EARLY WARNING MODELS FOR SYSTEMIC BANKING CRISES IN MONTENEGRO

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ABSTRACT: *The purpose of this research is to create an adequate early warning model for systemic banking crises in Montenegro. The probability of banking crisis occurrence is calculated using discrete dependent variable models, more precisely, estimating logit regression. Afterwards, seven simple logit regressions that individually have two explanatory variables are estimated. Adequate weights have been assigned to all seven regressions using the technique of Bayesian model averaging. The advantage of this technique is that it takes into account the model uncertainty by considering various combinations of models in order to minimize the author's subjective judgment when determining reliable early warning indicators. The results of Bayesian model averaging largely coincide with the results of a previously estimated dynamic logit model. Indicators of credit expansion, thanks to their performances, have a dominant role in early warning models for systemic banking crises in Montenegro. The results have also shown that the Montenegrin banking system is significantly exposed to trends on the global level.*

Key words: *early warning systems, systemic banking crises, logit model, Bayesian model averaging, credit expansion, Montenegro*

JEL Classification: G01; C25; C11

1 INTRODUCTION

Considering high costs of resolving systemic banking crises and their significant negative effects on the economy and therefore on the standard of living, it is necessary to dedicate a lot of attention to research on how and why crises happen in order to try to predict them. Neither are the most developed economies spared of financial crises, including banking, currency and debt crises. The global economic crisis that has started as the US mortgage market crisis unequivocally shows that even developed economies do not pay enough attention to early warning models for systemic banking crises. Namely, these models, even when implemented, are not adequately used. Also, nowadays when there are very significant interdependencies between financial markets, consequences might hardly stay only within the borders of countries hit by the financial crisis. Unlike nowadays, during previous decades these models related mostly to currency crises since currency crises used to occur more often than banking crises.

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Extensive empirical literature indicates that, in general, there are two approaches for designing early warning systems that are most commonly used. The first one is a signal approach (non-parametric) that studies and compares behavior of economic indicators for the period before and during the crisis. This approach developed by Kaminsky & Reinhart (1996), and Kaminsky, Lizondo & Reinhart (1998), is also known as the KLR method. The second approach (parametric) calculates the probability of banking crisis occurrence using discrete dependent variable models, estimating usually probit or logit regression (Demirgüç-Kunt & Detragiache, 1998; Eichengreen & Rose, 1998). Besides logit regression, the Bayesian model averaging technique is also applied in this paper. Bayesian model averaging (BMA) takes into account the model uncertainty by taking into consideration various combinations of models, and therefore it enables the author's subjective judgment to be minimized when determining reliable early warning indicators.

The basic motive 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. There is no early warning model for banking crises in Montenegro. One of the main characteristics of the Montenegrin financial system is its relatively simple structure that is a common feature of many developing countries. Banks have a dominant role in the financial system; primarily in financing the private sector because it doesn't have enough own funds accumulated. The banking sector that consists of eleven banks and six microcredit financial institutions is based on the traditional banking. Development of the Montenegrin banking sector during the pre-crisis period is characterized with enormously high credit growth rates. Montenegro was one of European developing countries with the fastest economic growth. Therefore, in 2007 its economic growth reached the peak of 10.70%, while the lowest growth rate was -5.70% in 2009.

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. A significant problem is that some borrowers are not able to repay regularly loans approved mostly during the credit expansion. One of the reasons due to which the Montenegrin economy has found itself in a very unfavorable situation is the reduced intermediation function of Montenegrin banks. The banking crisis and later also the economic crisis have caused the deterioration of the fiscal position of Montenegro. One of the most significant consequences of the crisis is an intensive growth of sovereign debt. Namely, during 2010 and 2011, the emission of Euro bonds in the amount of EUR 380 million contributed largely to the growth of sovereign debt. In order to prevent a scenario like this to happen again, it is necessary to create and implement early warning models for systemic banking crises.

2 METHODOLOGY AND AVAILABILITY OF DATA

When compared with the signal approach, the advantage of the logit model is that it enables estimation of all variables simultaneously. However, unlike the signal approach, using this method it is not possible to rank indicators according to their relative prognostic power in predicting systemic banking crises. Ranking indicators according to their deviation from the normal behavior would be of a great help to monetary policy holders, because they could determine more easily what corrective measures would be necessary.

This shortcoming might be partially overcome using Bayesian model averaging. Namely, applying this technique it is possible to assign adequate weights to simple logit models with at most two explanatory variables. Although individual variables do not have weights, their relative importance can be approximately determined on the basis of weights assigned to the model that contains these variables.

Logit regression is used in this paper in the same manner as in the most papers dealing with early warning systems for banking crises. The observed time period is divided into two periods: the signal horizon where the dependent variable takes the value 1, and the period out of the signal horizon where the dependent variable takes the value 0. However, there is a difference between performances of the banking system and the overall economy in the period preceding the signal horizon and the period after the signal horizon, where the period after the signal horizon is considered to be the crisis period. Division in these two periods remains due to the still existing crisis in Montenegro, therefore there is probability that results will be biased to some extent.

Babecký et al. (2012) emphasize that there are at least two problems with simple regression when there are many potential explanatory variables. First, putting all potential variables in one regression might significantly increase standard errors if irrelevant variables are included. Second, the use of sequential testing in order to exclude unimportant variables might lead to misleading results taking into consideration the fact that there is a probability that a relevant variable is excluded every time when the test is done. In order to solve these problems, the technique of model averaging is usually applied (Babecký et al., 2012, p.19). Bayesian model averaging considers model uncertainty by taking into account combinations of models and assigning them weights in accordance with their performance. There are only two papers related to the model uncertainty in the literature dealing with early warning systems, and one of them is related to systemic banking crises. Article by Crespo-Cuaresma & Slacik (2009) studied currency crises in 27 developing countries, and Babecký et al. (2012) studied banking, debt and currency crises in 40 developed countries.

The main limitation of early warning models for systemic banking crises in this paper is the fact that models are created on the basis of only one systemic banking crisis that happened in Montenegro. However, all requisite information cannot be provided by studying only one case. Taking into consideration the fact that not all banking crises happen according to the same pattern and when making conclusions just on the basis of a small number of events, there is a high probability that conclusions will be biased. Also, it is necessary to emphasize that in situations when an adequate database of historic data is available, general conclusions are often made on relative importance of individual indicators.

Selection of potential indicators is based mostly on the economic reasoning that takes into account theoretical assumptions and indicators already used in previous researches.

The choice of indicators also depends largely on the availability of data. Regarding the Montenegrin banking system, data on the monthly level are less available for the period until 2009, thus in terms of diversity it is more advisable to use quarterly data. However, concerning the data frequency, it is preferable to use monthly data because trends that indicate higher probability of crisis occurrence will be noticed earlier and necessary corrective measures will be undertaken in due time. Therefore, in this paper all indicators are used on the monthly basis starting from January 2005 to September 2012.

Variables in the paper which are not expressed as growth rates and interest rates, are expressed as natural logarithms. Applying the augmented Dickey-Fuller test for a unit root, it is determined that the most of time series are 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.

Although stationarizing implicitly brings the recent history of variables into the forecast, lagging of explanatory variables also allows varying amounts of recent history to be brought into the forecast. Therefore, lagging of explanatory variables enables predicting what will happen in the period t based on the knowledge of what happened up to the period t-1. A choice of the most adequate model is based upon the Information Criteria, what means that the model with the smallest value of the Schwarz Information Criterion (SIC) and the Akaike Information Criterion (AIC) is selected. Definitions of variables used in the paper are given in the following table.

Table 1: *Definitions of variables used in the paper*

Variable	**Definition**
ASSETS	Total assets at the aggregate level of the banking system
LOANS	Total gross loans at the aggregate level of the banking system
LLP	Total loan loss provisions at the aggregate level of the banking system
NET_LOANS	Total net loans at the aggregate level of the banking system, calculated as gross loans minus loan loss provisions
DEPOSITS	Total deposits at the aggregate level of the banking system
BORROWINGS	Borrowings from central banks, banks and other credit and financial institutions, and borrowings from the Government at the aggregate level of the banking system
CAPITAL	Total capital at the aggregate level of the banking system
LOANS_DEPOSITS	Loans-to-deposits coefficient at the aggregate level of the banking system
INT_INCOME	Total interest income at the aggregate level of the banking system
RESERVE_REQ	Total amount of reserve requirements at the level of the banking system
MONEX20	Index value that consists of twenty the most liquid companies on the Montenegrin stock exchange
PRICES	Annual growth rate of consumer prices in Montenegro
PRICES_M	Monthly growth rate of consumer prices in Montenegro
EURIBOR_1M	1-month EURIBOR
EURIBOR_3M	3-month EURIBOR
INDPR_SERBIA	Index of industrial production in Serbia
EUR_USD	Exchange rate EUR to USD

3 LOGIT APPROACH AND BAYES MODEL AVERAGING

As Wooldridge (2002; p. 530-533) suggests, considering models of binary response, their interest lies primarily in the response probability:

$$P(y=1|x) = P(y=1|x_1, x_2, \ldots, x_k)$$

where x denotes a set of explanatory variables.

In order to avoid limitations of the linear probability model, it is necessary to consider the class of binary response models which have the following form:

$$P(y=1|x) = G(\beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k) = G(\beta_0 + x\beta)$$

where G is a function that takes values strictly between 0 and 1, for all real numbers z. This enables that estimated probabilities are strictly between 0 and 1. The expression xβ denotes $\beta_1 x_1 + \ldots + \beta_k x_k$.

The following expression should be considered[2]:

$$Pi = E\left(Y=1|X_i\right) = \frac{1}{1+e^{-(\beta_1+\beta_2 X_i)}}$$

which may be denoted in a simpler way:

$$Pi = \frac{1}{1+e^{-Z_i}} = \frac{e^Z}{1+e^Z}$$

as a cumulative logistic distribution function, where $Z_i = \beta_1 + \beta_2 X_i$.

It is easy to verify that as Z_i ranges from -∞ do +∞, P_i ranges between 0 and 1, and that P_i is nonlinearly related to Z_i (i.e., X_i)[3]. P_i is nonlinear not only in X, but also in the parameters, what means that the standard OLS method can not be used for estimation of the logit model. However, this problem might be resolved in a relatively simple manner.

If P_i denotes the probability that crisis is going to occur, therefore $1-P_i$ denotes the probability that the crisis is not going to occur, presented like this:

$$1 - P_i = \frac{1}{1+e^{Z_i}}.$$

[2] See: Gujarati, 2004; p. 595-597.

[3] *Gujarati* (2004, p. 595) notes that as $Z_i \rightarrow +\infty$, e^{-Z_i} tends to zero, and as $Z_i \rightarrow -\infty$, e^{-Z_i} increases indefinitely.

The previous expression may also be denoted as:

$$\frac{P_i}{1-P_i} = \frac{1+e^{Z_i}}{1+e^{-Z_i}} = e^{Z_i}.$$

The expression $P_i/1\text{-}P_i$ represents the odds ratio in favor of crisis occurrence – the ratio of the probability that crisis will occur to the probability that crisis will not occur. Therefore, if for example $P_i = 0,8$, it means that odds are 4 to 1 in favor of crisis occurrence.

If we take the natural log of the previous expression, we obtain:

$$L_i = \ln\left(\frac{P_i}{1-P_i}\right) = Zi = \beta_1 + \beta_2 X_i$$

where L, the log of the odds ratio, is not only linear in X, but also linear in the parameters[4]. L is called the logit model.

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 in total loans that is 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, and in the fourth quarter 2008 deposits decreased by -14.42% in comparison with the previous quarter. Furthermore, at the end of 2007, the Central Bank of Montenegro introduced a temporary measure of credit growth restriction since credit activity of banks has already become exaggerated. In accordance with the aforesaid, the author of this paper has determined October 2008 as the starting month of the crisis, when signs of crisis have already been shown in the form of deposit outflows. The signal horizon is defined 24 months prior to the crisis, what means that the dependent variable *y* takes the value 1 from November 2006 to October 2008. Estimation results of the dynamic logit model are presented in the following table.

Regarding nonlinear models, marginal effects give more information than coefficients. If only coefficients are taken into consideration, the size of change in probability of 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. Marginal effects of explanatory variables on dependent variable are presented in the following table.

[4] *Gujarati* (2004, p. 596) emphasizes that linearity assumption of OLS does not require that explanatory variables are linear, however linearity in the parameters is crucial.

Table 2: *Estimation results of the dynamic logit model*

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-4.354124	1.189709	-3.659823	0.0003
LOANS	65.16109	20.44709	3.186815	0.0014
DEPOSITS	-45.13485	16.03267	-2.815181	0.0049
EURIBOR_1M	7.367738	2.893002	2.546745	0.0109
INDPR_SERBIA	-0.104783	0.050407	-2.078739	0.0376
LLP	31.47855	11.20501	2.809327	0.0050
EUR_USD	-23.04270	12.33094	-1.868689	0.0617
CAPITAL	26.51234	12.08045	2.194648	0.0282
LOANS_DEPOSITS_1	0.381331	0.167479	2.276891	0.0228
PRICES_3	1.180913	0.657362	1.796442	0.0724
McFadden R-squared	0.594652		Mean dependent var	0.269663
S.D. dependent var	0.446299		S.E. of regression	0.295038
Akaike info criterion	0.697293		Sum squared resid	6.876770
Schwarz criterion	0.976915		Log likelihood	-21.02953
Hannan-Quinn criter.	0.810000		Restr. log likelihood	-51.88017
LR statistic	61.70129		Avg. log likelihood	-0.236287
Prob(LR statistic)	0.000000			
Obs with Dep=0	65		Total obs	89
Obs with Dep=1	24			

Source: Author's calculations in EViews 6

Table 3: *Marginal effects*

Variable	Marginal effects
C	-0.206890
LOANS	3.096187
DEPOSITS	-2.144623
EURIBOR_1M	0.350085
INDPR_SERBIA	-0.004979
LLP	1.495731
EUR_USD	-1.094894
CAPITAL	1.259757
LOANS_DEPOSITS_1	0.018119
PRICES_3	0.056112

Source: Author's calculations in EViews 6

It is necessary to evaluate the predictive power of the estimated model. 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 88.76% observations. Furthermore, the model has precisely predicted the crisis in 79.17% cases (i.e. months), and the normal period in 92.31% cases. The model has proved to be unsuccessful in 11.24% cases. Prediction ability of the estimated logit model is presented in the following table.

Table 4: *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	60	5	65	65	24	89
P(Dep=1)>C	5	19	24	0	0	0
Total	65	24	**89**	65	24	89
Correct	**60**	**19**	**79**	65	0	65
% Correct	92.31	79.17	88.76	100.00	0.00	73.03
% Incorrect	7.69	20.83	11.24	0.00	100.00	26.97
Total Gain*	-7.69	79.17	15.73			
Percent Gain**	NA	79.17	58.33			
	Estimated Equation			**Constant Probability**		
	Dep=0	**Dep=1**	**Total**	**Dep=0**	**Dep=1**	**Total**
E(# of Dep=0)	58.26	6.74	65.00	47.47	17.53	65.00
E(# of Dep=1)	6.74	17.26	24.00	17.53	6.47	24.00
Total	65.00	24.00	89.00	65.00	24.00	89.00
Correct	58.26	17.26	75.52	47.47	6.47	53.94
% Correct	89.63	71.91	84.85	73.03	26.97	60.61
% Incorrect	10.37	28.09	15.15	26.97	73.03	39.39
Total Gain*	16.59	44.94	24.24			
Percent Gain**	61.53	61.53	61.53			

*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. 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.

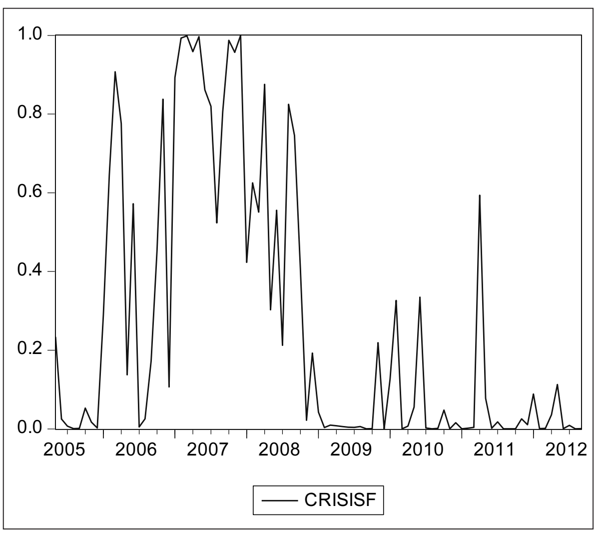
The next graph represents the forecasted probability of systemic banking crisis calculated from the dynamic logit model. The model sends signals within the signal horizon that is defined 24 months preceding the crisis – from November 2006 to October 2008. As it can be concluded from the graph, the highest probability of systemic banking crisis is during the first year of the signal horizon. This suggests that the model sends warning signals in the early stage, namely a year before the beginning of the crisis.

Table 5: *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	8.E-07	0.0002	8	7.99958	0	0.00042	8	0.00042
2	0.0004	0.0013	9	8.99276	0	0.00724	9	0.00725
3	0.0014	0.0043	9	8.97551	0	0.02449	9	0.02456
4	0.0049	0.0106	9	8.93227	0	0.06773	9	0.06824
5	0.0160	0.0423	9	8.77340	0	0.22660	9	0.23245
6	0.0479	0.1375	8	8.19409	1	0.80591	9	0.05134
7	0.1727	0.3344	7	6.71711	2	2.28289	9	0.04697
8	0.4049	0.6251	3	4.29662	6	4.70338	9	0.74874
9	0.6448	0.8755	2	1.80876	7	7.19124	9	0.02531
10	0.8926	0.9997	1	0.30990	8	8.69010	9	1.59156
		Total	65	65.0000	24	24.0000	89	2.79683
H-L Statistic			2.7968		Prob. Chi-Sq(8)		0.9465	
Andrews Statistic			42.1494		Prob. Chi-Sq(10)		0.0000	

Source: Author's calculations in EViews 6

Graph 1: *The forecasted probability of systemic banking crisis*



Source: Author's calculations in EViews 6

In order to check the robustness of obtained results, Bayesian model averaging is also applied. As Babecký et al. (2012, p. 19-20) suggest, the following linear regression model should be considered:

$$y = \alpha_y + X_y\beta_y + \varepsilon \qquad \varepsilon \sim (0, \delta^2 I)$$

where *y* is a dummy variable denoting crisis, α_y is a constant, β_y is a vector of coefficients, and ε is a white noise error term. X_y represents a subset of all available relevant explanatory variables, i.e. potential early warning indicators X. The number K of potential explanatory variables yields 2^K potential models. Mark γ is used to refer to one specific model from 2^K models. The information contained in models is then averaged using the *posterior* model probabilities that are considered under the Bayes' theorem:

$$p\,(M_\gamma, \mid y, X) \propto p\,(\,y \mid M_\gamma, X)\; p\,(M_\gamma)$$

where $p(M_\gamma, \mid y, X)$ represents *posterior* model probability, which is proportional to the marginal likelihood of the model $p\,(y \mid M_\gamma, X)$ times the prior probability of the model $p\,(M_\gamma)$.

The essence of Bayesian model averaging is assigning weights to estimated models in order to determine which models have the best performance. For this purpose it is necessary to calculate the Schwarz Information Criterion as one of the most commonly used information criteria in order to determine which specification is more appropriate for the data nature. This criterion is known as the Bayes Information Criterion which is actually approximation of the Bayes Factor. A higher value of weight is given to the model with a smaller value of SIC, thus the model that has a smaller value of SIC is considered to be a more favorable specification.

As already mentioned, using logit regression it is not possible to rank indicators according to their relative prognostic power when predicting systemic banking crises. This disadvantage can be partially overcome using Bayesian model averaging, because it is possible, by applying this technique, to assign adequate weights to simple logit models with at most two explanatory variables. Although individual variables do not have weights, their relative importance can be approximately determined on the basis of weights assigned to the model that contains these variables. Estimation results of implementation of the Bayesian model averaging technique are presented in the following table.

On the basis of weights assigned to individual models that are calculated using SIC, it may be concluded that estimated models have very similar performances. The best performance is that of the model with explanatory variables Monex20 which represents one of two indices on the Montenegrin stock exchange and net loans with weight 0.16408. The model with the lowest performances is one that contains variables - 3-month Euribor and monthly growth rate of consumer prices with weight 0.12907. Marginal effects of explanatory variables are presented in the following table.

Table 6: *Estimation results of implementation of the Bayesian model averaging technique*

Model	Variable	Coefficient	Statistic significance	Weight (0-1)
	ASSETS	106.23	0.0001	
Model 1	DEPOSITS	-69.62	0.0010	0.14370
	CAPITAL	13.42	0.0153	
Model 2	BORROWINGS	19.33	0.0003	0.13973
	LOANS	50.23	0.0000	
Model 3	RESERVE_REQ	-11.66	0.0205	0.15971
	EURIBOR_1M	5.35	0.0043	
Model 4	LLP	16.08	0.0024	0.13106
	LOANS_DEPOSITS	37.15	0.0010	
Model 5	INT_INCOME	7.60	0.0226	0.13266
	EURIBOR_3M	6.06	0.0138	
Model 6	PRICES_M	1.44	0.0113	0.12907
	MONEX20	-9.46	0.0011	
Model 7	NET_LOANS	47.32	0.0000	0.16408

Source: Author's calculations in EViews 6

Table 7: *Marginal effects*

Variable	Marginal effects
ASSETS	16.28
DEPOSITS	-10.67
CAPITAL	2.22
BORROWINGS	3.19
LOANS	7.46
RESERVE_REQ	-1.73
EURIBOR_1M	0.80
LLP	2.41
LOANS_DEPOSITS	5.87
INT_INCOME	1.20
EURIBOR_3M	0.98
PRICES_M	0.23
MONEX20	-1.25
NET_LOANS	6.24

Source: Author's calculations in EViews 6

Application of the Bayesian model averaging technique represents an important part of the analysis. Namely, this 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. As can be seen, the dynamic model has captured eight variables, while using the Bayesian model averaging technique 14 variables are included where 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. Therefore, it is possible to determine which indicators are more reliable for prediction of systemic banking crises.

4 INTERPRETATION AND DISCUSSION

McFadden R^2 indicates a relatively good goodness-of-fit of the estimated model. Results of the estimated dynamic logit model suggest that loans have the highest marginal effect on the dependent variable. Therefore, if this indicator increases by 1%, the estimated probability of occurrence of the systemic banking crisis will increase by 3.10, holding constant the remaining variables. If the value of variable LLP that represents loan loss provisions increases by 1%, the probability of systemic banking crisis will increase by 1.50. Also, if the loans-to-deposits coefficient increases by 1%, the probability of systemic banking crisis will go up by 0.02. On the other hand, if deposits increase by 1%, the probability of systemic banking crisis will decrease by 2.14. If capital increases by 1%, the probability of systemic banking crisis will increase by 1.26.

Considering macroeconomic variables, it can be concluded that if 1-month Euribor increases by 1%, the probability of systemic banking crisis will go up by 0.35. Similarly, if EUR/USD exchange rate increases by 1%, the estimated probability of occurrence of systemic banking crisis will decrease by 1.09. Montenegro is a euroised economy, and one of the main advantages of fixed exchange rate regimes is that they enable achieving the macroeconomic stability thanks to a solid nominal anchor. However, it is necessary to emphasize that fixed exchange rates do not *a priori* provide macroeconomic stability. The main deficiency of fixed exchange rates is that they reduce flexibility of monetary policy. The reason for considering EUR/USD exchange rate as an early warning indicator is that Montenegro is a small and open euroised economy, so the trend of this variable might have a significant impact on the domestic economy. Concerning inflation, if the annual growth rate of consumer prices in Montenegro increases by 1%, the probability of systemic banking crisis will increase by 0.06.

One of the most important variables that are related to international indicators is economic growth of the country that represents the main trading partner of the domestic country. 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, therefore the most significant trading partner of Montenegro is Serbia. If the index of industrial production in Serbia increases by 1%, the probability of systemic banking crisis occurrence will decrease by 0.005. It can be concluded that it is a variable with the lowest marginal effect in this model.

Seven simple logit regressions that individually have two explanatory variables are estimated, and thus there are 14 statistically significant indicators, while in the previous dynamic logit regression there are 9 indicators. Adequate weights have been assigned to all seven regressions using the technique of Bayesian model averaging. These results largely coincide with results of the previously estimated logit model.

If indicator that represents total assets in the banking system increases by 1%, the probability of systemic banking crisis occurrence will increase by 16.28, holding constant the remaining variables. Similarly, if loans increase by 1%, the probability of systemic banking crisis occurrence will go up by 7.46, and if net loans increase by 1%, the probability of systemic banking crisis occurrence will increase by 6.24. If loan loss provisions increase by 1%, the probability of systemic banking crisis occurrence will go up by 2.41. That can be explained by the fact that banks approved more risky loans during credit expansion, therefore, relatively shortly after that, they had to allocate a larger amount of loan loss provisions.

If deposits increase by 1%, the probability of systemic banking crisis occurrence will decrease by 10.67. Also, if the loans-to-deposits coefficient increases by 1%, the estimated probability that the systemic banking crisis will occur increases by 5.87. If capital increases by 1%, the probability of systemic banking crisis occurrence will go up by 2.22. Also, if borrowings which banks mostly take from their parent bank increase by 1%, the probability of systemic banking crisis occurrence will increase by 3.19.

Variable reserve requirements represent one of very few monetary instruments which the Central Bank of Montenegro has at its disposal, since Montenegro is a euroized economy. Actually, it is more appropriate to say that it is a liquidity instrument. If this variable increases by 1%, the probability of systemic banking crisis occurrence will decrease by 1.73. If 1-month Euribor increases by 1%, the estimated probability that systemic banking crisis will occur increases by 0.80, and with the increase of 3-month Euribor by 1%, the probability of systemic banking crisis occurrence will increase by 0.98.

If interest income increases by 1%, the probability of systemic banking crisis occurrence will go up by 1.20. Also, if the monthly growth rate of consumer prices in Montenegro increases by 1%, the probability of systemic banking crisis occurrence will increase by 0.23. Finally, if variable Monex20 increases by 1%, the probability of systemic banking crisis occurrence will decrease by 1.25.

Indicators relating to a credit boom thanks to very good performances, have a dominant role in early warning models for systemic banking crises. The accelerated economic growth influenced the banks to initiate the exaggerated lending activity that led to credit expansion with three-digit yearly credit growth rates, and that in turn even additionally encouraged overheating of the economy. Funds taken as borrowings from parent banks during the credit expansion were mostly used for the lending activity. It was just a question of time when it would come to the bursting of the bubble that reached enormous proportions especially on the housing market. Besides developments in the domestic banking sector and in the overall economy, the crisis occurrence is also accelerated by negative global trends influenced by the global economic crisis.

It is interesting that some indicators related to macroeconomic developments in the region and in the European Union, have also shown very good performances. These are 1-month Euribor and 3-month Euribor, EUR/USD exchange rate and the index of industrial production in Serbia. Therefore, it can be concluded that the Montenegrin economy and the banking system are exposed significantly to the trends on the global level. Developments on international markets have a significant impact on the domestic banking system and its stability, and therefore on the probability of systemic banking crisis occurrence.

5 CONCLUDING REMARKS

Although many economists, especially critics of economics as science, consider that these models have proved to be unsuccessful because they failed to predict occurrence of the present global crisis, the economic policy can not be conducted today in an appropriate and efficient manner without reliable quantitative information. However, it is necessary to take into account qualitative estimates made by economic experts. The use of early warning models for systemic banking crises have to be adequately integrated within broader analyses that take into consideration all important aspects, as it is inevitable that some of these aspects will be overlooked by one of these models. These models can have an important complementary role as an objective measure of the banking system vulnerability.

Regarding developing countries, it should be taken into account that they usually go through the catching-up phase in order to reach developed economies, and therefore they have higher economic growth rates. Economic growth during that phase is relying largely on the lending activity and it is sometimes difficult to differentiate between the credit expansion and the increased credit activity.

Results of the estimated models have shown that the systemic banking crisis in Montenegro has its roots in the domestic economy. Causes of crises originate from the period of unsustainable credit expansion. A very low level of credit activity during the period before the beginning of the credit expansion has encouraged banks to race for a market share. Also, results have shown that although roots of crisis are in the domestic economy, there is a significant impact of international trends on the Montenegrin banking system and overall economy.

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