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EVALUATING BANKING CRISIS PREDICTIONS IN EU AND V4 COUNTRIES

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Abstract: Relying on a recently published database of financial crises, this paper assesses an early warning model for predicting banking sector distress. The exercise employs discrete choice models and a signaling approach to evaluate the performance of an existing model based on credit-to-GDP change and real house price growth in regard to predominantly post-crisis data for EU and Visegrad Group countries. As such, unbalanced panel data for 27 EU countries, spanning with annual frequency at longest the period of 2003-2017, as well as unbalanced panel data for 4 Visegrad Group countries covering at most the period 2008Q1-2017Q4 with quarterly frequency were analyzed. The results are generally in line with other empirical research featuring the same model and indicate that the model retains most of its predictive capabilities even when currently available data are used. However, the analysis identifies that the indicator of real house price growth may not be as useful of a predictor of banking crises in more recent periods for EU countries, as it might have been before the 2008 financial and economic crisis. Consequently, a simpler univariate early warning indicator approach might be sufficient for banking sector risk monitoring and management in EU and Visegrad Group countries in regard to identifying periods of distress similar to those in 2008.

Keywords: Banking Crisis; Early Warning Models; Discrete Choice Models; Signaling Approach; Credit-to-GDP; House Price Index

JEL Classification: C25, C52, E50, G01

INTRODUCTION

Following the outbreak of the 2008 financial and economic crisis, achieving a more resilient banking sector had become a task of paramount importance for many international and national organizations. In response, the growing agreement among policymakers seems to be that a regulation in line with the macroprudential approach should be implemented (Galati and Moesner, 2018). The International Monetary Fund (IMF) addressed these issues in its Global Financial Stability Report (IMF, 2011), which among other topics elaborated upon predicting the probability of banking crisis occurrences. This work was later expanded by Arregui et al. (2013), who shifted from the fixed effects probit model framework used by the aforementioned authors to the random effects logit framework. The logit framework was also utilized by the European Systemic Risk Board Expert Group (Detken et al., 2014), which estimated multivariate models as one of the approaches for constructing early warning systems.

The European Systemic Risk Board has used the results from its Expert Group (Detken et al., 2014) to underpin the recommendation to implement a countercyclical capital buffer. Lainà, Nyholm, and Sarlin (2015) have also provided additional input for macroprudential tools for Finland as well as for a broader group of developed European Union (EU) countries through their analysis of quarterly panel data using univariate signal extraction and multivariate logit models. Other country-specific analyses aimed at supporting the setting of corresponding rules were carried out by Valinskytė and Rupeika (2015) for Lithuania as well as for groups of Baltic countries. As part of the analysis, the performance of suggested early warning indicators and models was tested in regard to Lithuania. In addition, country-specific threshold values of the early warning models[1] tested throughout the analysis were estimated. This particular exercise was among the inspirations for performing similar analysis for the case of Visegrad Group or Visegrad Four (V4) countries to explore how well the examined early warning model can be applied in another group of distinct EU countries given past experience from the 2008 financial and economic crisis.

The analysis in this regard greatly benefits from the recently published Systemic Banking Crises Database II, constructed by Laeven and Valencia (2020). Utilizing available annual data for 27 EU countries spanning at longest 2003-2017, the paper provides assessment via the signaling approach of the same early warning model of Arregui et al. (2013), which was tested by Valinskytė and Rupeika (2015) for Lithuania, as well as of additional estimates of the same specification. Furthermore, the analysis also uses quarterly data for V4 countries spanning at longest 2008Q1-2017Q4 to verify the validity of results obtained using annual data.

The results indicate that the early warning model of Arregui et al. (2013) performs rather well when the more recent, mostly post-crisis annual data for V4 countries are used for the assessment. The newly estimated model for the more recent data does not yield substantially better predictions than the original one, even if it is fitted to the sample used for evaluation. However, it appears that the indicator of house price growth does not seem to sufficiently contribute to crisis prediction.

The remainder of the paper is organized as follows. Section 1 provides a list of signaling approach measures utilized for evaluation of all early warning models throughout the analysis, followed by a brief summary of the estimation methods used for the replication of the original discrete choice model. Predictors included in the assessed early warning model, their data sources, and the indicators of banking crisis are described in Section 2. Section 3 presents the obtained results and compares them with the findings of previous analyses by Arregui et al. (2013) and Valinskytė and Rupeika (2015). Closing remarks are provided in the concluding section.

1. METHODOLOGY

Since the presented analysis was inspired by a similar evaluation conducted by Valinskytė and Rupeika (2015), the performance of the early warning model of Arregui et al. (2013) is assessed using analogous methods and measures. Additionally, the subsequent estimation of the same model using more recent data was performed following the approach of Arregui et al. (2013).

1.1 Evaluation Methods

In addition to evaluating the original early warning model of Arregui et al. (2013), the proposed model was estimated anew during the analysis by utilizing the currently available data used for the evaluation. To replicate the original model as closely as possible, the random effects logit model framework, which was also used by Arregui et al. (2013), was employed. The original model was obtained by calibrating model parameters to the values provided by the authors, yielding the same model evaluated by Valinskytė and Rupeika (2015).

The model framework used is predicated on idiosyncratic errors being distributed according to the logit distribution, while country-specific random effects were assumed to be normally distributed. The distribution of random effects was approximated throughout the estimation using the adaptive Gauss-Hermite quadrature (for more details, see Greene, 2012). Following Arregui et al. (2013), the joint statistical significance of real house price growth and its interaction term was examined using the Wald test (for more details on the test, see StataCorp, 2013).

1.2 Discrete Choice Models

In addition to evaluating the original early warning model of Arregui et al. (2013), the proposed model was estimated anew during the analysis by utilizing the currently available data used for the evaluation.

[1] A more recent advancement in this area indicates that in practice an aggregate result of a panel of different early warning models and methods might be preferable to a result of a single model. For more details see Holopainen and Sarlin (2017).

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2. VARIABLE DESCRIPTION AND USED DATA

As the analysis aims to evaluate the model of Arregui et al. (2013), economic indicators featured in this early warning model and their respective sources are presented in the first part of the section. The following section describes the banking crisis indicator used as the dependent variable and as a reference for the purposes of evaluation.

2.1 Predictors of the Early Warning Model

An identical specification to the one presented by Arregui et al. (2013) was used for the replication of the early warning model and its evaluation. The specification considered the indicators of the credit-to-GDP ratio and real house price index as predictors of banking crises. The authors included these indicators since the IMF (2011) reported that they had a statistically significant influence on the probability of banking sector distress. In the case of both studies, the indicators were featured in the form of changes (annual difference) for the credit-to-GDP ratio and of growth rates for the real house price index. Additionally, Arregui et al. (2013) included an interaction term between a dummy variable for substantial annual changes in credit-to-GDP and real house price index growth. The dummy variable obtained a value of 1 if changes in credit-to-GDP were greater than 3 p.p. and 0 otherwise.

For evaluation based on annual frequency, the credit-to-GDP ratio was obtained from publicly accessible Eurostat database for each EU Member State as a series "Household debt, consolidated including Non-profit institutions serving households - % of GDP [TIPSPD22] (Percentage of gross domestic product (GDP))" (Eurostat, 2020e). Similarly, the real house price index was computed as a fraction of "House price index - annual data [TIPSHO20] (Annual average index [INX_A_AVG])" (Eurostat, 2020c) and "Final consumption expenditure of households and non-profit institutions serving households - annual data [TIPSNA51] (Price index (implicit deflator), 2010=100, national currency)" (Eurostat, 2020a), both of which were acquired from the Eurostat database for every EU country.

However, since the focus of the analysis was on V4 countries, the number of observations for these countries would be very limited if only time series with annual frequency were used. Therefore, data with quarterly frequency for V4 countries were also utilized. Again, these were both in the case of credit-to-GDP ratio and in the case of real house price index obtained from Eurostat database as series "Financial balance sheets [nasq_10_f_bs]" (Eurostat, 2020b) for "Liabilities of Households (S13)", "Non-financial corporations (S11)", and "Non-profit institutions serving households (S15)", regarding the items "Loans (F3)" and "Debt Securities (F4)", all as "Percentage of gross domestic product (GDP)" and "House price index, deflated - quarterly data [TIPSHO30]" (Eurostat, 2020d), respectively.

Obtained data for credit-to-GDP ratio and for the log[2] of real house price index were seasonally adjusted using the additive moving average method (difference from moving average) and, as a robustness check, X-12-ARIMA of the U.S. Census Bureau[3] (Wang and Wu, 2012). For the sake of brevity, only the results

[2] The log of real house price index was adjusted rather than the level of the data because Arregui et al. (2013) features this indicator in the early warning model in the form of logarithms.

[3] Both seasonal adjustments were computed using EViews environment as the x12a.exe program required for the Stata routine proposed by Wang and Wu (2012) was during the time of the analysis no longer publicly available from U.S. Census Bureau website.

for the additive moving average method are presented, as the differences in the results were rather negligible.
Next, growth rates of real house price index in % were similarly to the IMF (2011) computed as log-differences, and changes of credit-to-GDP ratio in percentage points were computed as level differences. This was done irrespective of the frequency of data used, so a difference of one period was performed both in the case of annual panel data and in the case of quarterly panel data[4].
The order of integration of quarterly panel data was examined by panel unit root tests proposed by Maddala and Wu (1996) and Choi (2001), which utilize Fisher's method to combine independent Dickey-Fuller (1970) tests. These tests were preferred over the panel stationarity test of Hadri (2000) due to their higher reported finite sample power[5] and not requiring at least a moderate number of cross-sectional units. The annual data were not subjected to the same analysis because the panel tests used require that the temporal dimension approaches infinity, and after that, the cross-sectional dimension approaches infinity (Choi, 2001), which can hardly be met in panels with the temporal dimension smaller than the cross-sectional dimension. The resulting test statistics (s.) and p-values (p.) of inverse chi-square test (P) statistic and inverse-normal test (Z) static are presented together with additional descriptive statistics in Tab. 1.

Tab. 1: Summary statistics for annual (EU) and quarterly (V4) data

Variable		Mean	Std. Dev.	Min	Max	Observations		Unit Root		
Credit-to-GDP										
Annual	Overall	46.687	31.048	0.200	142.500	Sum	663			
	Between		27.980	11.358	113.925	N	28			
	Within		14.335	4.995	84.376	T	23.679		Level	Dif.
Quarterly	Overall	80.219	19.410	42.150	135.969	Sum	274	P (s.)	6.680	16.048
	Between		9.001	69.452	91.021	N	4	P (p.)	0.572	0.042
	Within		17.624	36.172	125.167	T	68.500	Z (s.)	-0.153	-1.791
								Z (p.)	0.439	0.037
Log of Real House Prices										
Annual	Overall	2.214	8.402	-45.102	37.500	Sum	495			
	Between		2.263	-6.107	5.2778	N	28			
	Within		8.152	-45.034	35.910	T	17.679		Level	Dif.
Quarterly	Overall	4.669	0.143	4.212	5.034	Sum	216	P (s.)	9.675	29.920
	Between		0.026	4.652	4.708	N	4	P (p.)	0.289	0.000
	Within		0.142	4.229	4.995	T	54	Z (s.)	0.491	-2.845
								Z (p.)	0.688	0.002

Source: Data Eurostat, own calculation

2.2 The Banking Crisis Variable

The indicator of banking crises recently published by Laeven and Valencia (2020) in Systemic Banking Crises Database II was used as the dependent variable. In the case of data with quarterly frequency, the correct setting of the dependent variable was verified by comparison with analogous banking crisis indicators by Babecký et al. (2014). However, Laeven and Valencia (2020) did not provide their banking crisis indicator for Malta, which led to Malta being excluded, and only 27 EU countries were used for the analysis of data with annual frequency.

[4] In case of the quarterly data, the quarterly differences were used instead of annual (quarter-on-quarter) differences due to results of the unit root tests indicating that annually differenced data might conform to the assumptions of the tests, including the unit root assumption. This step was in contrast to the approach of Lainà, Nyholm, and Sarlin (2015) or Valinskytė and Rupeika (2015) who utilized annual differences. Nevertheless, the quarterly differences were preferred in the presented analysis in order to minimize the risk of spurious regression.

[5] Hadri (2000) reports empirical test power in case of stationary data between 0.0756 (N=1, T=50, λ=0.0001) and 0.1826 (N=15, T=50, λ=0.001), while Choi (2001) reports average size-unadjusted (size-adjusted) empirical test power for N=5, T=50, α=0.97 of inverse chi-square test (P) and inverse-normal test (Z) to be P=0.20 (0.19), Z=0.27 (0.29) and P=0.19 (0.20), Z=0.27 (0.30) for moving average errors and autoregressive errors, respectively.

Regardless of the frequency of the data, all of the explanatory variables were featured with a two-year prediction horizon, i.e., lagged by two years (yielding two period lags for data with annual frequency and eight period lags for data with quarterly frequency) to mimic the approach used by Arregui et al. (2013). After omitting any observations for which any of the indicators was missing, two unbalanced panel datasets were constructed, one with annual frequency, spanning at longest 2003-2017 for 27 EU countries and the other with quarterly frequency, covering at most the period 2008Q1-2017Q4 for 4 V4 countries. Regarding the distribution of banking crisis occurrences for the annual dataset, 18 out of 27 analyzed countries experienced periods of distress. However, these periods were relatively brief, so the crisis was present only in 70 out of 366 available annual observations. In the case of V4 countries, only Hungary has experienced a banking crisis for 3 years, yielding 12 quarterly observations of banking sector distress out of 136 observations available in the quarterly dataset.

3. RESULTS AND DISCUSSION

In the first part of the section, new parameter estimates of the early warning model for predicting banking crises are presented, which are then evaluated in the following part of the section together with the original model of Arregui et al. (2013) in regard to currently available data.

3.1 New Estimates for the Banking Crisis Model Based on Currently Available Data

Similar to the results obtained by Arregui et al. (2013), the change in credit-to-GDP ratio has positively impacted the probability of future banking crises, as shown in Tab. 2. Furthermore, the parameter is statistically significant regardless of whether annual data for EU countries or quarterly data for V4 countries are used. This effect on crisis probability is dramatically greater than that estimated by the aforementioned authors, who reported a parameter value of 0.0592. The effect appears to be even greater for V4 countries in comparison to the results for EU countries at the annual level. This difference might have been caused by the use of data with quarterly frequency and/or shift in the period or country coverage.

Tab. 2: Estimated models for predicting banking crises based on annual (EU) and quarterly (V4) data

	Annual	Quarterly
Change in Credit-to-GDP	0.173***	0.199**
	(0.046)	(0.092)
Growth rate in real house prices	-0.019	-0.236
	(0.028)	(0.169)
Growth rate in real house prices * DUM[Change in Credit-to-GDP>3]	-0.012	0.443
	(0.034)	(0.395)
Constant	-2.026***	-8.586***
	(0.300)	(2.583)
Observations	366	148
No. of countries	27	4
Log-likelihood	-164.128	-24.612
Wald test for real house prices	2.915	2.275
Wald test for real house prices (p-val.)	0.233	0.321

Source: Data Eurostat, own calculation

The estimated effect of the real house price growth based on annual data appears to be quite similar to the results of Arregui et al. (2013), who obtained a corresponding parameter at value -0.0176. Similar to the previous case, the effect of real house price growth is shown to be even more pronounced for V4 countries, according to quarterly data. Mirroring the presented results, the parameter was also statistically insignificant in the case of the aforementioned authors. On the other hand, the estimated impact of the interaction term between real house price growth and substantial growth in credit is also negative for the annual data, which is in stark contrast with the estimates of Arregui et al. (2013), who reported a positive and statistically significant parameter at level 0.0734. The estimated effect of the interaction

term appears to be more in line with the aforementioned authors for quarterly data of V4. However, the other extreme is that the parameter is orders of magnitude higher than the reference. For the obtained results, the interaction term is insignificant both when assessed individually or jointly with the real house price growth using the Wald test regardless of the dataset used, as seen from the last rows of Tab. 2.
As mentioned before, the differences between the presented results and those obtained by Arregui et al. (2013) can in part, in the case of V4 countries, be attributed to the use of quarterly data, which have a higher frequency than the data used by the aforementioned authors. Similarly, some differences between the obtained results might also be explained by the use of only V4 country data instead of a broader sample. This reasoning, however, does not hold for the model obtained for EU countries, estimates of which are still quite different from those presented by Arregui et al. (2013). Nevertheless, it is important to stress that the aforementioned authors used data for the period 1970-2010, while the presented results are for a rather shorter and more recent period. The estimates may, therefore, indicate that while house price growth was a significant predictor of banking crises in the past, the evidence from the data immediately preceding and succeeding the 2008 financial and economic crisis does not appear to support this claim.

3.2 Evaluation of Early Warning Models in Regard to EU and V4 Countries

Tab 3. provides the results for the assessment of the original early warning model of Arregui et al. (2013), which is designated in the Model column as "Original" as well as for the newly estimated models (parameters of which are presented in Tab 2.), which are designated in the Model column as "Estimated" and are distinguished by the Sample column.

Tab. 3: Results for the assessment of banking crisis models using a signaling approach

Sample	Model	AUROC	Optimal threshold	Signal ratio	Noise ratio	Usefulness
EU (Annual)	Original	0.581	0.041	0.614	0.419	0.098
	Estimated	0.674	0.153	0.600	0.324	0.138
V4 (Annual)	Original	0.812	0.046	1.000	0.231	0.385
	Estimated	0.880	0.162	1.000	0.205	0.397
V4 (Quarterly)	Original	0.645	0.049	0.533	0.008	0.263
	Estimated	0.676	0.000	0.600	0.083	0.259

Source: Data Eurostat, own calculation

When the early warning model is examined on the sample of EU countries, the optimal threshold is set substantially higher for the newly estimated model compared with the original one. With a rather strict threshold, the original model provides a higher share of correctly identified signals but also a higher share of misinterpretations of tranquil periods as signals than the newly estimated model does. The benefit of the tradeoff between the signals and noise is, however, in favor of the newly estimated model, as its usefulness is considerably higher. Furthermore, the AUROC measure shows that the newly estimated model to some degree outperforms the original model regardless of the set threshold. Such a result can be expected, as the newly estimated model was fitted to the data that were used for the evaluation, while the original was constructed using a rather vintage dataset.
Drawing on the results for V4 countries based on the data with annual frequency, the gains in performance from the newly estimated model in comparison with the original model appears to be relatively smaller than they were in the case of the entire EU. Although the proportion of the optimal threshold for the two models appears to be roughly the same as before, the differences in usefulness measures and AUROC measures are only in the second decimal place. It is also interesting to note that the results for the original model for V4 countries based on annual data are rather similar to the results of Valinskytė and Rupeika (2015), who for assessment in case of Lithuania reported AUROC measure at 0.98, optimal threshold at 0.06, signal ratio at 1, noise ratio at 0.06, and usefulness at 0.41.
The difference between the original model and newly estimated model for V4 countries is even less apparent when quarterly data are used. However, the ratio of the optimal thresholds for the two models

is in reverse, as the newly estimated model shows an optimal threshold around value 0. Nevertheless, the optimal threshold of the original model appears to be quite similar to one obtained during the assessment of data with annual frequency. Based on these thresholds, both models appear to have comparable signal ratios, but the noise ratio of the estimated model is substantially greater. Therefore, its usefulness is slightly smaller than in the case of the original model. On the other hand, the AUROC measure is somewhat higher for the newly estimated model in comparison with the original model.
The conclusion based on the datasets used appears to be rather consistent in both cases, indicating that if there are any gains from the newly estimated model at all, they are quite small. Interestingly, this conclusion was reached despite potential differences in the time span covered by the two datasets and/or the different frequency of the data.

CONCLUSION

The paper presents an evaluation of the early warning model proposed by Arregui et al. (2013) for predicting banking sector distresses and utilizing discrete choice models and signaling approach as well as recently published data for EU countries. Provided that the data capture to a large extent the period after the 2008 financial and economic crisis, the analysis investigates how a model parametrized using mostly pre-crisis data performs in a post-crisis period, especially in the case of V4 countries.
The results appear to suggest that estimating the same model using more recent annual data would not dramatically increase its predictive power in the post-crisis period, especially in regard to V4 countries, if there would be increases at all.
However, the data that are currently available for EU countries as well as V4 countries tend to show that the real house price growth within the early warning model might be redundant for examined countries in crisis and post-crisis periods. This suspicion can be raised based on both annual and quarterly models, as in both cases, the parameters for the indicator itself as well as for its interaction term are individually and jointly statistically insignificant. Furthermore, there appears to be no loss in predictive capabilities when the effect of the interaction term between real house price growth and substantial growth in credit decreases the probability of crisis instead of increasing it (as seen when comparing the original and newly estimated model for annual data). Therefore, disregarding not only the predictor of house price growth, as was suggested by Arregui et al. (2013) but also its interaction term might be warranted for EU and V4 countries based on the experience during and after the 2008 financial and economic crisis. It might be sufficient for future banking sector risk monitoring and management to revert from multivariate early warning model back to a univariate early warning indicator of credit growth to detect similar crises as the one in 2008.

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