

# BUILDING AN EARLY WARNING TOWARDS THE RESILIENCE OF ISLAMIC BANKING IN INDONESIA<sup>1</sup>

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## Abstract

**Background** – An early warning system (EWS) is widely used as surveillance mechanism for preserving financial system stability. It is conducted by identifying some potential variables that can issue alarm preceding crisis. Islamic banking which is part of financial system, is also prone to crisis due to adverse external shocks and given interconnectedness nature in the financial system.

**Research questions** – This paper addresses one primary question, namely which macroeconomic variables that are capable of signaling adverse shocks towards the resilience of Islamic banking in Indonesia.

**Literature Review** – Given that systemic risk exposure and bank run could create severe Islamic banking crisis, the monitoring system should be developed and able to detect the magnitude and nature of economic and financial vulnerability at an early stage. The studies for EWS mostly focus on timing horizon, thresholds, leading variables, and methodology. In terms of timing horizon, 24 months horizon is popularly used since the longer would bring sufficient time for policy makers to anticipate the crisis. In terms of threshold, various set of thresholds – normal, alert, extra alert and crisis- enable to capture the level of resilience of Islamic banking. In terms of methodology and variables, logit regression and an extraction signal are of the popular methods used for EWS. Financial ratios, monetary, credit, exchange rate, interest rate, and domestic economic activity variables are some of frequent variables for detecting crisis.

**Data and Methodology** – This research uses an extraction signal approach as EWS mechanism. The reasons are (a) this approach is the simplest approach for EWS, (b) the approach can be updated regularly, usually in monthly basis, (c) this approach has the lowest cost, and (d) the approach can develop a composite index that can be used as a signaling device. This paper employs various time horizons and thresholds in order to measure the predictive power of leading variables.

**Results** – The results suggest that there are several variables that (1) IBRI, which is composed from standardized deposit and financing since 2004 until 2016 in monthly basis, is able to figure out the resilience of Islamic banking. The resilience of Islamic banking was worst in 2004, but gradually decreased and stable. Interestingly, the resilience of Islamic banking was considered stable since the index was moving below the normal line during the global financial crises, and (2) Some selected macrofinancial variables, M2/reserve (M2res), credit growth (CG), real effective exchange rate (REER), and inflation rate (INF) empirically show low noise to signal ratio. It means that these four variables are capable of signaling vulnerabilities from adverse external shocks.

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<sup>1</sup> This research is submitted at 10<sup>th</sup> Call for Paper International Conference Bulletin of Monetary Economics and Banking, 08-09 August 2016, Jakarta – Indonesia.

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**Conclusion and Recommendation** – This paper is considered a very preliminary work in the area of early warning system for the resilience of Islamic banking. However, there is no clear cut leading indicators to comprehensively monitor its resilience. More macroeconomic and financial variables are needed to be included as leading indicators for capturing the resilience of Islamic banking. In addition, given that macroeconomic and financial variables play the important thing in providing the resilience, the macroprudential policy needs to be more specifically addressing procyclicality in the financial sector. Meanwhile, the resilience of Islamic banking needs to be supported by the resilience in the real sector. It is because the core operations of Islamic banking are dealing with productive sector. Therefore, the synergic policies are needed to establish strong resilience of Islamic banking, namely stable macroeconomic environment and strong real sector development.

*Keywords: early warning system, resilience of Islamic banking, extraction signal approach.*

JEL: E44, F15, G01

## **Introduction**

Islamic banking operation in Indonesia was started in 1992 when the first full-fledged Islamic bank was established, Bank Muamalat Indonesia. This Islamic bank provedly survived from the 1998 Asian financial crisis without any government assistance. The growth of Islamic banking proliferated rapidly after the new banking act was officially stipulated in 1998. Afterwards, the Islamic banks operations become widely expanded and well-accepted by all level of society in Indonesia. The growth of Islamic banking industry can be traced back from growth on its asset, deposit, and financing side. In terms of asset, it grew drastically from only Rp 21 trillion or 0.17% share out of total assets in the banking industry in 2005 to Rp 242 trillion or 4.89% out of total asset in banking industry in 2013. In terms of deposit, it increased from only Rp 16 trillion in 2005 to Rp 184 trillion in 2013. Likewise, in terms of financing side, there was a significant increase from only Rp 15 trillions in 2005 to Rp 184 trillion in 2013. Overall, asset, deposit, and financing grew steadily on average at 30% over the year 2005 to 2013.

There are two main risk assessments conducted by Bank Indonesia (BI) on Islamic banking, financing risk and liquidity risk. In terms of financing risk, in semester I 2015, the growth of gross Non-performing Financing (NPF) had dropped significantly from 65.15% in semester II 2014 to 20.79%. This condition is driven by a successful domestic banking consolidation, namely the adjustment of financing-to-Value (FTV) which enable banking industry aggressively to extend the financing towards value-added economic sectors for generating economic growth. However, the nominal NPF increased slightly in semester I around 4.72%, from 4.33% in semester II 2014. In general, according to financing risk assessment, the resilience of Islamic banking is on alert condition NPF ratio almost reaches the stipulated tolerance limit of BI around maximum at 5% (BI Regulation No 15, year 2013).

In terms of liquidity risk, Islamic banks faced a decrease liquidity ratio in semester I 2015. It was shown by dropping the ratio of liquid tools, namely liquid asset (LA) over negotiable certificate of deposit or banking deposit guarantee (NCD), and liquid asset (LA) over deposited funds (DPK), from 98.16% and 16.31%, in semester II 2014 to 71.30% and 12.60%, respectively in semester I 2015. A higher of ratios indicate that Islamic banking is having a sufficient liquid assets over the liabilities, or in other words Islamic banks are capable of avoiding and minimizing liquidity mismatch arising from banking operations. In this case, Islamic banking may expose to liquidity risk due to a decreased in the amount of liquid assets.

The resilience of Islamic banking can be defined as the ability of Islamic banking to resist adverse shocks originated from macroeconomic factors, so this ability can preserve the soundness of its balance sheet. The adverse shocks are exogenous shocks which then damage the resilience of Islamic banking due to incomplete markets in financial system. Incomplete markets denote a condition where markets become incapable to hedge all possible risks exposed into them. This incomplete market may create financial fragility, contagion, and bubbles in financial system due to the shocks are not smoothly absorbed. Likewise, Islamic banking can fall into default as its inability to withstand amplified shocks, shown by deterioration in its balance sheet. Given that the financial system is interconnected, the failure in Islamic banking can create panic behavior in the markets and ultimately encourage bank-run. The balance sheet then becomes worst as shocks become endogeneously deteriorating. A situation which makes Islamic banking fail and may trigger a larger crisis, expressed in a general worsening of Islamic banking's balance sheets, is due to a deterioration of the macroeconomic environment. On this regards, major crises in financial system cannot simply be avoided from macroeconomy stability due to there is a dynamic interaction between financial system - which Islamic banking is part of it - and macro conditions. Therefore, unanticipated response from financial system in absorbing shocks from macroeconomic environment can make Islamic banking fail and may cause chain reactions in a tightening surrounding, including worsening of bank's balance sheet.

The current study aims to identify which macroeconomic variables are capable of signaling adverse shocks towards the resilience of Islamic banking in Indonesia. This study uses the simple approaches in EWS mechanism as surveillance tools for the resilience of Islamic Banking in Indonesia.

## **Literature Review**

The development of the leading indicators of banking distress and early-warning systems has long been a main interest of central banks and academics. Studies on this were written by Caprio and Klingebiel (1996), Lindgren et al. (1996), Sachs et al. (1996), Honohan (1997), Eichengreen and Rose (1998), Demirgüç-Kunt and Detragiache (1998, 2000), Hardy and Pazarbasioglu (1999), Glick and Hutchison (2001), González-Hermosillo (1999), Kaminsky and Reinhart (1999), Duttagupta R. and P. Cashin (2011), Davis and Karim (2008). In practice, there are approaches commonly used to deal with early warning system (EWS), including non-parametric and parametric approaches.

Among those, Eichengreen and Rose (1998) use multivariate Probit regression for understanding the role of international shocks in determining banking crises in developing and emerging economies. They find that interest rate shocks stemming from OECD countries as well as their GDP growth rate have a significant and strong effect on bank fragility in developing countries. Hutchison (2002) estimates multivariate Probit models linking the probability of banking risks to domestic macroeconomic variables and institutional characteristics. He finds that the following variables are strongly and significantly associated to banking crisis: inflation, GDP growth, exchange rate turbulence 1 as well as variables describing the characteristics of the financial and the regulatory environments. Demirgüç-Kunt and Detragiache (1998) find that low GDP growth, high real interest rates, and high inflation are significantly correlated with the occurrence of a banking crisis. Demirgüç-Kunt and Detragiache (2000) compare the results with the signal

approach of Kaminsky and Reinhart (1999), and show that their model performs better in terms of in-sample prediction.

Yucel (2011) did some observations regarding a non-exhaustive collection of the early warning literature from 1971 to 2011. In terms of the methodologies, binary dependent variable (the logit analysis) has been the most popular used, meanwhile signal extraction analysis shares the second place.

In the literature, large number of empirical investigations has been carried out using multivariate logit or probit models for developing banking distress leading indicators. Wong et.al (2007), for example, developed a probit econometric model to identify a set of leading indicators of banking distress and estimate banking distress probability for Hong Kong and other EMEAP (Executives' Meeting of East Asia and Pacific Central Banks ) namely Australia, China, Indonesia, Japan, Korea, Malaysia, New Zealand, the Philippines, Singapore, and Thailand economies. Macroeconomic fundamentals, currency crisis vulnerability, credit risk of banks and companies, asset price bubbles, credit growth, and the occurrence of distress of other economies in the region are found to be important leading indicators of banking distress in the home economy. A case study of Hong Kong based on the latest estimate of banking distress probability and stress testing results shows that currently the banking sector in Hong Kong is healthy and should be able to withstand well certain possible adverse shocks. The study also finds that banking distress is contagious, suggesting that to be effective in monitoring banking distress, close cooperation between central banks should be in place.

Further, Wong et.al (2010) developed a panel probit econometric model to identify the leading indicators of banking distress and to estimate the banking distress probability for EMEAP economies. Macroeconomic fundamentals, currency crisis vulnerability, credit risks of banks and non-financial companies, asset price gaps, credit growth, and the occurrence of distress in other economies are found to be important leading indicators.

Matthieu Bussiere and Marcel Fratzscher (2006) developed an early warning system (EWS) model, based on a multinomial logit model, for predicting financial crises. It is shown that commonly used EWS approaches, which use binomial discrete-dependent-variable models, are subject to what we call a post-crisis bias. We show that applying a multinomial logit model, which allows distinguishing between more than two states, is a valid way of solving this problem and constitutes a substantial improvement in the ability to forecast financial crises. The empirical results reveal that, for a set of 20 open emerging markets for the period 1993-2001, the model would have correctly predicted a large majority of crises in emerging markets.

Another commonly adopted approach is the signal extraction approach. Extraction signal approach produced variable importance rankings that can be used in the stepwise specifications of logistic regression. This nonparametric approach makes fewer assumptions about the underlying populations, less sensitive to outlying observations, and easier for practitioners to understand. This approach was elaborated by Kaminsky and Reinhart (1996) by evaluating the usefulness of several leading indicators in signaling an impending crisis. Related to this approach, Gurnain et.al (2013) focused on a quantitative method to identify vulnerabilities, specifically an imbalance indicator model and its application to Canada. The model proves useful for isolating

historical imbalances that could be indicators of financial system vulnerabilities. It complements other sources of information, including market intelligence and regular monitoring of economic and financial data.

Manasse et.al (2013) employed a recent statistical algorithm (CRAGGING) in order to build an early warning model for banking crises in emerging markets. They perturb the data set many times and create “artificial” samples from which we estimated our model, so that, by construction, it is flexible enough to be applied to new data for out-of-sample prediction. The study finds that, out of a large number (540) of candidate explanatory variables, from macroeconomic to balance sheet indicators of the countries’ financial sector, they can accurately predict banking crises by just a handful of variables. Using data over the period from 1980 to 2010, the model identifies two *basic types* of banking crises in emerging markets: a “Latin American type”, resulting from the combination of a (past) credit boom, a flight from domestic assets, and high levels of interest rates on deposits; and an “Asian type”, which is characterized by an investment boom financed by banks’ foreign debt. The model is compared to other models obtained using more traditional techniques, a Stepwise Logit, a Classification Tree, and an “Average” model, and they find that their model strongly dominates the others in terms of out-of-sample predictive power.

## **Data and Methodology**

### **Research Approach**

This paper empirically identifies some selected macroeconomic variables that can affect the resilience of Islamic banking. An extraction signal approach was initially elaborated by Kaminsky and Reinhart (1996). An early warning system (EWS) mechanism evaluates the usefulness of several variables in signaling a crisis. This approach is considered as non-parametric approach since it involves monitoring the evolution of a number of economic variables. The EWS monitors behavior of variables which usually departs from “normal/tranquil” in the period preceding a crisis. Deviations of these variables from their “normal” level beyond a certain threshold values are considered as warning”signal” of a crisis within a specified period.

Kibritcioglu (2003) argued that there are three advantages of non-parametric approaches:

- (1) The developed index is an important component to extract a crisis and then useful as surveillance tool.
- (2) Non-parametric approach is easily employed within a single-country framework.
- (3) It can be used to differentiate between “normal” and “crisis” condition by setting a certain threshold.

Similarly, Adiningsih, et. al (2002), following the approach developed by Herrera and Garcia (1999), where they used the extraction signal approach for some reasons:

- (1) This approach is the simplest approach for EWS
- (2) The approach can be updated regularly, usually in monthly basis
- (3) It has the lowest feasible cost
- (4) It can be used to aggregate the individual leading indicators into a composite index, and this index is used as a signaling device.

## Stages for Building EWS Through Signal Approach

### 1. Defining The Resilience of Islamic Banking

Financially, a bank is exposed to the risk as the value of its asset and liability dynamically change in the financial market. Subsequently, the risk can lead to trigger instability in the financial system. Some of selected risks which are potentially exposed due to external shocks on Islamic banking are: (1) liquidity risk due to the presence of massive bank run; (2) credit risk due to rising non-performing loans. A bank's worth and failure in Islamic banking can be associated with the excessive risk taking behavior. Some studies incorporated massive bank run and withdrawals (Diamond and Dybvig, 1983), lending booms (Hanohan, 1997), and are considered among the most important causes that affecting the resilience of banking system, including Islamic banking.

In respect to repeated financial crisis in the modern financial system, this paper develops Islamic Banking Resilience Index (IBRI) to support monitoring tasks by incorporating some components. The components are intended to display the relative importance of the various risks in the composition of the IBRI.

There are two important risks covered in the IBRI, namely liquidity and credit risk. Credit risk relates with the banking operation in the midst high non performing loans. Banks are financial intermediaries whose liabilities are mainly short-term deposits and whose assets are considered short and long term. When the value of banks' assets fall short of the value of their liabilities, banks can be trapped into insolvent situation. This fall is mainly due to incapability of borrowers to fulfilling their current and future obligations and can affect the fall in banks' assets. Hence, credit risk can occur due to borrowers do not fulfill their obligations. In addition, given that banks are difficult due to borrowers' default, liquidity problems start to emerge. Capital position would be affected as banks need immediate injection to preserve its operation and mitigate systemic risk arises. This situation may attract some depositors to personally save their deposits by withdrawing from the bank account. The problems are compounded if the deposits are in massive numbers. Therefore, credit risk is perceived as triggering factor in causing liquidity risk.

According to those risks, a monthly IBRI is developed and used to investigate whether Islamic banking is considered under a resilient or crisis condition. IBRI is composed by two main two main Islamic banking variables, (1) deposits (DEP), and (2) financings (FIN). DEP is calculated by taking a sum of demand, saving, and time deposit collected by Islamic banks. In addition, FIN is obtained from a sum of various type of financings extended by Islamic banks. Technically, IBRI is calculated as follows:

$$IBRI_t = \frac{IDEP_t - \mu_{IDEP}}{\sigma_{IDEP}} + \frac{IFIN_t - \mu_{IFIN}}{\sigma_{IFIN}} \dots\dots\dots(1)$$

$$\text{Where: } IDEP_t = (DEP_t - DEP_{t-12})/DEP_{t-12} \dots\dots\dots(2)$$

$$IFIN_t = (FIN_t - FIN_{t-12})/FIN_{t-12} \dots\dots\dots(3)$$

Equation (1) shows the calculation of IBRI which is obtained by a sum of standardized values of DEP and FIN. The standardization enables the variance is standardized and avoids the possibility of any one or two components dominating the IBRI. The  $\mu$  and  $\sigma$  denote the arithmetic average and standard deviation of two components of IBRI. In addition, equation (2) and (3) are single index of respective component by taking 12-month change – avoiding seasonality data.

## 2. Defining The Signal of Crisis

Let assume  $i$  = a univariate variable,  $j$  = a particular country,  $S$  = signal variable, and  $X$  = variable. A variable relates to variable  $i$  and country  $j$  is expressed by  $X_i^j$  and the threshold for this variable is denoted as  $X * _i^j$ . Then, a signal variable relates to indicator  $i$  and country  $j$  is denoted by  $S_i^j$ . The binary model is then developed, where  $S_i^j = (0,1)$ , and if the variable crosses the threshold, a signal is emitted,  $S_i^j = 1$ . Mathematically, it can be described :

$$\{S_i^j = 1\} = \{X_i^j > X * _i^j\} \dots \dots \dots (4)$$

Meanwhile, if the indicator remains within its threshold boundary, it behave normally and does not issue a signal,  $S_i^j = 0$ .

$$\{S_i^j = 0\} = \{X_i^j \leq X * _i^j\} \dots \dots \dots (5)$$

Meanwhile, in terms of defining crisis, the research borrows the IBRI that has been developed in previous section, as follows:

$$\{C_t^j = 0\} = \{IBRI_t^j \leq Treshold\} \dots \dots \dots (6)$$

$$\{C_t^j = 1\} = \{IBRI_t^j > Treshold\} \dots \dots \dots (7)$$

### Interpreting Crisis and Signal Framework

Once the crisis and signal are defined, the evaluation criteria can be conducted by using matrix framework. Kaminsky, et. al (1998) developed matrix crisis-signal framework by using 24 months as signal window horizon, as follows:

**Table 1. The Performance of Individual Indicator by Matrix Crisis-Signal Framework**

	Crisis (C=1)	No Crisis (C=0)
Signal Issued (S=1)	A	B
No Signal Issued (S=0)	C	D

Source: Kaminsky, et. al (1998)

In this matrix, A is the number of months in which the indicator issued a good signal, B is the number of months in which the indicator issued a bad signal or “noise”, C is the number of months in which the indicator failed to issue a signal (which would have been a good signal), and D is the number of months in which the indicator refrained from issuing a signal (which would have been a bad signal). According to Kaminsky, et. al (1998), a perfect indicator would only produce observations that belong to the north-west and south-east cells of this matrix. It would issue a signal in every month that is to be followed by a crisis (within the next  $n$  months, example 24 months), so that  $A > 0$  and  $C = 0$ , and it would refrain from issuing a signal in every month that is not to be followed by a crisis (within the next  $n$  months, example 24 months), so

that  $B = 0$  and  $D > 0$ . For sure, none of the indicators fit the profile of a perfect indicator, but the matrix will be a useful reference to assess how close or how far is each indicator from that profile.

### 3. Determining Evaluation Criteria

This paper employs six evaluation criteria in order to assess the performance of leading variables which was identified through crisis-signal framework, as follows:

- (1) The proportion of observations correctly called =  $\frac{A+D}{(B+D)+(A+C)}$ , defined as the proportion that all observations correctly bring information about crisis and not crisis. This implies that the higher proportion occurred will lead to best evaluation criteria.
- (2) The noise-to-Signal-Ratio =  $\frac{B/(B+D)}{A/(A+C)}$ , it measures the false signals as a ratio of the good signals issued. The selection rule is to pick the variable or model that minimizes the noise to signal ratio (NTS).
- (3) The proportion of crises correctly called =  $\frac{A}{A+C}$ , defined as the proportion of crisis happened once the signal was issued. Thus, the higher of its proportion would be fitting of a perfect indicator in signaling the crisis.
- (4) The proportion of false alarm of total alarms issued =  $\frac{B}{A+B}$ , given that an individual indicator exposes a frequent false signal. Thus, the lower of its proportion would be good to minimize the panic behavior in the markets.
- (5) The proportion of crisis given an alarm issued =  $\frac{A}{A+B}$ , given that an individual indicator generates different signals. This criterion is to select indicators that can maximize the probability of a crisis, given a signal was issued as alarm.
- (6) The proportion of probability of crisis given no alarm issued =  $\frac{C}{C+D}$ , given the signal is important, an occurrence of crisis without signals was extremely reduced or minimized.

### 4. Determining Signaling Horizon

This paper involves various signaling horizons. This signaling horizons are range of period that has ability for anticipating a crisis. Kaminsky (1997) uses 24 month signaling horizon. He argued that the longer signaling horizon would enable policy makers to anticipate a crisis. Meanwhile, Bussiere and Fratzscher (2002) set 12 and 18 month as signal horizon. They argues that various time horizons would provide the best achievable trade-off between missing crises and wrong signal. In addition, this paper adds another 3 and 6 month as signaling horizons considering that a crisis is difficult to be predicted. Providing short horizon enables policy makers to react immediately as crisis starts to buildup.

### 5. Determining Thresholds

The economy evolves through phases of booms and recession. This change in phase of a particular series is captured empirically by finding a “threshold”. It turns a fluctuation of a given



variable into a signal of an upcoming recession or crisis. The threshold is the one that minimizes the noise-to-signal ratio of a particular indicator.

## 6. Determining Leading Indicators

Vulnerabilities in a financial system can build overtime and the system's operation depends on macroeconomic developments that ultimately can affect individual institutions. Developing a set of indicators is important to help detecting in advance macroeconomic and financial vulnerabilities that can affect the banking system. There is no clear-cut macroeconomic model to analyze the macro-fundamental that are relevant as leading indicators for the resilience of Islamic banking. This paper adopts some variables suggested by Susatyo (2002) in detecting currency crises. He used data since 1990-2000 in monthly basis by using 14 variables in order to identify leading indicators. He found that out of 14 variables, only M2/Reserve, inflatio rate, credit growth, and real effective exchange rate that are relevant as leading indicator for currency crises in Indonesia. Similarly, Garcia and Herrera (1999) studied on early warning for currency crisis and suggested M2/reserve, credit growth, real effective exchange rate, and inflation rate. Although these leading leading indicators are used for currency crises, Jacobs and Kuper (2004) argued that banking crises may be associated with currency crises trough a number of channels of causation or the other way round. Therefore, these leading indicators will be used in the case for banking crises in Indonesia, as follows:

1. M2/Reserve (M2Res) is used to capture the vulnerability as the sudden capital outflows. The higher ratio M2/total reserve denotes the increase of likelihood of banking crisis or reducing the resilience of Islamic banking
2. Credit growth (CG) is defined as the percentage change of the total credit approved in several banks, namely national banks, regional development banks, national private banks, and foreign banks. This variable indicates the fast expansion of loans which later give additional default risk in the banking system. In addition, Credit growth which is considered excessive may lead to systemic risk, given inconnectedness in the financial system. Rapid credit growth episode can increase likelihood of systemic risk and deterioration of banks' balance sheets.
3. Real effective exchange rate (REER) is defined as the variable which is obtained by deflating Nominal exchange rate with the ratio between standardized (based on a certain base year period). Consumer price index (CPI) United States of America over CPI of Indonesia. REER is important to measure comparatibe change in a country's real economic circuntances compared other country. If the REER of a country shows a downward trend (overvaluation), it implies that the price of domestic country is higher that foreign price, vice versa. Hence, the overvaluation in the real exchange rate may create an increased possibility of crises.
4. Inflation rate (INF) is defined as the difference of CPI between current CPI and previous CPI after being standardized. The higher degree of inflation implies that likelihood of crises would occur.

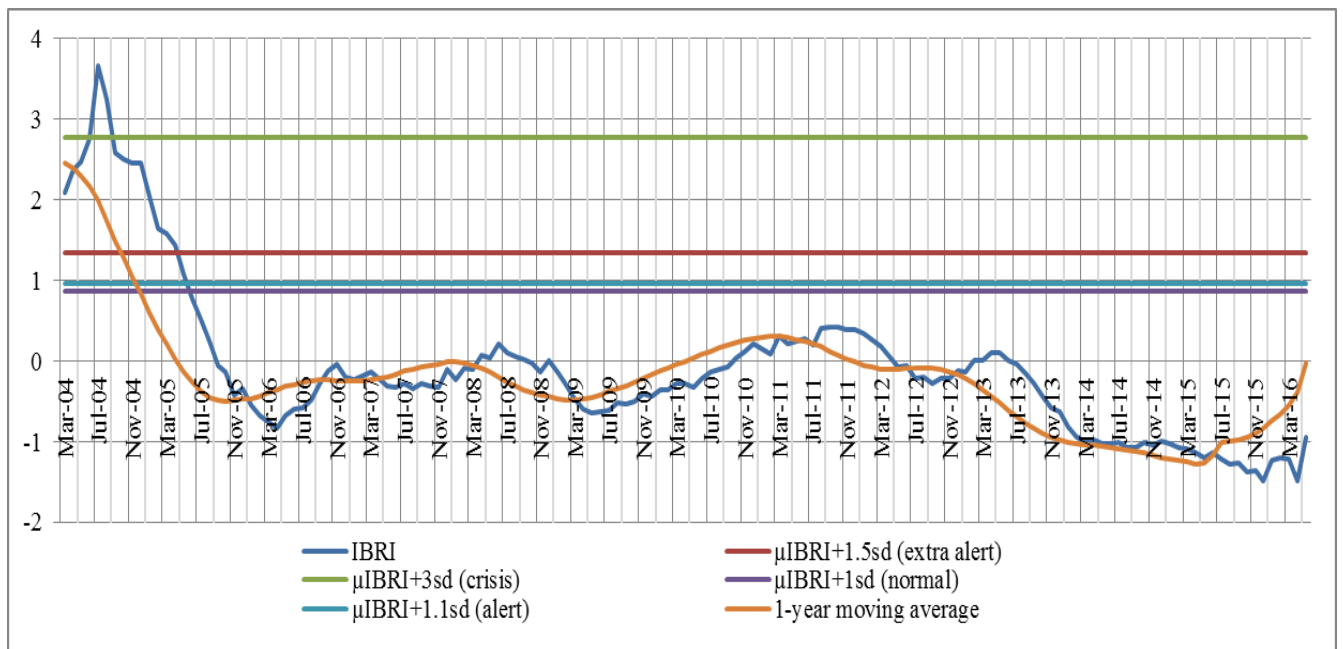
**Table 2. Summary of the Variable, Transformation, Frequency, and Threshold Position**

Variable	Transformation	Frequency	Threshold Position
M2/Res	Level	Monthly Data	Over Zero Line
CG	12 month change	Monthly Data	Over Zero Line
REER	Level	Monthly Data	Over Zero Line
INF	12 month change	Monthly Data	Over Zero Line

## RESEARCH FINDINGS

### The Performance of Islamic Banking Resilience Index and Leading Variables

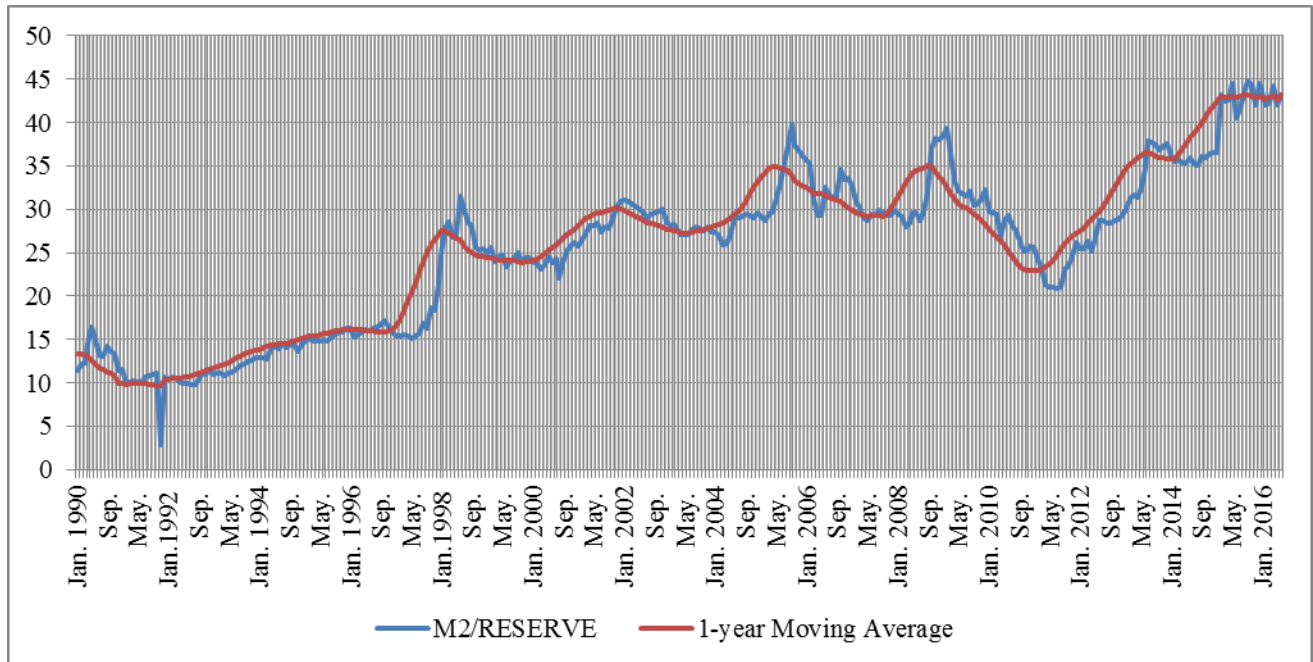
Figure 1 shows the Islamic Banking Resilience Index (IBRI) since March 2004 till May 2016. Generally, IBRI measures and monitors the level of resilience of Islamic banking in Indonesia. Empirically, IBRI is capable of providing information on the ups and downs in the resilience of Islamic banking with respect of various economic vulnerabilities. Figure 1 also presents facts that in 2004, the resilience of Islamic banking was worst, indicated the IBRI is above green line, which was in crisis area. But, the trend is gradually decreasing and until may 2016, the resilience is below normal area (purple line). In addition, according to orange line, which reflects the 1-year moving average of IBRI, the trend is increasing and showing excessive risk taking starts to happen in Islamic banking. Hence, the policy makers should keep prudent in regulating Islamic banking operations in Indonesia.



**Figure 1. Islamic Banking Resilience Index (IBRI)**

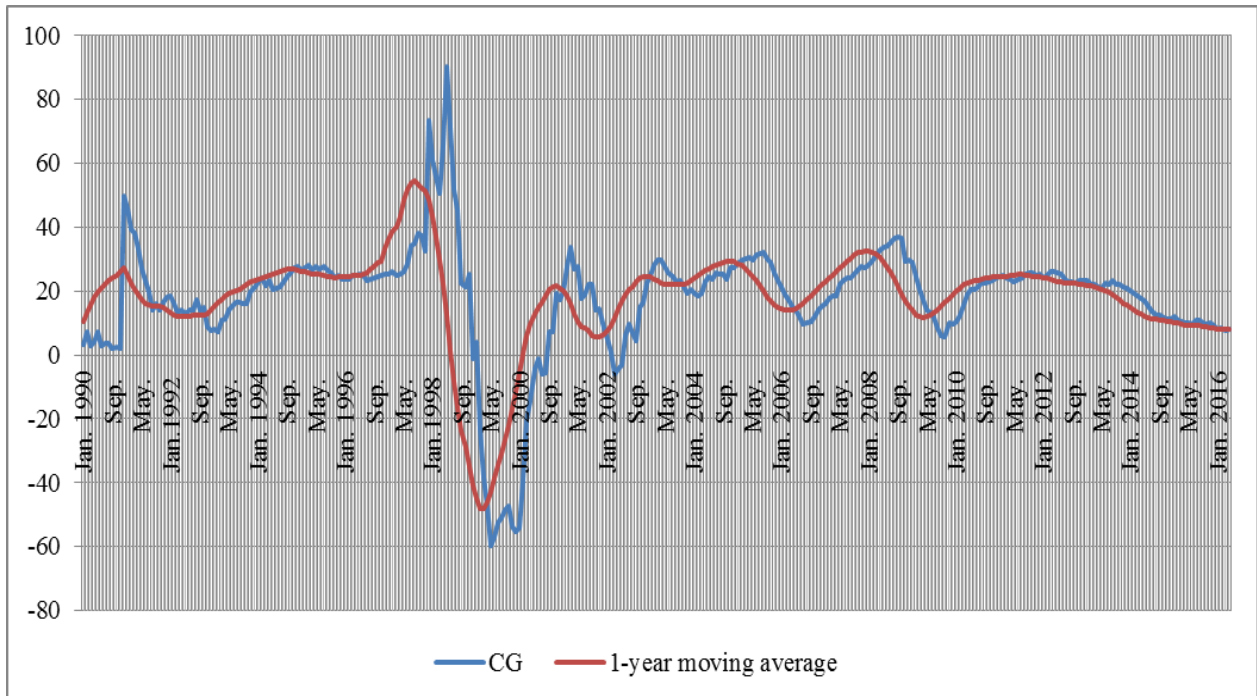
Figure 2 shows the performance of M2/res in Indonesia over 1990 – 2016 in monthly basis. According to the figure, the red line, which is the 1 year moving average, is exceeded several times by the blue line (M2/res variable). It indicates that M2/res is pressured and possibly got

shocks as economic deteriorated. Period of 1998, 2005, 2008, are the years where economic and financial distress hit severely into Indonesia's economy, as shown in the figure 1.



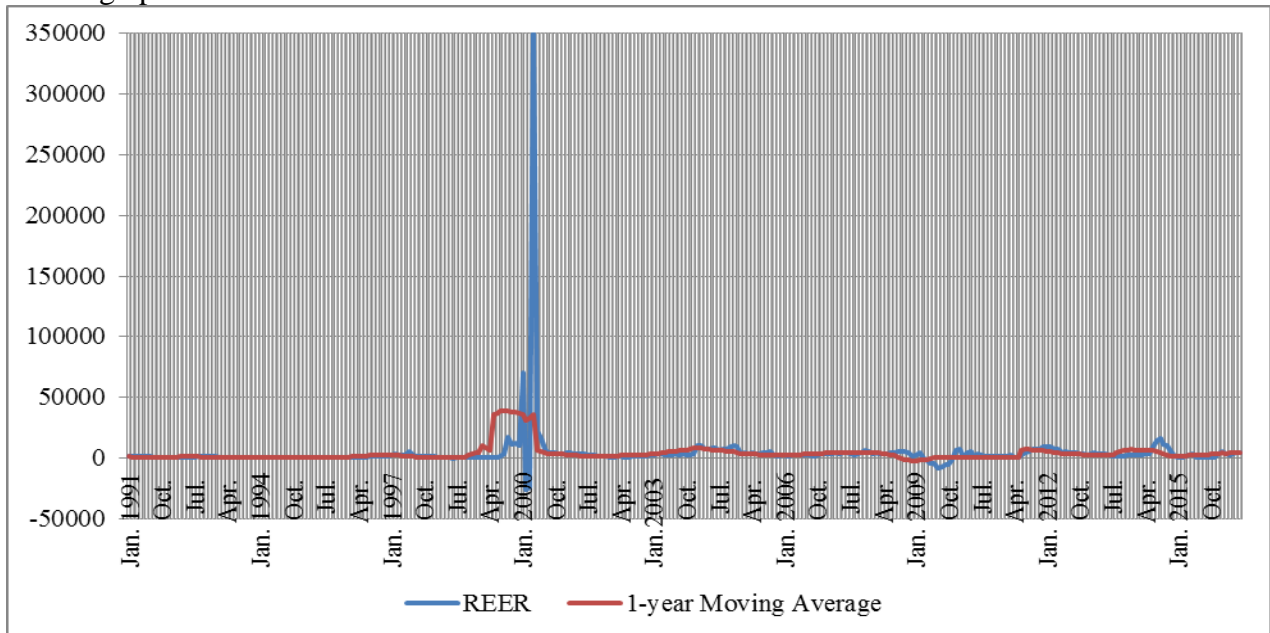
**Figure 2. The Performance of M2/Reserve in Indonesia, Period 1990 – 2016 (Monthly Basis)**

Figure 3 shows the performance of credit growth in Indonesia over the period of 1990-2016 in monthly basis. Figure 3 obviously presents some abnormal behavior of credit growth, indicated by exceeding the red line. There are six period where credit growth is considered showing abnormal behavior, namely in 1990, 1998, 2000, 2006, 2008, and 2014. In all these abnormal period, credit growth seems to be declining once it grows rapidly or excessively. Hence, credit growth can be seen to represent the period of boom and burst in the financial cycle.



**Figure 3. The Performance of Credit Growth in Indonesia, Period 1990 – 2016 (Monthly Basis)**

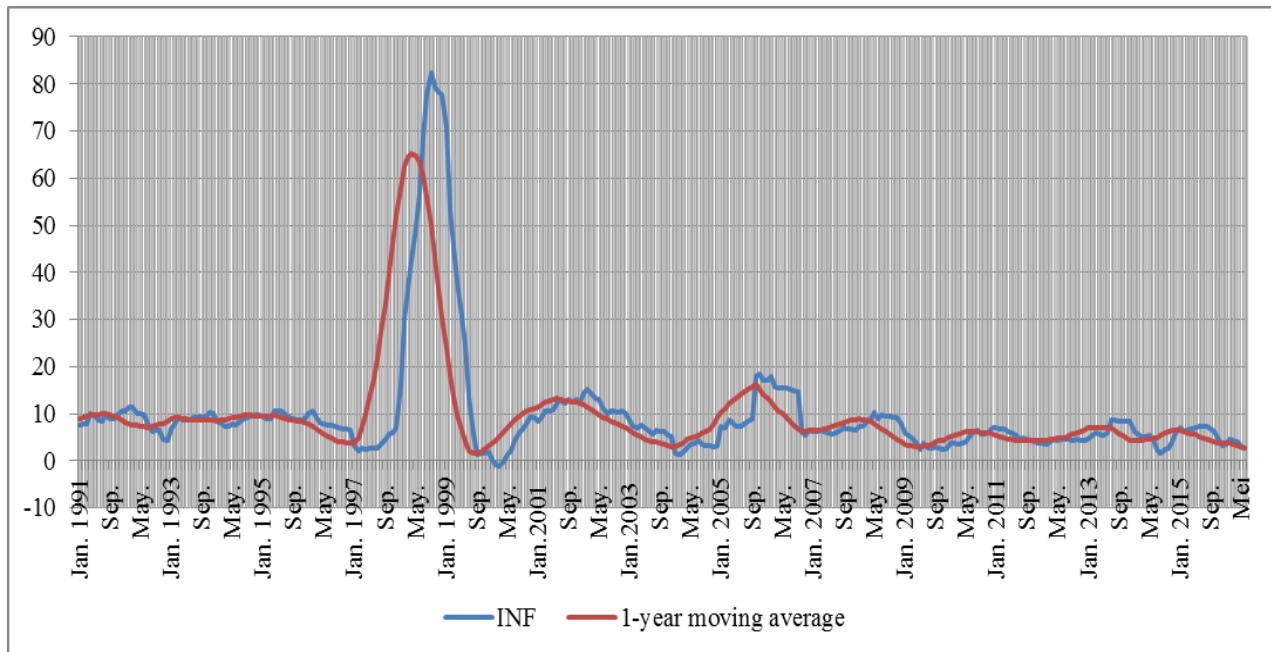
Figure 4 shows the performance of REER in Indonesia since 1990-2016 in monthly basis. Interestingly, over the period of observation, REER presents an abnormal behavior only during Asian financial crisis in 1998. It reflects during this crisis, Indonesia's economy is hit severely by crisis so losing its competitiveness eventhough theoretically REER is undervalued compared to foreign prices.



**Figure 4. The Performance of Real Effective Exchange Rate in Indonesia,**

### Period 1990 – 2016 (Monthly Basis)

Figure 5 shows the performance of inflation rate in Indonesia since 1990 to 2016. During Asian financial crisis, inflation rate was extremely high, but gradually decreases and shows a low level by 2016. Likewise, during global financial crises in 2007-2008, inflation rate was quite high and exceeded the red line. Hence, an increase in inflation rate could be a clear indication of a country's deterioration.



**Figure 5. The Performance of Inflation rate in Indonesia, Period 1990 – 2016 in Monthly Basis**

## The Signal Generating Mechanism on Several Leading Variables

This section explains the performance of every leading variable by using signal extraction signal approach. This paper applies several threshold multiplier, namely according to kaminsky (1996) – 3 standard deviation, Garcia (1999) - 1.5 standard deviation, Park (2001) – 1.1 standard deviation, and Lestano, et.al (2003) – 1.0 standard deviation. In addition, to evaluate the predictive power of every leading variable in detecting crisis, this paper uses different time horizon, namely 3 month, 6 month, 12 month, 18 month, and 24 month. The results are summarized as follows:

### 1. Evaluation of the M2/Res as Leading Variable

Table 3 shows the results of evaluations by using signal approach. The main conclusion is that kaminsky is the best option to be used as leading indicator in various time horizon. The lowest level of noise to signal indicates that kaminsky's approach is capable of minimizing wrong signal and miss signal in detecting crisis.

**Table 3. Evaluation of M2/Res Variable**

M2/Res	Kaminsky						Garcia						Park						Lestano					
	24	18	12	6	3	Avrg	24	18	12	6	3	Avrg	24	18	12	6	3	Avrg	24	18	12	6	3	Avrg
Noise to Signal Ratio (-)	0	0	0	0	0	0	0,59	0,34	0,35	0,22	0,15	0,33	1,24	0,79	0,76	0,55	0,39	0,75	1,2	0,9	0,7	0,6	0,4	0,76
The proportion of observations correctly (+)	0	0	0	0	0	0	0,07	0,12	0,14	0,19	0,33	0,17	0,06	0,10	0,11	0,15	0,21	0,13	0,08	0,10	0,14	0,17	0,25	0,15
The proportion of crises correctly (+)	0	0	0	0	0	0	0,42	0,38	0,41	0,48	0,54	0,45	0,42	0,38	0,46	0,52	0,61	0,48	0,39	0,38	0,41	0,51	0,59	0,45
The proportion of false alarm of total alarms issued (-)	0	0	0	0	0	0	0,57	0,61	0,58	0,52	0,46	0,55	0,57	0,61	0,54	0,47	0,38	0,52	0,60	0,61	0,59	0,49	0,41	0,54
The proportion of crisis given an alarm issued (+)	0,11	0,07	0,07	0,04	0,02	0,06	0,43	0,33	0,31	0,17	0,08	0,26	0,63	0,55	0,46	0,32	0,18	0,43	0,65	0,59	0,48	0,33	0,19	0,45
The proportion of probability of crisis given no alarm issued (-)	1	1	1	1	1	1	0,94	0,93	0,92	0,92	0,91	0,93	0,92	0,90	0,89	0,89	0,88	0,90	0,91	0,89	0,88	0,87	0,86	0,88

### 2. Evaluation of Credit Growth Variable as Leading Indicator

Table 4 explains some evaluations criteria of credit growth variable by using signal extraction approach. According to the table 4, kaminsky's approach shows the lowest value of noise to signal ratio, specifically in 3 month time horizon. It implies that policy makers should aware in a shortly period concerning the behavior of credit growth in Indonesia.

**Table 4. Evaluation of Credit Growth Variable**

CG	Kaminsky						Garcia						Park						Lestano					
	24	18	12	6	3	Avrg	24	18	12	6	3	Avrg	24	18	12	6	3	Avrg	24	18	12	6	3	Avrg
Noise to Signal Ratio (-)	0,12	0,07	0,07	0,04	0,02	0,07	0,59	0,45	0,33	0,12	0,18	0,34	0,24	0,50	0,40	0,15	0,29	0,30	0,34	0,61	0,24	0,22	0,35	0,35
The proportion of observations correctly (+)	0,03	0,04	0,04	0,09	0,20	0,08	0,02	0,02	0,03	0,06	0,10	0,04	0,05	0,03	0,05	0,10	0,08	0,06	0,04	0,03	0,05	0,10	0,08	0,06
The proportion of crises correctly (+)	0,5	0,5	0,5	0,5	0,5	0,5	0,43	0,43	0,43	0,33	0,63	0,45	0,13	0,28	0,25	0,23	0,54	0,29	0,16	0,31	0,19	0,28	0,57	0,30
The proportion of false alarm of total alarms issued (-)	0,5	0,5	0,5	0,5	0,5	0,5	0,57	0,57	0,57	0,67	0,38	0,55	0,87	0,71	0,75	0,76	0,45	0,71	0,84	0,69	0,81	0,71	0,43	0,69
The proportion of crisis given an alarm issued (+)	0,11	0,07	0,07	0,03	0,01	0,06	0,43	0,37	0,30	0,19	0,09	0,28	0,61	0,55	0,47	0,32	0,19	0,43	0,63	0,57	0,50	0,34	0,20	0,45
The proportion of probability of crisis given no alarm issued (-)	0,99	0,99	0,99	0,99	0,99	0,99	0,98	0,98	0,98	0,98	0,97	0,98	0,96	0,97	0,96	0,95	0,96	0,96	0,96	0,97	0,96	0,95	0,95	0,96

**3. Evaluation of Real Effective Exchange Rate Variable as Leading Indicator**

Table 5 shows some evaluation criteria for REER variable. The results explains that noise to signal remains the lowest by using kaminsky’s approach in all time horizon. It indicates that the predictive power in extracting signal is strong if setting a threshold according to kaminsky’s approach.

**Table 5. Evaluation of REER Variable**

REER	Kaminsky						Garcia						Park						Lestano					
	24	18	12	6	3	Avrg	24	18	12	6	3	Avrg	24	18	12	6	3	Avrg	24	18	12	6	3	Avrg
Noise to Signal Ratio (-)	0	0	0	0	0	0	0,50	0,56	0,43	0,27	0,15	0,38	0,64	0,54	0,68	0,73	0,43	0,60	0,63	0,65	0,98	0,86	0,66	0,76
The proportion of observations correctly (+)	0	0	0	0	0	0	0,05	0,06	0,08	0,13	0,22	0,11	0,17	0,20	0,16	0,15	0,21	0,18	0,22	0,23	0,16	0,18	0,21	0,20
The proportion of crises correctly (+)	0	0	0	0	0	0	0,39	0,47	0,50	0,53	0,59	0,49	0,27	0,30	0,42	0,59	0,63	0,44	0,26	0,33	0,47	0,61	0,70	0,47
The proportion of false alarm of total alarms issued (-)	0	0	0	0	0	0	0,61	0,52	0,50	0,53	0,59	0,49	0,72	0,70	0,57	0,41	0,37	0,55	0,73	0,66	0,53	0,38	0,30	0,52
The proportion of crisis given an alarm issued (+)	0,11	0,07	0,11	0,04	0,02	0,07	0,43	0,38	0,29	0,18	0,08	0,27	0,61	0,53	0,46	0,32	0,18	0,42	0,61	0,54	0,52	0,34	0,21	0,44
The proportion of probability of crisis	1	1	1	1	1	1	0,96	0,95	0,94	0,94	0,94	0,95	0,85	0,84	0,86	0,87	0,88	0,86	0,14	0,15	0,16	0,15	0,14	0,15





Table 7 summarizes the performance of several leading indicators included in the paper. Table 7 informs that four variables are relevant as leading indicators for the resilience of Islamic banking in Indonesia. It is reflected by the low noise to signal ratio, almost zero, and low the proportion of false alarm of total alarms. These results are obtained by using kaminsky approach which employ 3, 6, 12, 18, 24 month time horizon. Looking at time horizon, the 3 month is seen as best horizon to predict the likelihood of a crises into Islamic banking. It seems relevant in the midst of fast changing of current domestic and global economy. The short time horizon indicates the need for policy makers to prepare early anticipation as macrofinancial variables start to behave abnormal. Meanwhile, lestano's approach is consistently able to capture best result on the proportion of crisis given an alarm. It implies that this approach is suitable to detect a signal followed by a crisis in the following 24 month.

**Table 7. The Summarize of Performance on Leading Indicators**

Variable	Evaluation Criteria					
	Noise to Signal Ratio (-)	The proportion of observations correctly called (+)	The proportion of crises correctly called (+)	The proportion of false alarm of total alarms issued (-)	The proportion of crisis given an alarm issued (+)	The proportion of probability of crisis given no alarm issued (-)
M2/Res	Kaminsky – 0 (3,6,12,18,24)	Garcia – 0,33 (3)	Park – 0,61 (3)	Kaminsky – 0 (3,6,12,18,24)	Lestano – 0,65 (24)	Lestano – 0,86 (3)
CG	Kaminsky- 0,02 (3)	Kaminsky- 0,09 (6)	Garcia – 0.63 (3)	Kaminsky- 0,5 (3,6,12,18,24)	Lestano – 0,63 (24)	Park and Lestano – 0,95 (3,6)
REER	Kaminsky – 0 (3,6,12,18,24)	Lestano – 0,23 (18)	Garcia – 0,59 (3)	Kaminsky – 0 (3,6,12,18,24)	Lestano – 0,61 (24)	Lestano – 0,61 (3,24)
INF	Kaminsky – 0 (18)	Garcia – 0,19 (3)	Kaminsky – 1 (18)	Kaminsky – 0 (18)	Lestano – 0,62 (24)	Lestano – 0,62 (24)

(+), (-) denotes the value of each evaluation criteria, (+) means bigger better, and (-) means smaller better.  
(3,6,12,18,24) indicates time windows horizon

## Conclusion and Recommendation

### Conclusion

This paper is basically attempting to build an early warning system for the resilience of Islamic banking in Indonesia. The Islamic Banking Resilience Index (IBRI) is developed to help monitoring and anticipating the potential vulnerabilities in Islamic banking. In addition, some selected macrofinancial variables are employed, such as M2/reserve, credit growth, real effective exchange rate, and inflation rate. Technically, this paper uses several level of thresholds which are able to capture the level of resilience of Islamic

banking in Indonesia. Moreover, some time horizon, such as 3, 6, 12, 18, and 24 months are incorporated to obtain predictive power of above selected macrofinancial variables in signaling a crisis.

This research suggests several findings, as follows:

1. IBRI, which is composed from standardized deposit and financing since 2004 until 2016 in monthly basis, is able to figure out the resilience of Islamic banking. The resilience of Islamic banking was worst in 2004, but gradually decreased and stable. Interestingly, the resilience of Islamic banking was considered stable since the index was moving below the normal line during the global financial crises.
2. Some selected macrofinancial variables, M2/reserve (M2res), credit growth (CG), real effective exchange rate (REER), and inflation rate (INF) empirically show low noise to signal ratio. It means that these four variables are capable of signaling vulnerabilities from adverse external shocks.

## Recommendation

This paper is considered a very preliminary work in the area of early warning system for the resilience of Islamic banking. However, there is no clear cut leading indicators to comprehensively monitor its resilience. More macroeconomic and financial variables are needed to be included as leading indicators for capturing the resilience of Islamic banking. In addition, given that macroeconomic and financial variables play the important thing in providing the resilience, the macroprudential policy needs to be more specifically addressing procyclicality in the financial sector. Meanwhile, the resilience of Islamic banking needs to be supported by the resilience in the real sector. It is because the core operations of Islamic banking are dealing with productive sector. Therefore, the synergic policies are needed to establish strong resilience of Islamic banking, namely stable macroeconomic environment and strong real sector development.

## References

- Adiningsih, S., Setiawati, D. N., & Sholihah. (2002). *Macroeconomic Vulnerability in Indonesia. EADN Regional Project*. Bangkok. Retrieved from <http://tdri.or.th/archives/download/reports/published/eadn/indo1.pdf>
- Bank Indonesia. Kewajiban Penyediaan Modal Minimum Bank Umum, Pub. L. No. 15/12/PBI/2013 (2013). Indonesia: Bank Indonesia. Retrieved from [http://www.bi.go.id/id/peraturan/perbankan/Documents/pbi\\_151213rev.pdf](http://www.bi.go.id/id/peraturan/perbankan/Documents/pbi_151213rev.pdf)
- Bussiere, M, and M. Fratzscher (2002). "Towards a New Early Warning System of Financial Crises", *European Central Bank Working Paper*, No. 145

- Caprio, G. Jr. and Klingebiel, D. (1996), "Bank Insolvency: Bad luck, Bad Policy or Bad Banking?", Paper presented at the 1996 Annual Bank Conference on Development Economics, *World Bank Economic Review*, January 1997
- Davis, E. and D., Karim (2008). "Comparing Early Warning Systems for Banking Crisis", *Journal of Financial Stability*, 4, 89-120
- Demirgüç-Kunt, A. and E. Detragiache (1998). 'The Determinants of Banking Crises: Evidence from Developing and Developed Countries', *IMF Staff Papers*, 45, 81-109.
- Demirgüç-Kunt, A. and E. Detragiache. (2000). "Monitoring Banking Sector Fragility: A Multivariate Logit", *World Bank Economic Review*, 14(2), 287-307.
- Duttagupta R. and P. Cashin (2011). "Anatomy of Banking Crises in Developing and Emerging Market Countries", *Journal of International Money and Finance*, 30, 354-376.
- Eichengreen, B. and A. Rose (1998). "Staying Afloat When the Wind Shifts: External Factors and Emerging-Market Banking Crises", *NBER Working paper* no. 6370, January
- Glick, R. and M. Hutchison (2001). "Banking and Currency Crises: How Common Are Twins?" in R. Glick, R. Moreno and M. Spiegel (eds.), *Financial Crises in Emerging Markets*, Cambridge University Press, Cambridge, UK.
- González-Hermosillo, B. (1999). "Determinants of Ex-Ante Banking System Distress: A Macro-Micro Empirical Exploration of Some Recent Episodes", *IMF Working Paper* 99/33, March.
- Gurnain Pasricha, Tom Roberts, Ian Christensen & Brad Howell (2013) Assessing Financial System Vulnerabilities: An Early Warning Approach, *Bank of Canada Review*, Autumn 2013, pp. 10-19
- Hardy, D. and C. Pazarbasioglu (1999), "Determinants and Leading Indicators of Banking Crises: Further Evidence", *IMF Staff Papers*, 46, 3, 247-58.
- Herrera, S., & Garcia, C. (1999). *User's Guide to an Early Warning System for Macroeconomic Vulnerability in Latin American Countries* (No. 2233). *Policy Research Working Paper*. Washington DC. Retrieved from [http://siteresources.worldbank.org/BRAZILINPOREXTN/Resources/3817166-1185895645304/4044168-1186403960425/77pub\\_br167.pdf](http://siteresources.worldbank.org/BRAZILINPOREXTN/Resources/3817166-1185895645304/4044168-1186403960425/77pub_br167.pdf)
- Honohan, P. (1997), "Banking System Failures in Developing and Transition Countries: Diagnosis and Predictions", Working Paper 39, Bank for International Settlements.
- Hutchinson, M. (2002). "European Banking Distress and EMU: Institutional and Macroeconomic Risks", *Scandinavian Journal of Economics*, 104(3), 365-389
- Kaminsky, G., Kizondo, S., and Reinhart, C. M. (1998). Leading Indicators of Currency Crises. *IMF Staff Papers Staff Papers*, 45(1), 48. [http://doi.org/10.1016/S1566-0141\(02\)00002-X](http://doi.org/10.1016/S1566-0141(02)00002-X)

- Kaminsky, G.,L., and Reinhart, C. (1996). “Banking and Balance of Payment Crises: Models and Evidence”. Washington DC: Board of Governor of the Federal Reserve System.
- Kaminsky, G. and Reinhart, C.M. (1999), ‘The Twin Crises: the Causes of Banking and Balance of Payments Problems’, *American Economic Review*, 89, 473-500
- Kibritcioglu, Aykut, (2003) “Monitoring Banking Sector Fragility, *The Arab Bank Review*, Vol 5, No.2 October.
- Lindgren, C. J., Garcia, C., and Saal, M. (1996), *Bank Soundness and Macroeconomic Policy*, International Monetary Fund, Washington DC.
- Lestano, Jan Jacobs, and Gerard H. Kuper. (2003) “Indicators Of Financial Crises do Work!: An Early Warning System for Six Asian Countries”, CCSO Working Paper 13, Department of Economics, University Of Groningen, Netherland.
- Matthieu Bussiere & Marcel Fratzscher (2006), Towards a new early warning system of financial crises, *Journal of International Money and Finance* 25, pp. 953-973.
- Manasse, Paolo , Roberto Savona & Marika Vezzoli (2013) Rules of Thumb for Banking Crises in Emerging Markets, *Quaderni - Working Paper* DSE No. 872, University of Bologna, Italy.
- Park, Won-Am. (2001) “An Indicators on the Sustainable Development of Korea”, Paper prepared for EADN meeting, Singapore, June 25-27, 2001.
- Sachs, J. D., Tornell, A., and Velasco, A. (1996), “Financial Crises in Emerging Markets: the Lessons from 1995”, Working Paper 5576, National Bureau of Economic Research.
- Wong, Jim and Wong, T. C. and Leung, Phyllis (2007) A Leading Indicator Model of Banking Distress - Developing an Early Warning System for Hong Kong and Other EMEAP Economies (December 18, 2007). *Hong Kong Monetary Authority Working Paper* No. 22/2007. Available at SSRN: <http://ssrn.com/abstract=1078765> or <http://dx.doi.org/10.2139/ssrn.1078765>
- Wong J, TC Wong & P Leung (2010) Predicting banking distress in the EMEAP economies, *Journal of Financial Stability*, vol. 6, issue 3, pp.169-179
- Yucel, E. (2011). A Review and Bibliography of Early Warning Models. *Munich Personal RePEc Archive*, (32893), 19. Retrieved from [https://mpra.ub.uni-muenchen.de/32893/1/ewm11\\_004.pdf](https://mpra.ub.uni-muenchen.de/32893/1/ewm11_004.pdf)