)		0.011*** (0.001)
Property price to income (16)				0.028*** (0.004)	0.035*** (0.004)	0.030*** (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

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 analysed model and model without any explanatory variables (only with constant).