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Assesing Early Warning System Model for Banking Crisis in ASEAN Countries

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ABSTRACT

It is really necessary to understand that the banking sector is one of important part in the economy of a country. Banking acted as intermediary institutions between the parties with the excess funds were underfunded and the role of banking sector as part of the payment system, it needs to be maintained stability. If the banking industry has problems, then it will affect stability of economy in a country. The study aimed to develop an early warning system of banking crisis in Asian. This is necessary due to the detection of early symptoms of a banking crisis the losses caused by the crisis can be minimized. Moreover, it also can be done countermeasures so that a crisis can be avoided. The research used an ex-pose facto approach in constructing the models of early warning system is combining econometric techniques and signalling method. Sample of this research are ASEAN countries, namely Indonesia, Malaysia and Thailand. The study period was divided into two periods that are in-sample and out-sample. The important results persuasively show, that the predictive models were able to provide predictive power for the possibility of a crisis in out-sample period. This implies that the better the predictive, the better the banking system to avoid banking crisis system in ASEAN countries. In practically, banking in ASEAN countries should apply the Early Warning System.

Keywords: Early Warning System, Banking Crisis, Asean
JEL Classifications: F45, G2, H12

1. INTRODUCTION

It is important to note that, the banking system plays an important role in the economy. The nature of banks which are part of the payment system has resulted in the emergence of the view that the problems in the banking industry can cause negative effects on the economy. In this case the concern that arises is the emergence of a snowball effect of the downfall of a bank that led to the collapse of other banks and other companies that have business relations with the bank. At the time of the banking sector in financial distress as indicated by the tightening of credit, this will cause delays in financing for other sectors and when the banking system stops functioning, and then banking crisis is arise. The banking crisis will be linked to the slowdown in economic activity, higher inflation and the fiscal burden, as well as the exchange rate crisis that led to the economic crisis (Chan-Lau et al., 2004).

Eichengreen and Arteta (2000) revealed the need to examine the banking crisis. First, the banking crisis has to macroeconomic effect because when the banks experienced liquidity problems will have an impact on financing the real sector. Second, the fragility of the banking sector due to the condition of the banking assets is much less liquid than liabilities. If there is a withdrawal of funds on a large scale by the customer because of the distrust of banks will collapse. When the bank's portfolio of assets linked to the interbank money market, the bank runs in one bank will have an impact to the banking else that will cause the systemic banking crisis. Third, Banks do not like the non-financial companies in general more difficult for banks seeking liquidity at the time they had to restructure. Because banks rely on the trust factor resulting from the public to be able to get deposits. It would be difficult to make it happen when people have started to not believe in the bank. Then this condition will increase the risk of bank defaults in the event of shocks. And this happens in almost all developing countries.

Although many studies have tried to analyze and make a generalization to eliminate the possibility of banking and financial crisis, but a crisis still occurre such as in the United States in (2007) and Europe in (2011). The sub-prime mortgage crisis in the US in the middle of 2007, triggers a variety of financial and banking crisis across the world. In the United States, the banking sector in crisis and many banks are closed so the government had to bail-out to prevent a larger crisis. Banking failures marked by the closure of banks in the United States continues to increase, which in 2007 were 3 banks were closed, and increase to 25 banks in 2008 and to 35 banks in May 2009 (Bloomberg, 2009). The crisis in Europe since August 2011 starting with the Greek sovereign debt crisis in European countries has spilled over into the first layer such as Ireland and Portugal. This contagion effect spread to second-tier countries in Europe such as Italy and Spain. The European crisis has led many European banks experiencing liquidity problems.

Various models have been developed to try to predict the failure of individual financial institutions through an early warning system since the 1970s. The model was applied to the banking systems of developed countries, with a focus on early identification of financial difficulties (financial distress) financial institutions. Model predictions of failure and early warning systems have proven to be an important tool for the supervisory board for the early identification of difficulties in doing banking following corrective actions (Sahut and Mili, 2011).

Many studies have attempted to build early warning system by using different methods. Kaminsky and Reinhart (1999) was the first to apply the technique of early warning system for financial crises, potential crises characterized as risk factors or indicators used exceeds the threshold preset. Edison (2000), Borio and Lowe (2002), as well as Borio and Drehmann (2009) also build the same approach. They considered that the use of a threshold is still very important in maintaining the quality of forecasting.

Other method performed by Demirgüç-Kunt and Detragiache (1998) using multivariate logit regression analysis to predict the financial crisis. Logit multivariate logit econometric models which are equipped with data and estimate the possibility of crisis by maximizing the likelihood function. This model produces a probability estimate the size of the crisis. More formally, the dependent variable is reflected with a value of zero if there is no crisis and the value of one if there is a crisis.

Davis and Karim (2008) compared the logistic regression (logit) and signal extraction method. The study found that the selection of the model estimates to make a difference in terms of performance indicators and prediction of the crisis. Specifically, logit models are better used as a global early warning system and signal extraction better used as early warning system of a country. Davis and Karim (2008) also tested the Early Warning System based on the Logit and binomial tree approach can help predict the subprime crisis in the US and the UK. Through the use of twelve indicators of macroeconomic, financial and institutional variables, it was found that the logit approach is the best global early warning system for the US and the UK.

Discriminant analysis (DA) is a statistical technique that can be used to analyze and predict bank failures, e.g., Altman (1968), Karels and Prakash (1987), Uchenna and Okelue (2012). Method of neural network (NN) is also used by researchers to predict bank failures (Tung et al., 2004; Kim et al., 2004; Boyacioglu et al., 2009; Zhong and Li-Yuan, 2011). Therefore, it is really necessary to conduct the research on predictive power of predictive models of crisis as early warning systems in ASEAN banking crisis period of 2013-2018.

2. THEORITICAL FRAMEWORK

2.1. Early Warning System

There are several approaches to construct an early warning system in order to detect the onset of the banking crisis.

2.1.1. Signaling model

Kaminsky and Reinhart (1999) stated that the issuance of early warnings made by policy makers (decision maker) is an important concern in crisis prevention. Issuance of warnings will lead to some kind of precaution. There are five phases of activity in developing an early warning system to signal the approach method (Goldstein et al., 2000). These stages are the identification of the period of crisis, chose early indicators of the crisis period, set a threshold limit value of early indicators are selected, make a composite index of early and predicted the crisis.

2.1.2. Econometric model

Demirgüç-Kunt and Detragiache (1998) estimate the probability of a banking crisis using multivariate logit models in the respective period of the country experiencing a crisis or not. The dependent variable used is dummy crisis, zero if there is no crisis and one if there is a crisis. Changes in the explanatory variables will have a different effect on the likelihood of a crisis, depending on the possibility of the beginning of the crisis the country.

2.1.3. Nueral network model

Fukushima (1975) was first reseacher who had the idea of using computer algorithms to emulate biological NN processing. A NN is a set of computing nodes that are interconnected and are distinguished by the algorithms used by the node, the node number, complexity and interconnection direction, and the weight given to the input and output of the node. Tam and Kiang (1992) was the first to apply the concept to predict bank failures. They use multilayer NN with backpropagation learning algorithm (connectionist models) to perform DA with a sample of 118 banks in Texas with 20 financial ratios for 3 years. They found NN models more accurate and robust than the previous methods.

Lin et al. (2006) used a neuro-fuzzy approach (NN) to identify the causes of the currency crisis and found that the same causes may increase the predictive power of the crisis. NN models still under development and most of these studies focus on the improvement of the model compared to the other methods such as analysis of logit (logit), DA (MDA), proportional hazard model, and signaling that has been widely accepted. Where these models are now used to analyze the characteristics that are most closely associated with troubled banks (Kimmel, 2011).

Gramlich et al. (2010) revealed that the EWS can be tailored to the specific needs of the user. By concentrating on the user's purpose can help improve the efficiency of EWS to keep the design simple and avoid excessive specifications. Instead, many users EWS with a unique purpose used in accordance with their respective needs. It means that there is no single approach that is right. Therefore, the EWS should be understood as a trade-off between the goals of users, complexity of the models, and data availability.

3. METHOD

The research is an ex-pose facto. It was conducted in several countries of ASEAN, namely Indonesia, Malaysia, and Thailand. Year study period 2015-2018 with the data in 2017 and 2018 using prediction data which is calculated using the moving average method. The study period was divided into two namely in-sample (1995-2012) and out-sample (2013-2018). In the sample period for the preparation of the model predictions of the crisis, while the sample period to test out an early warning system of crisis prediction model created in the previous period.

Sources of data in this study is the data published by the IMF in the form of IFS (IMF Financial Statistics), World Bank, and each site central banks of the countries object of research. All data obtained through searches on the Internet.

The study was conducted through the following steps: (1) Using a predictive model of the crisis that has been prepared by Musdholifah et al. (2013) using a sample period 1995-2012, (2) building early warning system model using signaling techniques adopted from the model Kaminsky and Reinhart (1999) which has been modified by Demirgüç-Kunt and Detragiache (1998). Period of constituting early warning models use out sample period 2013-2018. The results of this analysis as compared to a certain threshold value, which in this study adopts the threshold value used by Demirgüç-Kunt and Detragiache (1998) and Wong et al. (2010) is 1%. If the value of the analysis model is more than the threshold, then given a score of 1 means no signal crisis and if the value is less than the threshold then given a score of 0. Furthermore, the numbers are compared with the reality that occurred in the period out sample so as to form a table.

Table 1 clearly shows that A is if the model does not issue a crisis signal and there is no banking crisis in fact. B is if the model does not issue a crisis signal but in fact banking crisis actually occurs, and so that B is called a Type I error. C is if the model issues crisis signal, but in fact there is no banking crisis, then C is called Type II errors. D is if the model issue crisis signal and in fact baking crisis actually accours. Furthermore, to determine the accuracy of the model of early warning, then seen scores of each classification:

Table 1: Crisis probablity

Conditions	No banking crisis occurs	Banking crisis actually occurs
The model does not issue crisis signal	A	B
The model issues crisis signal	C	D

Source: Wong et al. (2010)

1. Percentage of correct classification: A+D/(A+B+C+D)
2. Proportion of correct signal conditional of occurrences of crisis: D/(B+D)
3. Type I error: B/(B+D)
4. Type II error: C/(A+C).

4. RESULTS

The analysis model in-sample period derived prediction model crisis in Asia for the year 1995-2012 as follows:

$Y = 11.465 - 0.431\ X1_{t-1} - 0.273\ X2_{t-1} + 41.924\ X5_{t-1} + 0.629\ X10_{t-1} - 0.034\ X11_{t-1} - 7.315\ X13_{t-1} - 6.396\ X15_{t-1} + 0.294\ X16_{t-1} - 5.172\ X20_{t-1} + 0.432\ X23_{t-1} + e$

Where: Growth of gross domestic product (GDP) riil (X1), inflation rate (X2), CAR1 (X5), EAR1 (X10), EAR2 (X11), EAR4 (X13), LIQ2 (X15), SEN1 (X16), institutional quality (X20), and US real interest rate (X23).

Model predictions of the crisis showed that the variables real GDP growth negatively affect the banking crisis. This may imply that the current economic growth is represented by real GDP growth decreased the likelihood of a banking crisis increases. Low economic growth indicate a slowdown in economic activity both real sector and the financial sector, of course, this will have an impact on the banking sector. When the real sector experienced a slowdown in growth, the production activities will be blocked and will affect the banking sector as a financial institution serving on the financing side. The impact on the banking sector is the possibility of a breakdown of the credit facility granted by the bank to the real sector actors. The results of this study are consistent with the findings of Demirgüç-Kunt and Detragiache (1998), Beck et al. (2006), and Wong et al. (2010) which showed that banking distress is usually preceded by a slowdown in economic growth. Similar result was conducted by Bhattacharya and Roy (2009) in India.

The inflation rate has negative effect to the possibility of a banking crisis. This means that when inflation is low, the probability of experiencing a crisis of the banking sector is increasing. English (1996) found similar results that there is a negative relationship between inflation and banking difficulties. English (1996) argue that when inflation experienced drastically lowering, banks see this as a problem because one of the main sources of income is lost, and banking problems will appears. Davis and Karim (2008) found similar results that inflation negatively affect the banking crisis. They argue that this negative effect due to the procyclical behavior of asset prices typically occur in times of crisis. In the ideal economic conditions indicate by high economic growth and low inflation, but this condition is actually causing over-convidence attitude in the economy which resulted in the loans granted over the banking sector. Boom conditions will also lead to asset bubles that excessive lending during boom conditions caused revenue expectations are not realistic and unrealistic asset valuation. This is called a procyclical effect. Procyclical behavior of assets can trigger the crisis. These results are consistent with Komulainen and Lukkarila (2003) and Zistler (2010) which shows negative effect inflation to probability of banking crisis.

The capital adequacy ratio (CAR) has positive effect to probability of banking crisis. It means that, the higher CAR, higher probability of a banking crisis in Asia. Higher reserve funds held to show prudence behavior of the bankers, but this behavior may hamper the delivery of funds to the real sector and thus lowering their chances to get benefit from the distribution of these funds because the funds deposited in reserves. Beck et al. (2006) revealed that high capital reserves may make banks have a buffer to be more resilient to liquidity shocks, but it is also a high burden for the banking sector because it will reduce profitability and increase bank fragility. This research has similar result with Arena (2008).

In this study profitability (ROA) has positive influence to probability of the crisis in Asia. González-Hermosillo (1999) showed the same result as well as the findings of the Arena (2008) who studied in East Asia and Africa. Banking assets is actually much more illiquid than it obligations. If there is a withdrawl of funds on a large scale by the customer because of distrust, then the banks will collapse. If a large number of bank asset portfolios linked to the interbank money market, the bank runs in one bank will have an impact to the banking else that will cause a systemic banking crisis (González-Hermosillo, 1999). Another explanation for the increase in ROA can be associated with moral hazard behavior of the bankers for their implicit government guarantee that is ready for bailing out banks in trouble and guarantee the investor's future revenue. Moral hazard will lead to excessive borrowing and lending which then creates bad loans (Goldstein et al., 2000). Bad loans have further encourages asset impairment quite dramatically which caused panic in the market, causing a speculative attack that ended in capital outflow and encourage banks experiencing liquidity problems that triggered the banking crisis.

Hardy and Pazarbasioglu (1999) in their study found a strong tendency for credit to the private sector following the pattern of boom assets and patterns before the crisis broke. It means that before crisis, there was a sharp increase over credit growth, but then declined continuously during the crisis. The boom conditions typically encourage increased bad loan that is owned by the banking sector so that it will increase the risk of default. ROA is determined by the amount of net income and assets. Where banking asset is mixing of 90% of not risk-free because it comes from third party funds and loans. i.e., the greater the assets in the calculation of ROA, the risk faced by banks getting bigger. If the risk is associated with bad loans, then the likelihood of default increases.

Otherwise, ROE where the denominator is derived from capital (equity) are relatively small risk. It means that profitability which measured by ROE will reduce the risk of a crisis because of the large profits can be used for additional capital in order to anticipate the occurrence of bank runs. The results of this study indicate that the ratio of profitability as measured by ROE has negative effect on the possibility of a banking crisis in Asia. It can be concluded that higher ROE, lower probability of a crisis.

Another measurement of profitability is the ratio of interest income to operating income that significantly influence to possibility of crisis. Bongini et al. (2001) revealed that there are two explanations to the effect of interest income to operating income ratio. First, the ratio of interest income to operating income can increase the volatility of income if the income from the service more unstable. On the other hand, a high ratio can make the banks are not vulnerable to crises if the banks are more focused on its core business which makes them better in terms of the allocation. The results of this study indicate that the ratio of interest income to operating income negatively affect the possibility of a banking crisis. This means that higher ratio, possibility of a crisis is getting smaller. This result also supports Demirgüç-Kunt et al. (2006) research.

Variable liquidity as measured by ratio of loan to deposit ratio (LDR) had a negative impact on the likelihood of a banking crisis. The results of this study support research Ahumada and Budnevich (2001), which revealed that higher LDR ratio indicates high liquidity of banks. In the short term this will reduce percentage of non-performing loans (NPL). It means risk of bank failures even lower, in other words more liquid bank indicates that the bank is risk averse. A similar sentiment was expressed by the research of Barrell et al. (2010) in OECD countries.

The ratio of bank assets to liabilities in foreign currency is used as a proxy for sensitivity of banks to the financial markets mainly to exchange rate fluctuations. The higher ratio, the higher the possibility of banking crisis. The results showed that the ratio of assets to liabilities in foreign currency bank positive effect on the likelihood of the crisis in Asia. Domac and Peria (2003) explain that this ratio is used to reveal a discrepancy (mismatch) of the bank's management on exchange rate risk with the probability of banking crisis. This means that higher the ratio of assets to liabilities in foreign currency, the bank risks associated with changes of exchange rate is higher so that the risk of banking crisis is getting bigger. The results also support the findings of De Young et al. (1999).

Variable of institutional quality is measured by the index of corruption have a negative impact on the probability of a crisis. The higher (lower) value of the index shows smaller (larger) the level of corruption in a country, this affects the lower (higher) the possibility of a crisis. The results support the study of Demirgüç-Kunt and Detragiache (1998) which describes more conducive institutional environment in a country is reflected in the low level of corruption will decrease the chance of a financial crisis. Angkinand (2009) revealed the quality of the institutional environment that can either be considered as a form of good governance. Institutional quality can be attributed to the quality control and supervision of the central bank.

Variable US real interest rates give the results of a positive influence on the likelihood of a banking crisis. This means that the higher the real interest rates in the US will encourage capital outflow from domestic to foreign. So, domestic economy will be experiencing liquidity problems. Decreasing of domestic fund flows will increase competition among banks in obtaining funds to maintain liquidity. This will increase the risk of bank defaults. The results of this study are consistent with the findings of Calvo et al. (1993), Eichengreen and Rose (1998), and Mishkin (1996).

4.1. Early Warning System

The analysis period in samples obtained predictive models of the crisis in Asia for 1995-2012:

$$Y = 11.465-0.431\ X1_{t-1}-0.273\ X2_{t-1}+41.924\ X5_{t-1}+0.629\ X10_{t-1}-0.034\ X11_{t-1}-7.315\ X13_{t-1}-6.396\ X15_{t-1}+0.294\ X16_{t-1}-5.172\ X20_{t-1}+0.432\ X23_{t-1}+e \quad (1)$$

This prediction model states that the banking crisis in ASEAN for the period 1995-2012 was influenced by the decline in real GDP, inflation rate, the increase in the CAR, increase profitability ratio (ROA), a decrease in profitability ratios ROE and the ratio of interest income to operating income, a decrease in the ratio liquidity, an increase in the ratio of sensitivity to market, decrease in institutional quality, as well as an increase in US real interest rates.

The next step is to create an early warning system of banking crises based on the prediction model for the 2013-2018 out-sample period. Data for 2016-2018 is data predictions made by researchers using trend analysis. Early warning system simulation process is performed to measure the predictive power of the model for years after the model was made. Signalling method from Wong et al. (2010) employed to describe Condition A, indicating no signal crisis and no crisis in the period. Condition B showed no signal of crisis, but crisis occur, it is then called a Type I error. Condition C illustrates there is a crisis signal but there is no crisis occurs, so it is called a Type II error. Finally, D indicates there is a crisis signal and indeed there was a crisis in the period. The threshold used in this research adopts from Wong et al. (2010) which is equal to 0.01 (1%).

As clearly depicted in Tables 2 and 3, the accuracy of the prediction model as an early warning system for the banking crisis period T+1, T+2, T+3, T+4, T+5, and T+6. Then, we calculated scores from each of the following classifications:

1. Percentage of correct classificasion: A+D/(A+B+C+D)
2. Proportion of correct signal conditional of occurrences of crisis: D/(B+D)
3. Type I error: B/(B+D)
4. Type II error: C/(A+C).

The next important results is that, in Indonesia this prediction models provide the correct signals to predict a banking crisis in the period T+1. The prediction model can provide the correct signals for Malaysia in all out-sample periods except for the period of T+3. Prediction model can not provide a good signal to all periods for Thailand. Based on the results of exposure can be concluded that the predictions made by the model can predict the crisis exactly at the in-sample period especially for Malaysia.

5. DISCUSSION

Some principal findings are: First, the accuracy of predictive models to being early warning system in three ASEAN countries (Indonesia, Malaysia and Thailand). It is necessary to calculate as displayed in Table 3. This convey important message that the predictions of crisis model which has developed by researchers can be used as an early warning system for banking sector in three ASEAN countries during out sample period T+1-T+6 or 2013-2018. This research adopted criteria that hasmade by Wong et al. (2010) because it has a strong predictive power.

Second, Classification 1 in Table 3 shows the value of proportion of the accuracy of forecasting for possibility signals of crisis and not crisis of the total probability of occurrence of either the right or wrong predictions. This classification category A and D add up to the total incidence (A+B+C+D). Category A means predicted no crisis and indeed no crisis, while category D means predictable crisis and indeed there was crisis. In the first score point 1 which is equal to 67%, which means that the proportion of the predicted crisis or no crisis when compared with the fact that 67% of the predictive power of the model is correct. For second up to 6th year

Table 2: Distribution of crisis prediction

Period	T+1 2013				T+2 2014				T+3 2015				T+4 2016				T+5 2017				T+6 2018			
Country	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
Indonesia	*						*				*				*				*				*	
Malaysia	*				*						*		*				*				*			
Thailand			*				*				*				*				*				*	
	2	0	1	0	1	0	2	0	0	0	3	0	1	0	2	0	1	0	2	0	1	0	2	0
Total	3				3				3				3				3				3			

A: indicating no signal crisis and no crisis in the period; B: showed no signal of crisis, but crisis occur, it is then called a type I error; C: illustrates there is a crisis signal but there is no crisis occurs, so it is called a type II error; D: indicates there is a crisis signal and indeed there was a crisis in the period; *The country is in this condition

Table 3: Classification distribution of early waring system

Classification	T+1 2013 (%)	T+2 2014 (%)	T+3 2015 (%)	T+4 2016 (%)	T+5 2017 (%)	T+6 2018 (%)
Percentage of correct classificasion: (A+D)/(A+B + C+D)	67	33	0	33	33	33
Proportion of correct signal conditional of occurrences of crisis: D/(B+D)	0	0	0	0	0	0
Type I error: B/(B+D)	0	0	0	0	0	0
Type II error C/(A+C)	33	67	100	67	67	67

period out of sample predictive power of the model is 33%. It means that this model is still able to detect the possibility of a crisis even though the percentage decreases. This is reinforced by evidence that during the observation period in the case of Malaysia this model is able to predict the possibility of a banking crisis.

The next important finding is that, Classification 2 gives an overview the proportion of the accuracy signal to the crisis. This classification is calculated by comparing D signal to the proportion of total crisis signal (B+D). The results showed that in this classification during the observation period out samples at 0%. This means that during the observation period there is no evidence to suggest that there is a banking crisis and indeed signal the banking crisis in the ASEAN countries. In other words, during the observation period there is no incidence of banking crisis.

Another fudamental finding is that, Classification 3 describes the proportion of Type I error. Type I error is failure that arise due to differences in results between predictions and reality. Type I error means if the prediction model does not give a signal the crisis, but the banking crisis were occurs. This error is quite dangerous because it can not give the starting signal the emergence of a banking crisis. If this is true then it is possible that the recovery will cost big enough to cope with the banking crisis, because the banks and regulators did not catch any signal the emergence of a banking crisis. In this study, classification 3 is 0% during the observation period out sample. This means that the prediction model is still capable of being the advent of early warning systems in ASEAN banking crisis.

The last crucial finding is that, the proportion of the onset of Type II errors. Type II errors are failure that arise due to the fit between predictions and actual events signal, wherein the prediction model signals a banking crisis, but in reality this crisis did not happen. During the observation period (2013-2018) the proportion of Type II error is quite large, especially in 2015. By 2015 the value of classification 4 showed a value of 100%, which means that in the three countries sampled according to prediction models there is a crisis signal, but the reality is not. As for the following years classification 4 were 67%. In this inexplicable crisis provide an early warning signal for the banking sector to be introspective be the emergence of a banking crisis. So with these signals, especially the banking sector is expected by the bank supervisory authorities quickly and swiftly take steps preventive measures to prevent the banking crisis. It can be proved that during the year 2014-2015 in Indonesia's banking sector experienced a lot of pressure, especially a decrease in profitability, increasing the risk of bad loans is between 2.4% and 2.5%, the downward trend is the result of declining credit and economic growth is predicted to continue continued until 2016 (Reuters, 2015). In Thailand during the observation period out sample also been a trend increase in the ratio of NPL in the year 2013-2015 in the amount of 2.3-2.69% (Bank of Thailand, 2016). In Indonesia, the preventive measures undertaken by the regulator to hold the risk of a banking crisis is the issuance of Law PPKSK in 2016, namely the Law of Prevention and Crisis Management Financial System developed as an effort to encourage the prevention of crises through the strengthening of the banking supervision function primarily systemic banks. It concluded that although the prediction model result a crisis signal but the regulator has been able to reduce it by formulating policy instruments that could rescue the banking sector from the banking crisis.

6. CONCLUSION

The early warning system built from the crisis prediction model in this study that using sample year period 2013-2018. To encourage 2016-2018 data researchers calculated using trend analysis. The simulation results show that the early warning system of crisis prediction model can predict the crisis well in the period out sample shown by the percentage of the predicted greater than the percentage of errors. Overall it can be concluded that the predictive models generated have a pretty good predictive power to detect a possible crisis in the future. Governments and banks have to be careful, especially with internal variables, especially bank profitability as measured by ROA and capital reserve ratio as measured by CAR. Despite the higher the ROA shows a good condition of the bank's profitability. The implication of this study show that higher ROA will increase the propbability of banking crisis. ROA component which is determined by the amount of net income and assets, where the asset mix of 90% is not risk-free because it comes from third party funds and loans, which means the greater the assets in the calculation of ROA, the risk faced by banks getting bigger. If this risk is associated with bad loans, then the probablity of default increases. It mean banks have to be careful again with the assets at the time of the higher value of ROA of banking. CAR demonstrated high capital reserve ratio is large enough to make the banks have a buffer become more resilient to liquidity shocks, but it is also a high burden for the banking sector because it will reduce profitability and increase bank fragility. This convey message that, the banking sector should also be more cautious dealing with the higher capital reserve ratios. The study focuses on the object of research using annual period. It going to be the limitation of the study because it is less able to address the needs of the predictions of the crisis in shorter term. For further research to fulfilling the limitation by using shorter (monthly, quarterly and semester), in order to obtain a better prediction results.

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