Proceeding International Conference on Religion, Science and Education (2022) **1**, 657-664

Early Detection of Indonesian Financial Crisis Using Combination of Markov Regime Switching and Volatility Models

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Abstract: The financial crisis is one of a serious problem which ever hit various countries in the world was no exception Indonesia. The financial crisis had occurred in Indonesia in 1997 to 1998, 2008, and 2020 which caused the economy of Indonesia was down. The impact caused by the financial crisis is very detrimental for Indonesia. Based on this problem, it is proved that the Indonesian government has not yet been optimized overcome a possible financial crisis. Therefore, an early detection system of financial crisis is required so that the crisis it can be solved immediately. Some of the economic indicators which able to detect crisis signals is output and bank deposits indicators because they have high fluctuation and regime changing during the crisis. The data used is secondary data from each indicators start in January 1990 until March 2021. Combination of markov regime switching and volatility models can be used to detect financial crisis. The volatility model can explain the volatility which included in the indicators, while markov regime switching model explain the regime changing of time series data. The results show that output and bank deposits indicators can be modelled using MRS-GARCH(1,1) and MRS-EGARCH(1,1). Based on the results of those two models also predicted that there is financial crisis signal in Indonesia in 2021 especially for output and bank deposits indicators.

Keywords: Early detect, financial crisis, financial indicators, markov regime switching, volatility models.

Abbreviations: MRS-GARCH (markov regime switching generalized autoregressive conditional heteroscedasticity), MRS-EGARCH (markov regime switching exponential generalized autoregressive conditional heteroscedasticity)

Introduction

The financial crisis which happened in every country gives impact that very detrimental on the economy in general and financial system in particular. Phenomena financial crisis that have ever occurred in Indonesia was in the middle 1997 to 1998, the end of 2007 until 2008, and in the middle 2020. The financial crisis in 1997 started by the Thailand banking sector which experienced crisis in baht currency. Furthermore, the global financial crisis impact in 2008 was also felt in Indonesia. The crisis caused by the bankruptcy property business United States of America (subprime mortgage). The last crisis that just happened in 2020 is crisis caused by Covid-19 pandemic was also felt in all countries in the world including Indonesia.

Kaminsky et al. (1998) declared that the threat from the crisis can be detected by seeing the economic indicators. According to Kaminsky et al. (1998) there were 15 indicators which can be used as a reference in indicates that there is a financial crisis in a country. These indicators such as export, import, terms of trade, real exchange rate, stock prices, M2 or international reserves, output, M1, M2 multiplier, domestic credit, real interest rate, bank deposits, ratio M2 of international reserves, ratio domestic credit of GDP, and lending rate or deposit rate. Two of the indicators used in this research, there are output and bank deposits indicators.

ISSN 2829-3355 | EISSN 2828-8467

Output and bank deposits are two indicators that can indicates the occurrence of crisis, because both indicators are very related to economic growth. Output indicators and bank deposits indicators has connected of each other. The higher value of bank deposits from a country, so that profit of banks will increase. It means the banks were able to distributed credits with effectively and efficiently. The enhancement of bank deposits value would affect improve of economic growth that viewed from a large of real economic output produced on a country.

Considering that the impact from financial crisis was very broad, which is also caused by the unpreparedness of a country in facing a crisis from the beginning and the occurring possibility of a crisis, therefore an early financial crisis detection system is needed to anticipate the arrival of crisis early so that Indonesian government can prepare measures to reduce the impact of the crisis. The indicators used in this research have the heteroscedasticity effect so that it is smaller precise if it is modelled by a model of stationary time series as the model of the autoregressive moving average (ARMA). The more suitable model to use is with the volatility models.

Engle (1982) has developed a model to estimate the volatility of a data which give heteroscedasticity cases. The model used is autoregressive conditional heteroscedasticity (ARCH) model. Bollerslev et al. (1986) introduced the ARCH model generalization, it is generalized autoregressive conditional heteroscedasticity (GARCH) model. Both models were not calculated the changes of conditions in economic variables caused by the economic crisis, war, or other reasons that caused value on data significantly changed. To solve that problem, Hamilton and Susmel (1994), introduced a model that is able to explain the changes in volatility on the economic data. This model was known as markov regime switching (MRS). This research discusses the early detection of financial crisis in Indonesia based on output and bank deposits indicators using combination of markov regime switching and volatility models.

Materials and Methods

Study area

1. *Autoregressive Moving Average (ARMA) Model*

ARMA model is a stationary time series model that identifies regression equations using past values or combination of past values with past residuals. According to Tsay (2002), The ARMA (*p,q*) model can be denoted as

$$r_t = \phi_0 + \phi_1 r_{t-1} + \cdots + \phi_p r_{t-p} + \alpha_t - \theta_1 \alpha_{t-1} - \cdots - \theta_q \alpha_{t-q}$$

with r_t is log-return transformation at t time, ϕ_0 is model constant, $\phi_1, \dots, \phi_p$ are the AR model parameters, $\theta_1, \dots, \theta_q$ are the MA model parameters, and α_t is ARMA (*p,q*) model residual at t time. α_t must be white noise.

2. *Volatility Model*

In general, time series data modelling must fulfill the assumption that the residual has constant variance (homoscedastic). However, time series data in the real financial sector usually not filled in the residual variance assumption with constant variance. Therefore, to solve this problem there is a volatility model that aims to overcome the heteroscedasticity effect on the ARMA model. There are several volatility models as follows:

- Autoregressive Conditional Heteroscedasticity (ARCH)

  Tsay (2002) said that ARCH (*m*) model can be denoted as

  $$\sigma_t^2 = \alpha_0 + \alpha_1 + \alpha_{t-1}^2 + \cdots + \alpha_m \alpha_{t-m}^2$$
  $$= \alpha_0 + \sum_{i=1}^{m} \alpha_i \alpha_{t-1}^2$$

  With m is the ARCH model order, α_0 is ARCH model constant, α_i is ARCH model parameters, and σ_t^2 is residual of variance at t period.

- Generalized Autoregressive Conditional Heteroscedasticity (GARCH)

  Enders (1995), said that GARCH model built to avoid the orders were too high on the ARCH model with based on the principle of parsimony or choose the simpler model, so that it will ensure the variance to always be positive. According to Tsay (2002), $\alpha_t = \sigma_t \varepsilon_t$ where $\varepsilon_t \sim N(0,1)$ and $\alpha_t | \psi_{t-1} \sim N(0, \sigma_t^2)$ when ε_t following GARCH (*p,q*), if

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_p \sigma_{t-p}^2$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

- Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH)
  EGARCH *(p,q)* model built if there is an asymmetric effects on residue of GARCH model. EGARCH *(p,q)* model can defined as follows

$$ln\sigma_t^2 = \alpha_0 + \sum_{j=1}^{q} g_j(\epsilon_{t-j}) + \sum_{i=1}^{p} \beta_i ln\sigma_{t-i}^2$$

with

$$g_j(\epsilon_{t-j}) = \alpha_j \epsilon_{t-j} + \gamma_j(|\epsilon_{t-j}| - E|\epsilon_{t-j}|) \quad ,j = 1,\ldots,q$$

3. *The Combination of Markov Regime Switching and Volatility Model*

The aim of the combination volatility model with markov switching model is to see the changed of fluctuations that cannot be explained by volatility models.

- Markov Regime Switching Autoregressive Conditional Heteroscedasticity (MRS-ARCH)
  Hamilton and Susmel (1994) said that the MRS-ARCH *(K,m)* model can be denoted as

$$\sigma_{t,s_t}^2 = \alpha_{0,s_t} + \sum_{i=1}^{m} \alpha_{i,s_t} \alpha_{t-i}^2$$

  with m is the ARCH model order, K is the regime numbers, and σ_{t,s_t}^2 is the variance residuals regime at t time.

- Markov Regime Switching Generalized Autoregressive Conditional Heteroscedasticity (MRS-GARCH)
  Acording to Gray (1996), MRS-GARCH *(K,m,s)* model can be defined as

$$\sigma_{t,s_t}^2 = \alpha_{0,s_t} + \sum_{i=1}^{m} \alpha_{i,s_t}^2 \alpha_{t-1}^2 + \sum_{j=1}^{s} \beta_{j,s_t} \sigma_{t-j}^2$$

  with K is the regime numbers, m and s are GARCH model order.

- Markov Regime Switching Exponential Generalized Autoregressive Conditional Heteroscedasticity (MRS-EGARCH)
  MRS-EGARCH *(K,p,q)* model can be denoted as

$$ln\sigma_{t,s_t}^2 = \alpha_{0,s_t} + \sum_{j=1}^{q} g_{j,s_t}(\epsilon_{t-j}) + \sum_{i=1}^{p} \beta_{i,s_t} ln\sigma_{t-1}^2$$

  with K is the regime numbers, p and q are EGARCH model order.

4. *Transition Probability Matrix*

Taylor and Karlin defined that markov process $\{X_t\}$ is a stochastic process with the nature of value when it is given X_t, X_t value for $s > t$ unaffected X_u value for $u < t$. On the markov chain, a state in the next depends on state now. Process of markov chain can be written as follows

$$P(X_0 = i_0, \ldots, X_{n-1} = i_{n-1}, X_n = i) = P(X_{n+1} = j\}X_n = i) = P_{ij}$$

with P_{ij} is transition probability that is in the state i at n time into state j at n + 1 time or it can be said that the state suffered a transition from state I to state j. The one step transition probability matrix for infinite state is given as follows

$$P = [P_{ij}] = [P_{11}\ P_{12}\ \ldots\ P_{21}\ P_{22}\ \cdots\ \vdots\ \vdots\ \ddots\ ]$$

with $P_{ij} \geq 0$ for $i, j = 1,2, \ldots$ and $\sum_{j=1}^{\infty} P_{ij} = 1$ for $i = 1,2, \ldots, n$.

5. *Smoothed Probability*

According Kim and Nelson (1999), value of smoothed probability $(P_r(\psi_r)), t = 1,2, \ldots, T$ can be formulated as follows

$$(P_r(\psi_r)) = \sum_{s=1}^{3} P_r(\psi_r) P_r(S_t = i | S_{t+1} = s, \psi_T$$

with ψ_T is collection of all the information on the observation data to period T. The signal of the occurrence of a crisis can be shown from the magnitude of the predicted value of smoothed probability.

Procedures

Data of output and bank deposits indicators of Indonesia used in this research were secondary data obtained from the International Monetary Fund (IMF) website. Those are monthly data from January 1990 to March 2021. The data from January 1990 to March 2020 were used as training data while the data from April 2020 to March 2021 were used as testing data. The stages below are carried out in this research as follows.

(1) Plotting the data then check the data stationary with augmented dickey-fuller (ADF) test. If the data are not stationary, then doing the transformation to the data with log return transformation.
(2) Estimating the ARMA model. After that check residual diagnostic test the ARMA model. If the residual diagnostic test (normality, autocorrelation, and heteroscedasticity test) of the ARMA model not significance, then do the modelling using volatility models.
(3) Identifying the appropriate volatility models and also check sign bias test.
(4) Check again the residual diagnostic test of the volatility models.
(5) Creating the combination of markov regime switching and volatility model.
(6) Determining the financial crisis condition using the value of smoothed probability.
(7) Comparing the value of smoothed probability with the prediction from testing data to see the model accuracy.
(8) Predicting the financial crisis signal on April 2021 to December 2021.

Results and Discussion

Identification Model

Stage of identification model do is make a plot data and see the stationary data using Augmented Dickey-Fuller (ADF) test. Given a picture a plot of output and bank deposits indicators as follows.

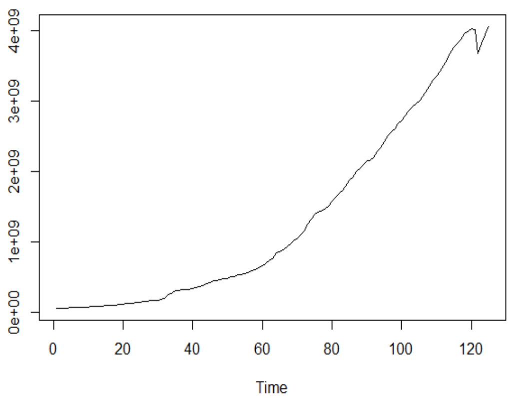

Figure 1. The plot of output indicators.

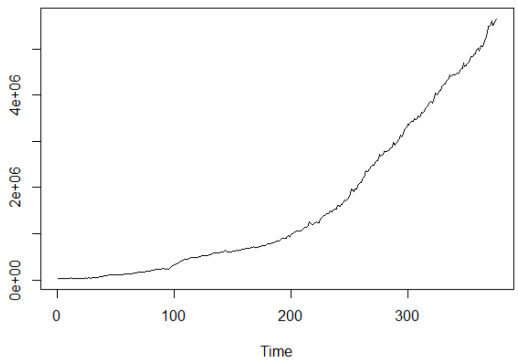

Figure 2. The plot of bank deposits indicators.

Figure 1 and Figure 2 shows that output and bank deposits data have a trend pattern and the data fluctuates overtime so thus indicates the data are not stationary. Based on ADF test, probability value of output and bank deposits indicators has the same probability value, it is 0.99 where the value of probability was more than significance standard of alpha (0.05). Therefore, it is proved that the data are not stationary. Because the data is not stationary, a log return transformation is used, so that the data becomes stationary. Plot data for every indicator trough given by log return transformation is in Figure 3 and Figure 4.

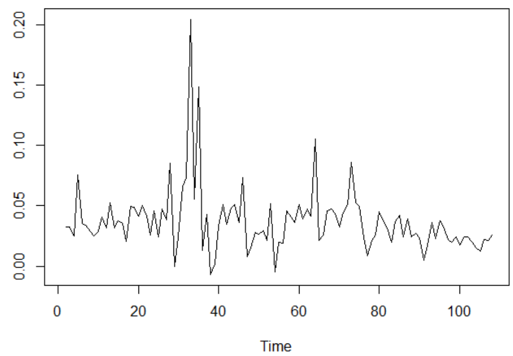

Figure 3. The log return transformation plot of output indicators.

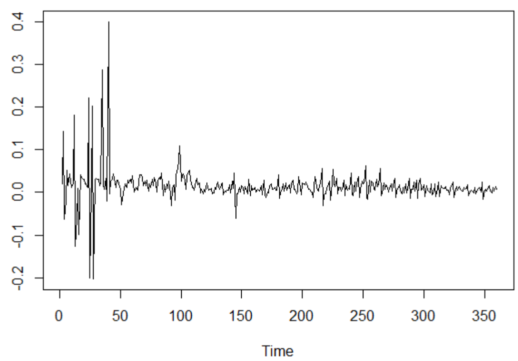

Figure 4. The log return transformation plot of bank deposits indicators.

Figure 3 and Figure 4 shows that the plot of the data indicators after having transformation have been stationary because the data fluctuations are around a constant average value and variance. Based on the ADF test, it is also given both data indicators after being transformed show a probability value as 0.01 which means it is smaller than the significance level and the data has been proven to be stationary.

Estimate the ARMA Model

The ARMA (*p*,*q*) model can be identified using PACF plots and ACF plots from the transformation data of each indicators. Based on the output indicators, the appropriate model is ARMA (3,0). It can be written as follows.

$$r_t = 0.0347 + 0.2221r_{t-1} + 0.4068r_{t-2} - 0.1836r_{t-3} + \varepsilon_t$$

The appropriate model for the bank deposits indicators is ARMA (1,0) and it is written as follows.

$$r_t = 0.0147 - 0.1900r_{t-1} + \varepsilon_t$$

Furthermore, residual diagnostic test were carried out using normality test, autocorrelation test, and heteroscedasticity test. The normality test used Shapiro-Wilk test, the autocorrelation test used the Ljung-Box test and the heteroscedasticity effect test could be performed using the Lagrange Multiplier (LM) test. Below is a table of residual diagnostic test probability values.

Table 1. Probability Value of Residual Diagnostic Test

Indicators	Model	Normality Test	Autocorrelation Test	Heteroscedasticity Test
Output	ARMA (3,0)	0.8099	0.7783	0.0132
Bank Deposits	ARMA (1,0)	0.8209	0.7484	0.0164

Based on Table 1, it can be seen that in the residue of the ARMA model both indicators has fulfilled normality assumption and autocorrelation but there are still a heteroscedasticity effect.

Identifying Volatility Model

The pattern of residue on a test of normality reveals the range of different, so it needs to cluster the residuals. Cluster analysis uses DTW distance because the data used in this study is time series data. The results of clustering analysis, the cluster value for each indicators are two. The volatility model for output indicators is GARCH (1,1) and can be formulated as

$$\sigma_t^2 = -0.0002 + 0.2082\alpha_{t-1}^2 + 0.7863\sigma_{t-1}^2$$

The volatility model for bank deposits indicators is GARCH (1,1) and can be formulated to as

$$\sigma_t^2 = -0.0002 + 0.1868\alpha_{t-1}^2 + 0.8118\sigma_{t-1}^2$$

Sign Bias Test

The next test is to check whether there is an asymmetric effect on the GARCH (1,1) model using the sign bias test. Given the sign bias test shown in Table 2.

Table 2. The Value of Sign Bias Test.

Indicators	Probability
Output	0.1496
Bank Deposits	0.0365

The results of sign bias test for output indicator show a probability value more than the alpha significance (0.05), so it can be said that the residue of the GARCH (1,1) model does not have an asymmetric effect (leverage effect), so that there is no need for further analysis of volatility modelling, while on bank deposits indicator the probability value shows less than the alpha significance (0.05), which means that the residue of the GARCH (1,1) model has an asymmetric effect, so that the asymmetric effect volatility modelling is carried out on the bank deposits indicator, it is EGARCH (1,1). The EGARCH volatility model for bank deposits indicators can be formulated as follows

$$ln\sigma_t^2 = -0.0002 + 0.0861(|\epsilon_{t-1}| - E|\epsilon_{t-1}|) + 0.996\ ln\sigma_{t-1}^2$$

After the volatility model is formed, the residual diagnostic test is reevaluated back. The following given the result of residual diagnostic test volatility model on Table 3.

Table 3. Probability Value of Residual Diagnostic Test Volatility Models

Indicators	Model	Normality Test	Autocorrelation Test	Heteroscedasticity Test
Output	GARCH (1,1)	0.8430	0.5038	0.8750
Bank Deposits	EGARCH (1,1)	0.8485	0.1638	0.5338

Based on Table 3, the output and bank deposits indicators fulfilled all the residual diagnostic test of the model. So that it can be said that the GARCH (1,1) model is proved whether for use in modelling the financial output indicators and EGARCH (1,1) model for bank deposits indicators.

The Combined of Volatility Model and Markov Switching

Change of condition on the markov switching model regarded as a random variable not been observed that commonly called state. In modelling of the change in the conditions, matrix of transition probability is formed. The conditions of being referred to in this research was the low and high volatility. The matrix of transition probability with two regimes for output (P1) and bank deposits (P2) indicator can be written as

$P_1 = (0.84\ 0.16\ 0.07\ 0.92)$ $\quad$ $P_2 = (0.89\ 0.11\ 0.47\ 0.53)$

Formation of Smoothed Probability

Detection a crisis can carried out using the minimum of smoothed probability when the financial crisis occurred in Indonesia in 1997 and 2008. The result of smoothed probability show a financial crisis happens when smoothed probability value is greater than 0.68 for output indicators and 0,15 for bank deposits indicators. Plot of smoothed probability for each indicators can be seen below.

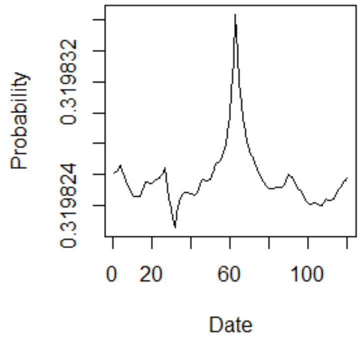

Figure 5. Smoothed probability plot for output indicators.

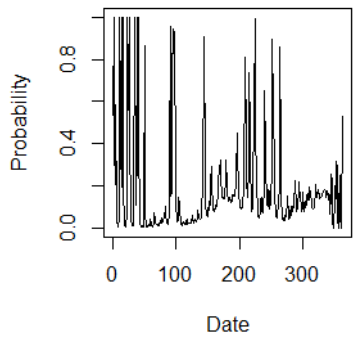

Figure 6. Smoothed probability plot for bank deposits indicators

The detection of financial crisis for each indicators can be seen in Table 4.

Table 4. Crisis Detection of Both Indicators.

Output (1990 - 2020)	Bank Deposits (1990 - 2020)
	March 1990 – May 1990
	November 1990 – May 1991
	November 1991 – March 1992
	October 1992 – May 1993
	June 1997 – March 1998
	September 2001 – January 2002
	October 2002 – December 2002
1997 Q1 – 1998 Q1	October 2003 – March 2004
	September 2004 – January 2005
	February 2006 – July 2006
	February 2007 – November 2008
	October 2009 – February 2011
	October 2011 – December 2011
	June 2017 – September 2018
	January 2020 – March 2020

After obtaining smoothed the probability value, then determined predictive value of smoothed probability for 2020 to 2021 on the output and bank deposits indicators.

Table 5. Prediction od Detection on Both Indicators

Period		Prediction in 2021			
Months	**Quarterly**	**Output**	**Output Condition**	**Bank Deposits**	**Bank Deposits Condition**
Apr-21				0.18446	Crisis
May-21	T2	0.693935	Crisis	0.19002	Crisis
Jun-21				0.19275	Crisis
Jul-21				0.19409	Crisis
Aug-21	T3	0.693955	Crisis	0.19474	Crisis
Sep-21				0.19506	Crisis
Oct-21				0.19522	Crisis
Nov-21	T4	0.693969	Crisis	0.19530	Crisis
Dec-21				0.19533	Crisis

The predicted values using output and bank deposits indicators in Table 5, all show the probability below the threshold. This shows that both indicators are in a state with high volatility or it can be concluded that the banking condition and economic condition of Indonesia is predicted to experience a crisis.

Discussion

This research used combination of markov switching and volatility models where volatility model can explain the volatility which included in the indicators, while markov regime switching model explain the regime changing of the residue from volatility models. The model can be applied for help the government to detect the future crisis at the country, so that the government could minimize the impact of the economic crisis caused by the financial crisis.

Conclusions

The appropriate models for modelling financial crisis detection on output and bank deposits indicators are MRS-GARCH (1,1) and MRS-EGARCH (1,1). Based on the prediction results, it is estimated that Indonesia will experience a financial crisis in 2021, especially in output and bank deposits indicators.

Acknowledgements: Gratitude to my lecturer Mr. Drs. Sugiyanto, M.Si and Mr. Muhammad Bayu Nirwana, S.Si., M.Sc. who have provided advice, support and helped to complete this research.

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