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Predicting Systemic Banking Crises Using Early Warning Models: The Case of Montenegro

Abstract: Very high costs of systemic banking crises emphasize the importance of early warning models for these crises. In order to create an early warning model for systemic banking crises a combined approach is implemented. The first approach applied in this paper is signal approach, however, with some modifications as compared with its standard application in the literature. On the basis of individual indicators two composite indices are created. Unlike other papers in this field, the author has chosen a 24-month period before the beginning of the crisis as a signal horizon, while the signal horizon in the literature is usually considered to be a period of 12 months before and 12 months after the crisis onset. The second approach represents logit model whereas the independent variables are actually the indicators with the best performances obtained within the signal approach. In order to check the robustness of indicators, the Bayesian model averaging technique is used. The indicator that represents the credit growth rate, besides being a part of the composite index, is statistically significant in all estimated specifications of the logit model, including the technique of Bayesian model averaging. Additionally, trends in the international market have a significant influence on the domestic banking system and its stability, and hence also on the probability of occurrence of a systemic banking crisis.

Key words: early warning models, systemic banking crises, Montenegrin banking system, signal approach, composite index, logit model, Bayesian model averaging, synthesis of signal and logit approach, credit expansion, economic cycle

JEL Classification: GO1; C25; C11.

1. Introduction

One of the important questions imposed on economists around the world is whether crises are inevitable or it is possible to prevent their occurrence. Previous studies have shown that banking and currency crises usually do not occur without warning but there are some behaviour patterns of certain indicators that are repeating during the period preceding the crisis. Banking crises are more difficult to predict than the currency crises, however, the negative effects on economic activity are far more long-termed after systemic banking crises. Banking crises often occur together with currency and debt crises (Laeven & Valencia, 2012; pp. 11-12). Triplet crises appear to be quite rare while among twin crises, currency crises associated either together with banking or sovereign debt crises are the most common. However, those involving both banks and sovereign debt crises are the least common. Although there are significant differences between the occurred crises, it is possible to identify some common factors of their origin in order to determine indicators which suggest that there is an increased probability of crisis emergence.

The motivation for this research is a great importance that early warning models have primarily for the stability of the banking system, as well as for the entire financial system of a country. In normal times, central banks should prepare contingency plans in order to allow a central bank to act in case of contingencies and/or a bank crisis or a systemic crisis in an efficient, effective, consistent and comprehensive manner (Kozarić & Fabris, 2012). One of the elements of such plans refers to early warning indicators.

One of the main characteristics of the Montenegrin financial system is its relatively simple structure that is a common feature of many developing countries. Development of the Montenegrin banking sector during the pre-crisis period is characterized by enormously high credit growth rates. Also, Montenegro was one of European developing countries with the fastest economic growth. Economic slowdown and sudden stop of credit activity supported by the global economic crisis has led to much more deepening of the crisis in Montenegro at the time. During the expansion period, we should turn to saving in order to protect the economy from overheating and price bubble bursting, and that is exactly what was missing on the eve of the global financial crisis and what could have prevented or mitigated its impact (Fabris & Galić, 2015).

Many authors point out that credit booms increase the probability of emergence of banking crises (e.g. Borio & Lowe, 2002; Eichengreen & Arteta, 2000; and Kaminsky & Reinhart, 1999). Although credit boom may be considered as a key determinant of a banking crisis, it is difficult to distinguish between healthy credit growth that includes financial development, and unsustainable credit growth that is associated with a deterioration of the balance sheet of banks. When it comes to developing countries, the hypothesis that they usually go through a catching-up phase should be considered, i.e. in order to reach the developed countries they have accelerated economic growth rate. This means that developing countries have higher growth rates than developed countries. The economic growth at that stage relies largely on credit growth, given that most often there is no possibility of financing from own accumulated funds.

Financial systems of South-eastern European countries are mainly bank-dominated and largely foreign-owned by banks from the euro area, primarily from Austria, France, Italy, Greece and Slovenia. Increased financial globalization has helped in creating a more developed financial system and had other positive effects, such as reducing the cost of borrowing, higher quality financial services that have become widely available, risk diversification, technological and institutional spillover. But the region has thus become more vulnerable to external shocks. It should be noted that there are papers on financial stability indicators and early warning systems for financial crises related to some of these countries (e.g. for Croatia see Dumičić, 2016; Ahec Šonje, 1999 and 2002) as well as the paper related to three EU candidate countries (i.e. Macedonia, Croatia, and Turkey, see Bučevska, 2011).

An extensive empirical literature on banking crises suggests that two approaches are commonly used when designing an early warning model for banking crises. The first one is signal approach which consists of systematised statistical procedures. This approach examines and compares the behaviour of economic indicators for the period before and after the crisis. According to this approach, the indicators with the best performances are identified on the basis of their values which may be above or below the specific value representing the threshold (Kaminsky & Reinhart, 1999). The second approach calculates the probability of occurrence of a banking crisis using discrete dependent variable models, usually by estimating probit or logit model (Demirgüç-Kunt & Detragiache, 1998, Eichengreen & Rose, 1998).

This paper synthesizes these approaches. Namely, indicators that showed the best performances within signal approach as well as the composite indices are estimated using logit models. Thus, the remainder of paper is structured as follows. In section 2, composite indices are created on the basis of indicators with the best performances that are selected using signal approach. Section 3 relates to the estimation of logit models and implementation of Bayesian model averaging. In section 4, robustness of the indices is checked using simple logit regressions and their reliability is compared by applying technique of Bayesian model averaging. Section 5 includes interpretation of results and discussion, while concluding remarks are presented in section 6.

2. Implementation of signal approach

The first approach in formulating the early warning model for systemic banking crises that has been applied in this paper is the signal approach, with certain modifications with respect to its standard use in the literature. The basic assumption of the signal approach introduced by Kaminsky & Reinhart (1996), and Kaminsky, Lizondo & Reinhart (1998) is that the economy behaves differently on the eve of the financial crisis, which is manifested in the evolution of a number of economic and financial indicators. The signal approach has the ability of predicting by defining the optimal threshold for each indicator. By requiring the specification of an explicit framework of early warning, signal approach insists on rather specific timing of a signal, which is not the case with other approaches. As Davis & Karim (2008) emphasize, the signal approach is more suitable for a specific country while logit models are more adequate for a set of countries.

Unlike the most papers in this field, signal horizon of 24 months before the crisis onset was selected for this paper. The signal period is defined in this way because it is one of the objectives of this research to formulate a model that will allow obtaining a signal as early as possible, and to determine which indicators will be the first to send a signal that the probability of systemic banking crisis is increased. Although many authors point out that there is a benefit to get a signal even 12 months after the emergence of the banking crisis, the author of this paper argues that it is more useful to focus research exclusively on the period before the crisis and that signal horizon should be 24 months before the crisis onset. Namely, signals sent by the model are not very useful when poor performances of the banking sector and the economy have already occurred, but are necessary before things become obviously bad. Therefore, there is a significant advantage of determining the signal horizon exclusively before the crisis onset, as compared to the conventional approach where the signal horizon is determined partly before and partly after the beginning of the banking crisis.

Also, the reason why the time horizon that partially covers a certain period after the onset of the crisis has not been taken is the fact that the author uses monthly data, whereas in previous studies, particularly those that relate to a set of countries, annual or quarterly data are usually used. The use of monthly data enables more accurately determination of the time period when the indicators start to send signals that there is an increased probability of systemic banking crisis occurrence. Therefore, monthly data enable obtaining signals earlier than quarterly data, which is of great importance when there is a risk of crisis occurrence since it is necessary to react as quickly as possible.

Within the signal approach, models with different signal horizons of 24, 18 and 12 months are estimated. The model with signal horizon of 24 months is the main model (benchmark model), while the other two models were evaluated to determine the robustness of the results obtained by estimating the main model. The model with a signal horizon of 24 months showed the best performances. The model with a signal horizon of 18 months had slightly weaker performances compared to the basic model, while the model with a signal horizon of 12 months had the weakest performances compared to the previous two models. Namely, the reliability of the indicators in the third model is lower than in the first and second model shown by the noise to signal ratio which increased in a significant number of indicators compared to the first two models.

In the majority of papers in this field, performance assessments of individual indicators are based on the noise to signal ratio. However, some authors indicate that if we rely solely on this ratio, we can get a picture that does not reflect the real situation (Mulder, Perrelli & Rocha, 2002; and Oka 2003). The reason is that this ratio will show the same value when there is the same proportion between the number of correct and the number of incorrect signals. For example, the noise to signal ratio for one indicator will be the same if it sends 12 correct and 6 incorrect signals, or if it sends only 2 correct and 1 wrong signals. These authors propose different ways to overcome this problem. Some authors propose the use of another indicator instead of the noise to signal ratio, while others suggest the use of weights which would reflect the preferences of policy makers towards I and II type of errors (Edison 2000, and Oka 2003).

A trade-off between two types of errors is common to all types of early warning models for banking crises (Bussière & Fratzscher, 2002). Generally, type II error (there is a signal, there is no crisis) may be less worrisome from the perspective of monetary policy holders since II type errors are less expensive than type I errors. Costs of type II errors may be the costs of taking precautionary measures. On the other hand, type I error (there is no signal, there is a crisis) often leads to higher costs because there is greater risk, particularly for depositors, and there are higher costs of recovery from crisis for the monetary authorities. Since the monetary authorities aim to minimize type I errors, the models can be adjusted to have lower type I error. In that case, the model will have a high type II error, and therefore a larger number of false signals.

In order to be as much objective as possible, the author considers that the monetary policy holders are equally interested in type I and II of errors. In addition to the noise to signal ratio, the author has taken into account whether the indicator sends signals continuously or periodically. Therefore, indicators that send less than eight signals continuously within the signal horizon have not been evaluated as indicators with the best performances. Also, in order to be assessed as an indicator with the best performances, and thus to be included within the composite index, an indicator should send signals for at least 12 months within the signal horizon (of which at least eight signals have to be sent in continuity, which represents one third of the signal horizon). These conditions are very demanding and the author has not found in the literature that this approach has been applied to date.

Monthly data from January 2005 to December 2012 are used in this paper. However, since most of the indicators are expressed as annual growth rates, time series effectually range from January 2006 to December 2012. Most of the indicators are used as annual growth rates, except the exchange rate, reference interest rates, measure of concentration of banking system and few ratios.[1] The other part of data related to the indicators of profitability, efficiency, liquidity, concentration of assets, loans, deposits and capital is calculated by the author using available database of the Central Bank of Montenegro. In order to use some of the important indicators available on quarterly and not on monthly basis, the author calculated their monthly values using the linear interpolation method.

The criterion commonly used for determining the starting date of systemic banking crises is a share of nonperforming loans in total loans at the level of a banking system. Considering the threshold of a 10% share of nonperforming loans proposed by Demirgüç-Kunt & Detragiache (1998), the beginning of the systemic banking crisis in Montenegro should be June 2009 when this indicator reached 10.03%. However, few months earlier, deposits were withdrawn after a longer period of growth. Namely, in the fourth quarter of 2008, deposits decreased by 14.42% comparing to the previous quarter. It is not advisable to rely only on event-based rules when determining the date of the crisis beginning because it

[1] Some authors use more flexible approach where two forms of specifications, level of indicator and yearly rate, are considered for every indicator. The choice between these two forms of specifications is based on their predictive power and both forms are selected if they have a good predictive power.

could be determined too late. In accordance with the aforesaid, the author determined October 2008 as the starting month of the crisis when signs of the crisis had already shown in the form of deposit outflows.

More than 60 indicators are estimated using the signal approach and two composite indices are created. The first composite index (Index 1) consists of 11 indicators that showed the best performances within the signal approach, while the second index (Index 2) besides these 11 indicators contains additional eight indicators that have slightly lower performances but are still more reliable compared to other estimated indicators. These indices are first created as non-weighted indices, and then the appropriate weights are assigned to the indicators thus creating weighted indices.

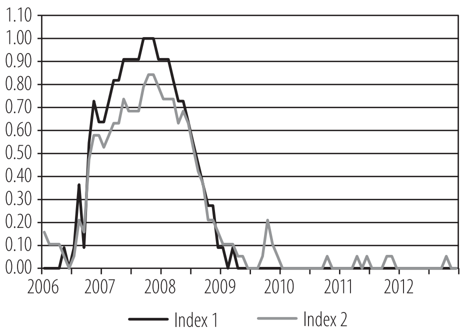
Table 1: Indicators with the best performances

	Indicator	A/(A+C)	B/(B+D)	B/(B+D) / A/(A+C)	Signal horizon	Sign
1.	Assets	0,67	0,02	0,03	24	+
2.	Loans	0,79	0,03	0,04	24	+
3.	Loans to privately owned companies	0,83	0,02	0,02	24	+
4.	Deposits	0,54	0,03	0,06	24	+
5.	Borrowings	0,83	0,02	0,02	24	+
6.	Capital	0,92	0,03	0,04	24	+
7.	1-month Euribor	0,83	0,02	0,02	20	+
8.	Net interest income	0,92	0,05	0,05	24	+
9.	Consumer prices	0,58	0,05	0,09	14	+
10.	Active interest rate	0,67	0,02	0,03	18	-
11.	Loan loss provisions/total loans	0,04	0,17	0,33	24	-
12.	Loan loss provisions	0,50	0,08	0,17	14	+
13.	Securities held by banks	0,63	0,13	0,21	24	+
14.	Rate of industrial production in Serbia	0,46	0,03	0,07	24	+
15.	Total payment operations	0,50	0,08	0,17	14	+
16.	Capital/assets	0,33	0,03	0,10	24	-
17.	Reserve requirements	0,38	0,08	0,22	23	-
18.	Currency and deposits with depository institutions held by banks	0,46	0,10	0,22	12	+
19.	Exchange rate EUR to USD	0,67	0,02	0,03	24	+

Source: Author's calculations

The non-weighted composite index is a simple average of the indicators that have been selected by implementation of the signal approach. This means that equal importance is given to all indicators representing components of this index, i.e. all of them contribute equally to the probability of emergence of a systemic banking crisis. The value of this index may range from zero to one. The following graph shows trends of both non-weighted indices.

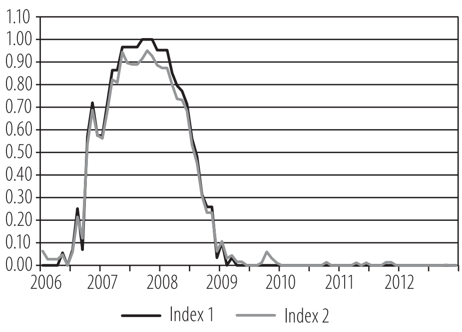
Graph 1: Non-weighted indices



Source: Author's calculations

As expected, considering that the first index consists of indicators with the best performances, the overall performances of this non-weighted index exceed the performances of the second index. The maximum value that is reached by the first non-weighted index is 1.00 for a period of three months of September, October and November 2007, when all 11 indicators exceeded the threshold and sent a signal. Thus, this index reached the maximum value 14 months before the crisis onset. The second non-weighted index reached its maximum value of 0.84 in October and November 2007, when 16 out of 19 indicators sent a signal. It is important to emphasize that beyond the signal horizon both non-weighted indices had very low values, which means that they sent a very low number of false signals.

Graph 2: Weighted indices



Source: Author's calculations

The weighted composite index is calculated by assigning adequate weights to all indicators selected by the implementation of the signal approach. Thus, the weighted composite index takes into account the predicting power of the individual indicators, which means that it provides more reliable information than the non-weighted index. Similar to the non-weighted index, the value of the weighted index can range from zero to one. The following graph shows trends of both weighted indices.

As expected, the performances of the first weighted index (which consists of 11 indicators) exceed the performances of the second index (which consists of 19 indicators). The maximum value that is reached by the first weighted index is 1.00 for the same period as the non-weighted index, i.e. in September, October, and November 2007 when all 11 indicators sent a signal for the crisis onset. The second weighted index also showed very good performances, and it reached the maximum value of 0.95 in October 2007. Quite predictably, both weighted indices had very low values beyond the signal horizon, which means that they sent a very low number of false signals.

Indicators of asset quality and capitalisation of the banking system suggest earlier than other indicators the possibility of an emergence of a banking crisis. Some other indicators, such as Euribor, can be added to these indicators. However, their overall performances indicate that their reliability is to some extent lower in comparison with the indicators of asset quality and capitalisation.

In order to predict conditional probability of a crisis occurrence, weighted indicators are used (for detailed explanation of the method see: Zhuang, J., 2005; pp. 54-55). It is necessary to divide observations from the sample into few categories while each group corresponds to certain part of composite index. Then for every group share of pre-crisis months is calculated (out of signal horizon). Therefore, it is possible to assign an adequate level of probability of crisis occurrence to every value of the composite index. Conditional probability for certain intervals of the composite index is calculated and presented in Table 2.

The obtained results suggest that both weighted composite indices have almost the same, very good performances. For example, if the first composite index ranges from 85-th to 100-th percentile, conditional probability of systemic banking crisis in Montenegro is 1.00 (i.e. 100%), and if the value of this index is zero, the probability of crisis occurrence is also zero.

Table 2: Composite indices and conditional probability of crisis

Percentile	Interval of Composite index	Conditional probability	Number of observations
	Index_1		
0	I = 0	0,00	51
0-65	0 < I < 6,82	0,00	3
65-75	6,82 < I < 56,36	0,44	9
75-85	56,36 < I < 82,60	0,88	8
85-100	82,60 < I < 100,00	1,00	13
	Index_2		
0	I = 0	0,00	34
0-65	0 < I <6,30	0,00	20
65-75	6,30 < I < 53,45	0,44	9
75-85	53,45 < I < 77,15	0,88	8
85-100	77,15 < I < 100,00	1,00	13

Source: Author's calculations

3. Estimation of logit models and Bayesian model averaging

The second approach in formulating early warning model for systemic banking crises that is applied in this paper is an econometric approach. A synthesis with signal approach is implemented in a way that indicators which showed the best performances within signal approach were selected as explanatory variables in the logit regression model. Monthly time series starting from January 2005 to December 2012 are used. Variables in the paper which are not expressed as growth rates and interest rates are expressed as natural logarithms. By applying the augmented Dickey-Fuller test for a unit root, it is determined that most of the time series is non-stationary. Therefore, non-stationary time series are differentiated, and by reapplying the ADF test after differencing time series it is determined that they are stationary. A few time series that are used in the paper have been differentiated two times in order to become stationary.

The estimation results of the first logit model showed that out of six variables, five are statistically significant, whereas three relate to the Montenegrin banking system and two of them to international macroeconomic developments. Afterwards, a dynamic component was introduced in the model in order to test the robustness of the results. Dynamic logit model contains nine variables wherein all are statistically significant. Comparing the value of the McFadden's coefficient of determination, it can be concluded that the dynamic model has better performances. Thus, the logit models in a function of early warning models for systemic banking crises for the Montenegrin banking system show that the explanatory variables (indicators) have a relatively high impact on the probability of a banking crisis onset. If only coefficients are taken into consideration, the size of change in the probability of a systemic banking crisis occurrence cannot be determined. Coefficients in the logit model show only the direction of change in probability, thus it shall be necessary to calculate marginal effects.

Table 3: Estimation results of the dynamic logit model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-5.518387	1.522988	-3.623396	0.0003
LOANS	96.00672	29.33180	3.273127	0.0011
DEPOSITS	-44.47305	17.49329	-2.542292	0.0110
EURIBOR_1M	5.163113	2.756631	1.872979	0.0611
INDPR_SERBIA	-0.113493	0.053317	-2.128649	0.0333
LLP	35.56611	13.66150	2.603382	0.0092
EUR_USD	-30.88451	12.75768	-2.420857	0.0155
CAPITAL	22.62495	11.16584	2.026265	0.0427
LLP_LOANS_LAG2	5.656185	3.140134	1.801256	0.0717
PRICES_LAG3	1.500413	0.658622	2.278110	0.0227
McFadden R-squared	0.593522	Mean dependent var		0.260870
S.D. dependent var	0.441515	S.E. of regression		0.295765
Akaike info criterion	0.684000	Sum squared resid		7.173109
Schwarz criterion	0.958107	Log likelihood		-21.46399
Hannan-Quinn criter.	0.794632	Restr. log likelihood		-52.80473
LR statistic	62.68149	Avg. log likelihood		-0.233304
Prob(LR statistic)	0.000000			
Obs with Dep=0	68	Total obs		92
Obs with Dep=1	24			

Source: Author's calculations in EViews 6

Regarding nonlinear models, marginal effects give more information than coefficients. Marginal effects of explanatory variables on dependent variable are presented in Table 4.

Table 4: Marginal effects

Variable	Marginal effects
C	-0.198728
LOANS	3.457396
DEPOSITS	-1.601564
EURIBOR_1M	0.185934
INDPR_SERBIA	-0.004087
LLP	1.280808
EUR_USD	-1.112214
CAPITAL	0.814770
LLP_LOANS_LAG2	0.203691
PRICES_LAG3	0.054033

Source: Author's calculations in EViews 6

Prediction ability of the estimated logit model is presented in Table 5. The cut-off value that separates the pre-crisis period from the normal period has been set at 0.5. The model has correctly predicted 88.04% observations. Furthermore, the model has precisely predicted the crisis in 70.83% cases (i.e. months), and the normal period in 94.12% cases. The model has proved to be unsuccessful in 11.96% cases.

Table 5: Prediction ability of the estimated logit model

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	64	7	71	68	24	92
P(Dep=1)>C	4	17	21	0	0	0
Total	68	24	92	68	24	92
Correct	64	17	81	68	0	68
% Correct	**94.12**	**70.83**	**88.04**	100.00	0.00	73.91
% Incorrect	5.88	29.17	**11.96**	0.00	100.00	26.09
Total Gain*	-5.88	70.83	14.13			
Percent Gain**	n.a.	70.83	54.17			
	Estimated Equation			**Constant Probability**		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	61.02	6.98	68.00	50.26	17.74	68.00
E(# of Dep=1)	6.98	17.02	24.00	17.74	6.26	24.00
Total	68.00	24.00	92.00	68.00	24.00	92.00
Correct	61.02	17.02	78.03	50.26	6.26	56.52
% Correct	89.73	70.90	84.82	73.91	26.09	61.44
% Incorrect	10.27	29.10	15.18	26.09	73.91	38.56
Total Gain*	15.82	44.81	23.38			
Percent Gain**	60.63	60.63	60.63			

*Change in "% Correct" from default (constant probability) specification

**Percent of incorrect (default) prediction corrected by equation

Source: Author's calculations in EViews 6

Results of the Hosmer-Lemeshow test and the Andrews test are presented in Table 6. A high value of the Andrews goodness-of-fit test and a low level of the Hosmer-Lemeshow test are desirable. Considering the Hosmer-Lemeshow test, if the associated p-value is significant ($p<0.05$), it might be an indication that the model doesn't fit the data. Since the H-L goodness-of-fit test statistic is much greater than 0.05, the null hypothesis that there is no difference between the observed and model-predicted values of the dependent variable is not rejected, implying that the model's estimates fit the data at an acceptable level.

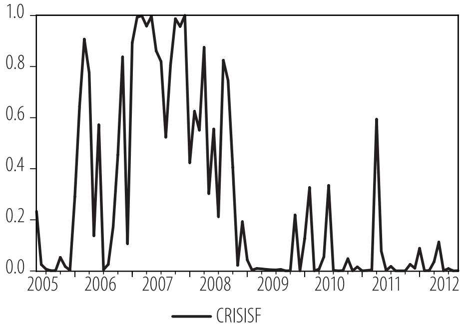
The next graph represents the forecasted probability of a systemic banking crisis calculated from the dynamic logit model. The model sends signals within the signal horizon that is defined 24 months preceding the crisis. The highest probability of systemic banking crisis is during the first year of the signal horizon which suggests that the model sends signals in the timely manner.

Table 6: Results of the Hosmer-Lemeshow test and the Andrews test

	Quantile of Risk		Dep=0		Dep=1	Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	4.E-12	0.0002	9	8.99961	0	0.00039	9	0.00039
2	0.0002	0.0010	9	8.99615	0	0.00385	9	0.00385
3	0.0013	0.0034	9	8.98085	0	0.01915	9	0.01920
4	0.0039	0.0092	9	8.93926	0	0.06074	9	0.06115
5	0.0111	0.0536	10	9.74853	0	0.25147	10	0.25796
6	0.0544	0.1714	7	7.94747	2	1.05253	9	0.96585
7	0.1787	0.3114	6	6.67975	3	2.32025	9	0.26832
8	0.3181	0.5237	6	5.29293	3	3.70707	9	0.22932
9	0.5831	0.9233	3	2.18555	6	6.81445	9	0.40085
10	0.9360	0.9999	0	0.22991	10	9.77009	10	0.23532
Total			68	68.0000	24	24.0000	92	2.44220
H-L Statistic			2.4422		Prob. Chi-Sq(8)		0.9644	
Andrews Statistic			44.2792		Prob. Chi-Sq(10)		0.0000	

Source: Author's calculations in EViews 6

Graph 3: Forecasted probability of systemic banking crisis



Source: Author's calculations in EViews 6

However, it is necessary to point out that there are certain problems with the logit regression in situations when there are a lot of potential explanatory variables. Firstly, putting all potential variables in one regression can significantly increase the standard errors if irrelevant variables are included. Secondly, the use of sequential testing in order to exclude irrelevant variables can lead to misleading results since there is a possibility to exclude relevant variable every time when the test is done.

One of the ways to overcome these problems is the implementation of the Bayesian model averaging that takes into account the uncertainty of the models, considering their combinations and weighting them in accordance with their performances. This technique has been used so far in a very small number of papers related to early warning models. Among the first ones, the paper by Crespo Cuaresma & Slacik (2009) who studied currency crises appeared, and then Babecký et al. (2012 and 2012a) did a research dealing with banking, debt and currency crises.

Therefore, seven simple logit regressions are estimated, which have two independent variables at most. By using the Bayesian model averaging technique, the weights are assigned to each of the seven regressions. This means that there are 14 statistically significant variables representing early warning indicators for systemic banking crises. The obtained results largely coincide with the results of the previous two models, i.e. static and dynamic logit models. Marginal effects are also calculated.

Table 7: Estimation results of implementation of the Bayesian model averaging technique

Model	Variable	Coefficient	Statistic significance	Weight (0-1)
Model 1	ASSETS	108,04	0,0001	0,14456
	DEPOSITS	-70,79	0,0009	
Model 2	CAPITAL	13,28	0,0167	0,14015
	BORROWINGS	19,77	0,0002	
Model 3	LOANS	51,04	0,0000	0,15993
	RESERVE_REQ	-11,82	0,0197	
Model 4	EURIBOR_1M	5,44	0,0040	0,13085
	LLP	16,26	0,0021	
Model 5	LOANS_DEPOSITS	37,57	0,0009	0,13140
	INT_INCOME	6,95	0,0299	
Model 6	EURIBOR_3M	6,32	0,0121	0,12868
	PRICES_M	1,40	0,0112	
Model 7	MONEX20	-9,61	0,0010	0,16444
	NET_LOANS	47,98	0.0000	

Source: Author’s calculations in EViews 6

Table 8: Marginal effects

Variable	Marginal effects
ASSETS	15,84
DEPOSITS	-10,38
CAPITAL	2,11
BORROWINGS	3,14
LOANS	7,26
RESERVE_REQ	-1,68
EURIBOR_1M	0,79
LLP	2,36
LOANS_DEPOSITS	5,78
INT_INCOME	1,07
EURIBOR_3M	0,98
PRICES_M	0,22
MONEX20	-1,20
NET_LOANS	6,01

Source: Author’s calculations in EViews 6

4. The robustness check of weighted composite indices

In order to check the robustness of weighted indices, simple logit regression is estimated with the first weighted composite index as the explanatory variable. The intercept and explanatory variable Index_1 are statistically highly significant at the level of 1%. Additionally, the intercept has negative sign while the coefficient in front of the variable Index_1 has positive sign; thus, an increase of Index_1 indicates a higher probability of crisis.

Table 9: Estimation of logit model with the first composite index

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-4.768472	1.235092	-3.860823	0.0001
INDEX_1	13.09421	3.643995	3.593365	0.0003
McFadden R-squared	0.863415	Mean dependent var		0.285714
S.D. dependent var	0.454467	S.E. of regression		0.159061
Akaike info criterion	0.211049	Sum squared resid		2.074629
Schwarz criterion	0.268925	Log likelihood		-6.864044
Hannan-Quinn criter.	0.234315	Restr. log likelihood		-50.25465
LR statistic	86.78120	Avg. log likelihood		-0.081715
Prob(LR statistic)	0.000000			
Obs with Dep=0	60	Total obs		84
Obs with Dep=1	24			

Source: Author's calculations in EViews 6

Predicting ability of estimated model is very high. Model correctly predicted 96.43% of observations. Model precisely predicted crisis in 91.67% cases (i.e. months), whereas it precisely predicted tranquil period in 98.33% cases. Model was unsuccessful only in 3.57% cases. Since H-L goodness-of-fit test statistic is much greater than 0.05 the null hypothesis that there is no difference between the observed and model-predicted values of the dependent variable is not rejected implying that the model's estimates fit the data at an acceptable level.

Table 10: Prediction ability of the model

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	59	2	61	60	24	84
P(Dep=1)>C	1	22	23	0	0	0
Total	60	24	84	60	24	84
Correct	59	22	81	60	0	60
% Correct	**98.33**	**91.67**	**96.43**	100.00	0.00	71.43
% Incorrect	1.67	8.33	**3.57**	0.00	100.00	28.57
Total Gain*	-1.67	91.67	25.00			
Percent Gain**	n.a.	91.67	87.50			
	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	58.13	1.87	60.00	42.86	17.14	60.00
E(# of Dep=1)	1.87	22.13	24.00	17.14	6.86	24.00
Total	60.00	24.00	84.00	60.00	24.00	84.00
Correct	58.13	22.13	80.26	42.86	6.86	49.71
% Correct	96.88	92.21	95.55	71.43	28.57	59.18
% Incorrect	3.12	7.79	4.45	28.57	71.43	40.82
Total Gain*	25.46	63.64	36.37			
Percent Gain**	89.09	89.09	89.09			

*Change in "% Correct" from default (constant probability) specification

**Percent of incorrect (default) prediction corrected by equation

Source: Author’s calculations in EViews 6

Results of the Hosmer-Lemeshow test and the Andrews test are presented in the following table.

Table 11: Results of Hosmer-Lemeshow test and Andrews test

	Quantile of Risk		Dep=0		Dep=1	Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0084	0.0084	8	7.93263	0	0.06737	8	0.06795
2	0.0084	0.0084	8	7.93263	0	0.06737	8	0.06795
3	0.0084	0.0084	9	8.92420	0	0.07580	9	0.07644
4	0.0084	0.0084	8	7.93263	0	0.06737	8	0.06795
5	0.0084	0.0084	9	8.92420	0	0.07580	9	0.07644
6	0.0084	0.0084	8	7.93263	0	0.06737	8	0.06795
7	0.0084	0.1865	8	7.68946	0	0.31054	8	0.32308
8	0.2005	0.9898	2	2.69626	7	6.30374	9	0.25670
9	0.9905	0.9996	0	0.03224	8	7.96776	8	0.03237
10	0.9996	0.9998	0	0.00313	9	8.99687	9	0.00313
Total			60	60.0000	24	24.0000	84	1.03995
H-L Statistic			1.0399		Prob. Chi-Sq(8)		0.9980	
Andrews Statistic			67.3956		Prob. Chi-Sq(10)		0.0000	

Source: Author's calculations in EViews 6

Table 12 presents estimation results of logit model where explanatory variable is the second weighted composite index. The intercept and explanatory variable Index_2 are statistically significant at the level of 1%. The intercept has a negative sign while the coefficient in front of variable Index_2 has a positive sign which means that an increase of its value indicates a higher probability of crisis.

Table 12: Estimation of logit model with the second composite index

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-4.833835	1.227638	-3.937507	0.0001
INDEX_2	13.96310	3.903487	3.577084	0.0003
McFadden R-squared	0.864123	Mean dependent var		0.285714
S.D. dependent var	0.454467	S.E. of regression		0.158326
Akaike info criterion	0.210201	Sum squared resid		2.055513
Schwarz criterion	0.268078	Log likelihood		-6.828441
Hannan-Quinn criter.	0.233467	Restr. log likelihood		-50.25465
LR statistic	86.85241	Avg. log likelihood		-0.081291
Prob(LR statistic)	0.000000			
Obs with Dep=0	60	Total obs		84
Obs with Dep=1	24			

Source: Author's calculations in EViews 6

Both models have the same value of McFadden coefficient of determination at 0.86. Comparing predictive ability of this model to the previous one, it may be concluded that they have the same performances, although when using signal approach, the first index has slightly better performances. Results of goodness-of-fit tests for this logit model showed that H-L goodness-of-fit test statistic is much greater than 0.05 that implies the model's estimates fit the data at an acceptable level.

Table 13: Prediction ability of the model

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	59	2	61	60	24	84
P(Dep=1)>C	1	22	23	0	0	0
Total	60	24	84	60	24	84
Correct	59	22	81	60	0	60
% Correct	**98.33**	**91.67**	**96.43**	100.00	0.00	71.43
% Incorrect	1.67	8.33	**3.57**	0.00	100.00	28.57
Total Gain*	-1.67	91.67	25.00			
Percent Gain**	n.a.	91.67	87.50			
	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	58.16	1.84	60.00	42.86	17.14	60.00
E(# of Dep=1)	1.84	22.16	24.00	17.14	6.86	24.00
Total	60.00	24.00	84.00	60.00	24.00	84.00
Correct	58.16	22.16	80.32	42.86	6.86	49.71
% Correct	96.93	92.33	95.62	71.43	28.57	59.18
% Incorrect	3.07	7.67	4.38	28.57	71.43	40.82
Total Gain*	25.50	63.76	36.43			
Percent Gain**	89.26	89.26	89.26			

* Change in "% Correct" from default (constant probability) specification

** Percent of incorrect (default) prediction corrected by equation

Source: Author's calculations in EViews 6

Results of the Hosmer-Lemeshow test and the Andrews test are presented in the following table. H-L goodness-of-fit test statistic is much greater than 0.05 implying that the model's estimates fit the data at an acceptable level.

Table 14: Results of Hosmer-Lemeshow test and Andrews test

	Quantile of Risk		Dep=0		Dep=1	Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0079	0.0079	8	7.93685	0	0.06315	8	0.06365
2	0.0079	0.0079	8	7.93685	0	0.06315	8	0.06365
3	0.0079	0.0079	9	8.92896	0	0.07104	9	0.07160
4	0.0079	0.0079	8	7.93685	0	0.06315	8	0.06365
5	0.0079	0.0095	9	8.91834	0	0.08166	9	0.08241
6	0.0098	0.0146	8	7.90695	0	0.09305	8	0.09415
7	0.0152	0.1366	8	7.70044	0	0.29956	8	0.31121
8	0.1711	0.9910	2	2.69973	7	6.30027	9	0.25908
9	0.9913	0.9994	0	0.03126	8	7.96874	8	0.03138
10	0.9994	0.9998	0	0.00377	9	8.99623	9	0.00377
Total			60	60.0000	24	24.0000	84	1.04454
H-L Statistic			1.0445		Prob. Chi-Sq(8)		0.9980	
Andrews Statistic			68.5153		Prob. Chi-Sq(10)		0.0000	

Source: Author's calculations in EViews 6

Marginal effects for both models are given in Table 15. Accordingly, Index_2 has slightly better performances comparing to Index_1. Intercept in both of models has negative sign with approximately the same marginal effect on dependent variable. The results suggest that both of the weighted composite indices are reliable indicators of systemic banking crises.

Table 15: Marginal effects

Model	Variable	Marginal effects
Model 1	C	-0.659916
	Index_1	1.812126
Model 2	C	-0.677025
	Index_2	1.955665

Source: Author's calculations in EViews 6

The results of Bayesian model averaging show that both indices are statistically significant with expected positive sign. Therefore, reliability of estimated indices is verified and robustness of indicators that are part of indices is checked indirectly. On the basis of weights assigned to the both of models, it may be concluded that these model have almost the same performances.

Table 16: Results of Bayesian model averaging

Model	Variable	Coefficient	Statistic significance	Weight (0-1)
Model 1	Index_1	13.09	0.0003	0.49979
Model 2	Index_2	13.96	0.0003	0.50021

Source: Author's calculations in EViews 6

5. Interpretation and discussion

McFadden R^2 indicates a relatively good goodness-of-fit of the estimated dynamic logit model. Results of the estimated model suggest that loans have the highest marginal effect on the dependent variable. The estimated probability of occurrence of the systemic banking crisis will increase in the case of increase of loans, loan loss provisions, loans-to-deposits ratio, and capital. Considering macroeconomic variables, the increase of 1-month Euribor leads to higher probability of systemic banking crisis while the increase of EUR/USD exchange rate implies the decrease of the estimated probability systemic banking crisis occurrence. Montenegro is a euroised economy and one of the main advantages of fixed exchange rate regimes is that they enable achieving macroeconomic stability owing to a solid nominal anchor. However, the main deficiency of fixed exchange rate regimes is that they reduce flexibility of monetary policy. The reason for considering EUR/USD exchange rate as an early warning indicator that Montenegro is a small and open country, so the trend of this variable might have a significant impact on the domestic economy.

In addition, the annual growth rate of consumer prices in Montenegro has a positive sign with a low marginal effect. However, the variable with the lowest marginal effect in the model is the index of industrial production in Serbia. In order to capture the most relevant international indicators the economic growth of the country that represents the main trading partner of the domestic country is considered. According to available data starting from 2005, the largest portion of Montenegro's trading exchange, taking into account both export and import, has been realized with Serbia.

The Bayesian model averaging technique enables estimation of more variables that can be relevant indicators of systemic banking crises, than it would be possible by using only a regular logit model. Putting a higher number of variables in one single regression may cause problems, such as multicolinearity. The dynamic model has captured eight variables, while using the Bayesian model averaging technique 14 variables are included wherein six of them are the same as in the dynamic logit model. Instead of estimating only a set of simple logit regressions, Bayesian model averaging gives an insight into relative importance of some variables in comparison with other variables.

The comparison of indicators that have had the best performances within the signal approach with results obtained by estimating logit models, as well as with the results obtained by applying the Bayesian model averaging technique leads to the conclusion that the indicators that showed the highest predicting power in the signal approach are statistically significant and have ha igh probability of predicting systemic banking crises within the logit models. The analysis of the results confirmed the reliability of the indicator of credit growth which is statistically significant in all estimated models and has very high marginal effects on the probability of systemic banking crisis occurrence in Montenegro. In addition, high influence of variables that relate to the international environment is confirmed, such as reference interest rates of the European Central Bank and EUR/USD exchange rate.

The synthesis of the signal approach and traditional econometric approach confirmed the reliability of the previously obtained results. Namely, simple logit model is estimated wherein the only explanatory variable is the first weighted composite index which has been formulated using the signal approach. The other logit model where the only explanatory variable is the second weighted composite index is also estimated. The author has not found this approach in the available literature on early warning models for systemic banking crises so far. Both indices are statistically significant at the level of 1% with a positive sign. These models have much better predicting ability compared with the previously estimated static and dynamic logit models.

Indicators that represent loans, deposits, loan loss provisions and 1-month Euribor that are the part of the composite indices formulated within signal approach are statistically significant in all estimated logit model specifications, including the Bayesian model averaging. However, it should be emphasized that the variable which represents deposits has a different sign in different approaches. Namely, this indicator has had positive sign within the signal approach, which suggests that an increase of deposits above the threshold implies the higher probability of systemic banking crisis. Although many authors argue that the sign should be negative since the beginning of the crisis is usually followed by deposit outflow, the objective of this paper is to select the indicators that send signals much earlier before a crisis begins. This means that when deposit outflow happens a crisis has already begun, thus the outflow of deposits cannot be an adequate early warning signal for a banking crisis. However, results of the logit models suggest that an increase of deposits imply a decrease of the probability of systemic banking crisis occurrence.

It is necesary to emphasize that the main limitation of early warning system created in this paper is the fact that models are constructed on the basis of only one systemic banking crisis in Montenegro. Considering that not all banking crises happen at the same pattern when drawing conclusions on the basis of small number of events, there is possibility that those conclusions are biased. On the other hand, in those situations when lot of historic data are available, often general conclusions about relative importance of individual indicators are made. However, the use of models have to be adequately integrated into broader analyses that take into account all relevant information since one model will inevitably overlook some of the relevant aspects.

6. Concluding remarks

Based on the results obtained by estimating early warning models for systemic banking crisis in Montenegro which are formulated in this paper, it can be concluded that the credit boom indicator play a dominant role in these models thanks to very good performances. The reliability of these indicators was confirmed in several ways through the use of various approaches and estimating several different specifications. It is necessary to emphasize that, in addition to being a part of composite index constructed within the signal approach, the indicator indicating a growth rate of loans is statistically significant in all estimated specifications of the logit model, including also the application of the Bayesian model averaging technique. In addition to these indicators, events on international markets have a significant impact on the domestic banking system and its stability, and consequently on the probability of the systemic banking crisis occurrence. This is even more emphasized given that the banking system in Montenegro is mainly foreign owned.

The process of financial development that is characteristic for developing countries is usually associated with the increased vulnerability of the banking and financial system. However, it should be noted that the impact of the global economic crisis was significant on the small and import dependent economy such as Montenegro. Although the roots of the crisis were in the domestic economy, the importance of influence of international trends is undisputed. This means that the global economic crisis has sharpened the problems in the domestic economy and, consequently, in the banking sector.

Although many economists believe that the models proved to be unsuccessful since they failed to predict the emergence of the current global economic crisis, economic policy cannot be adequately conducted without reliable quantitative information. The significance of the models should not be magnified, but their role cannot be diminished, particularly in uncertain times, when very important information can be obtained by using them. Early warning models for systemic banking crises enable getting the information (i.e. signals) based on which monetary policy holders can make decisions about when and how to take certain measures. However, these models cannot replace subjective evaluations by monetary policy holders, but they can play an important complementary role as an objective assessment of the banking system vulnerability.

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