# Financial Crisis Model in Indonesia Based on Indonesia Composite Index (ICI) and Dollar (US) Exchange Rates to Rupiah Indicators

Sugiyanto, Isnandar Slamet, Sri Subanti, Etik Zukhronah and Winita Sulandari
*Study Program of Statistics, Universitas Sebelas Maret Surakarta, Indonesia*

Keywords: Crisis, ICI, Dollar Exchange Rates to Rupiah, SWARCH.

Abstract: An open economy is a new order of the world economic system that has provided space for all countries to interact and have integrity with one another. The economy facilitates the entry of foreign investors, but it also impacts the threat of financial crisis that is transmitted through increasingly open trade relations. The movement of the Indonesia Composite Index (ICI) and the dollar (US) exchange rates to rupiah are used to compile a model of the financial crisis in Indonesia. Crisis occurs due to high volatility and changing conditions. Volatility models are used to explain volatility, while changes in conditions can be explained through Markov switching. Therefore combining the volatility and Markov switching models is the best solution to explain the crisis. The goal of this research is to find the model of the financial crisis in Indonesia based on ICI and dollar (US) exchange rates to rupiah. The data that users are monthly data from 1990 to the 2017 year. The result showed that for ICI indicator the combining model is MS(2)-ARCH(1) or SWARCH(2,1) model with a conditional average of AR (2). While based on the dollar (US) exchange rates to rupiah indicator, SWARCH (3.3) model with conditional average of AR(1).

## 1 INTRODUCTION

The open economy system has presented challenges to developing countries such as Indonesia, with the integration of the country's financial sector. But on the other hand, it can facilitate the spread of crises between countries, as happened in 1997 when the value of the Thailand currency fell sharply, and the impact spread to various countries. The crisis is a disruption of financial system stability in the economic order. To maintain this stability, it is necessary to monitor the occurrence of crisis, so that prevention and crisis recovery efforts can be carried out as early as possible.

Banking and capital markets in Indonesia become indicators of financial systems that continue to increase every year. This has caused the development of capital market developments and the growth of the banking sector because transactions in the capital market are carried out through the banking system. The higher the investment, the greater the savings and the opportunity to provide funds which will ultimately accelerate economic growth. The Indonesia Composite Index (ICI) and the dollar exchange rates to rupiah have a vulnerability to economic stability shocks, this causes these indicators to fluctuate and condition changes. In anticipation, Hamilton and Susmel (1994) introduced the Autoregressive Conditional Heteroscedasticity Markov Switching (SWARCH) model which is a combination of volatility and Markov switching models as an alternative time series data modeling by observing fluctuations and changes in conditions in the data. Sugiyanto et al. (2017) through the SWARCH model has shown that the bank deposits, real exchange rates and terms of trade indicators can explain the crisis of 1997, 1998 and 2008. Sugiyanto et al. (2018) through the SWARCH model has shown that the output real, domestic credit per GDP, and ICI indicators can explain the crisis of 1997, 1998 and 2008. In this study a combination of volatility and Markov switching models was formed which corresponded to the ICI indicator and the dollar exchange rates to rupiah to detect the financial crisis in Indonesia.



Sugiyanto, ., Slamet, I., Zukhronah, E., Subanti, S. and Sulandari, W.
Financial Crisis Model in Indonesia Based on Indonesia Composite Index (ICI) and Dollar (US) Exchange Rates to Rupiah Indicators.
DOI: 10.5220/0008517000460051
In *Proceedings of the International Conference on Mathematics and Islam (ICMIs 2018)*, pages 46-51
ISBN: 978-989-758-407-7

## 2 LITERATURE REVIEW

### 2.1 Autoregressive Moving Average (ARMA) Model

The ARMA (p, q) model has a general form

$$r_t = \sum_{i=1}^{p} \emptyset_i r_{t-i} + a_t - \sum_{i=1}^{q} \theta_i a_{t-i}, \quad (1)$$

where $r_t$ is the transformation value in the $t$-period, $\emptyset_0$ is a constant, $\emptyset_p$ is the parameter for AR, $\theta_q$ is the parameter for MA and $a_t$ is the T-period of residual of ARMA (p, q) model (Tsay, 2002).

### 2.2 Autoregressive Conditional Heterocedasticity (ARCH) Model

ARCH (m) model can be written as

$$a_t = \sigma_t \epsilon_t \text{ for } \epsilon_t \sim N(0,1) \text{ and } a_t|\psi_{t-1} \sim N(0, \sigma_t^2),$$
$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2, \quad (2)$$

where $\epsilon_t$ is the standardized residual volatility model, $\psi_{t-1}$ is the set of all period information $(t-1)^{th}$, m is the order of the ARCH model, $\alpha_0$ is the constant of ARCH model, $\alpha_i$ is the parameter of ARCH model, and $\sigma_t^2$ is T-period residual variance (Tsay, 2002).

### 2.3 Generalized Autoregressive Conditional Heterocedasticity (GARCH)Model

If the order of the ARCH model is too high, then the GARCH (m, s) model is used in the form

$$a_t = \sigma_t \epsilon_t \text{ for } \epsilon_t \sim N(0,1) \text{ and } a_t|\psi_{t-1} \sim N(0, \sigma_t^2),$$
$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2,$$

where $\beta_j$ is the parameter of GARCH model (Tsay, 2002).

### 2.4 Exponential Generalized Autoregressive Conditional Heterocedasticity (EGARCH) Model

If there is a leverage effect in the GARCH model, EGARCH (m, s) model is used in the form

$$a_t = \sigma_t \epsilon_t \text{ for } \epsilon_t \sim N(0,1) \text{ and } a_t|\psi_{t-1} \sim N(0, \sigma_t^2),$$

$$\ln \sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i \left( \left| \frac{a_{t-i}}{\sqrt{\sigma_{t-i}^2}} \right| \right) + \sum_{i=1}^{s} \beta_i \ln \sigma_{t-j}^2$$
$$+ \sum_{i=1}^{m} \gamma_i \frac{a_{t-i}}{\sqrt{\sigma_{t-i}^2}}.$$

where $\gamma_i$ is the EGARCH model parameter (Henry, 2007).

### 2.5 SWARCH Model

The SWARCH model according to Hamilton and Susmel (1994), can be written as

$$r_t = \mu_{st} + a_t, a_t = \sigma_{t,st} \epsilon_t,$$
$$\sigma_{t,s_t}^2 = \alpha_{0,s_t} + \sum_{i=1}^{m} \alpha_{i,s_t} a_{t-i}^2, \quad (3)$$

where $\mu_{st}$ is a conditional average in a state and $\sigma_{t,st}^2$ is the residual variance in a t-period state.

### 2.6 Smoothed Probability

In the Markov chain, the next state only depends on the current state. The Markov chain process can be written as

$$P(S_{t+1} = j | S_0 = i_0, \dots, S_{t-1} = i_{t-1}, S_t = i)$$
$$= P(S_{t+1} = j | S_t = i) = p_{ij},$$

where $p_{ij}$ is the transition probability that the process of being in state i at time t will go to state j at time t+1 or it can be said that the state undergoes a transition from state i to state j. The one-step transition probability matrix for infinite states is given as

$$\boldsymbol{P} = [p_{ij}] = \begin{bmatrix} p_{11} & p_{12} & \cdots \\ p_{21} & p_{22} & \cdots \\ \vdots & \vdots & \ddots \end{bmatrix},$$

where $p_{ij} \geq 0$ for i, j = 1,2, ... and $\sum_{j=1}^{\infty} p_{ij} = 1$ for i = 1,2, ….

According to Kim and Nelson (1999), the value of smoothed probability $(\Pr(S_t = i|\psi_T)), t = 1,2,\dots,T$ can be formulated as

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

where $\psi_T$ is a collection of all information in the observation data until the T-time.

# 3 METHODS

This study is a case study using the ICI monthly data and the dollar exchange rates to rupiah taken from 1990 to 2017. The data used was obtained from Bank Indonesia and the Central Statistics Agency. Calculation and estimation of the model is done with software R. The following steps are taken to achieve the research objectives on each indicator:

1. Making a data plot then perform Augmented-Dickey Fuller (ADF) test to determine the stationary of data. If it is not stationary, then the data is transformed.
2. Plotting the autocorrelation function (ACF) and the partial autocorrelation function (PACF) of the transformation data to form the ARMA(p,q) model, then testing of independency, normality, and heteroscedasticity of the residual ARMA models using the Ljung-Box test, Kolmogorov-Smirnov test, and the Lagrange Multiplier (LM) test respectively.
3. Establish and conduct diagnostic tests on the best model of volatility.
4. Clustering the residual value of the ARMA model.
5. Form a combination of volatility and Markov switching models based on the number of clusters.
6. Calculating the value of smoothed probability to detect the occurrence of a crisis in the past.

# 4 RESULTS AND DISCUSSION

## 4.1 Plot of Data

Plot of ICI indicator and dollar (US) exchange rates to rupiah indicators can be seen in Figure 1. Figure 1 shows that the data fluctuates from time to time so that it is indicated that the data is not stationary. Then the ADF test was conducted to see the stationary data. Based on ADF testing, the probability values are 0.6934 and 0.2793 for the ICI and the dollar exchange rates to rupiah indicators is greater than $\alpha = 0.05$, which means that the data is not stationary.

According to Tsay (2002), economic indicators tend to fluctuate from time to time so transformation needs to be done. The most suitable transformation for the ICI indicator and the dollar exchange rates to rupiah is the log return. Then the ADF was tested on the transformation data and obtained the probability values of 0.01 and 0.01 respectively, so it was concluded that the ICI and the dollar exchange rates to rupiah indicators of transformed data were stationary.

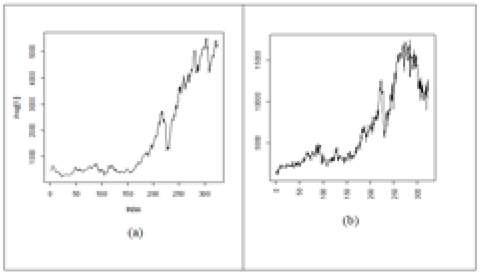


Figure 1: (a) ICI Data (b) Dollar exchange rates to rupiah Data

## 4.2 Form of ARMA(p,q) Model

The ARMA (p, q) model can be identified using ACF and PACF plots from the transformation data of each indicator. Based on the ICI indicator, using equation (1) it was obtained the best model was ARMA (1, 0) and written as

$$r_t = 0.21427 r_{t-1} + a_t.$$

While the best model for the dollar exchange rates indicator was ARMA (2, 0), which can be written as

$$r_t = 0.88425 + 1.089141 r_{t-1} - 0.327962 r_{t-2} + a_t.$$

Furthermore, the feasibility test of the ARMA model includes the independence test, normality test and heteroscedasticity test on the residues of the ARMA model for each indicator. Heteroscedasticity effect test can be done using the Lagrange Multiplier (LM) test, and it was obtained the probability values for ICI and dollar exchange rates to rupiah indicators of 0.0000 and 0.0000 respectively so that it can be concluded that there was an effect of heteroscedasticity on the residual of ARMA model of each indicator.

## 4.3 Form of Volatility Models

The estimation results for the ICI indicator using equation (2) are the best volatility model, ARCH(1), can be written as

$$\sigma_t{}^2 = 0.005048 + 0.182678a^2{}_{t-1}.$$

For the dollar exchange rates to rupiah indicator, the best volatility model is ARCH (3), that can be written as

$$\sigma_t{}^2 = 0.00005015 + 1.317a^2{}_{t-1} + 0.7475a^2{}_{t-2} + 0.2509a^2{}_{t-3}.$$

Furthermore, diagnostic tests were carried out on standardized residues of ARCH(1) model for ICI and dollar exchange rates to rupiah indicators. Based on Ljung-Box statistics, the probability value were 0.892 and 0.9936 which means that there was no residual autocorrelation. Based on LM test, it was obtained the probability of 0.07197 and 0.9936 respectively which means that there was no effect of heteroscedasticity in the residue. Based on the Kolmogorov-Smirnov test, probability is 0.6 and 0.2222 which means that the residue is normally distributed. Based on diagnostic tests that have been carried out on the two indicators, it can be concluded that the ARCH (1) model is good to use.

## 4.4 Cluster Analysis

Cluster analysis uses the ward hierarchy method to determine the number of cluster of volatility clustering that will be used in the Markov switching model and in determining the value of smoothed probability. The result of cluster analysis of ICI indicator can be seen in Table 1.

In column 1 Table 1, it can be seen that at stage 320th has coefficient 55.313 (column 4) and at stage 321st has 145.499. The increase of coefficient is not drastic, but the first drastic surge of 176,501 occur in the 321st and 322nd stages, from 145,499 to 322 this occurred when the agglomeration process produced two clusters for the ICI. The result of cluster analysis of dollar exchange rates to rupiah indicator can be seen in Table 2.

In column 1 Table 2, it can be seen that at stage 320th has coefficient 55.778 (column 4) and at stage 321st has 122.281 where this is the first drastic surge of the coefficient that is 66,503. It occurred when the agglomeration process produces three clusters.

Furthermore, the formation of SWARCH models with 2 states for ICI indicators and 3 states for dollar exchange rates indicators.

Table 1: Results of cluster analysis of ICI.

| Stage | Cluster Combined | | Coefficients | Stage Cluster First Appears | | Next Stage |
|---|---|---|---|---|---|---|
| | Cluster 1 | Cluster 2 | | Cluster 1 | Cluster 2 | |
| 303 | 16 | 17 | .591 | 291 | 286 | 310 |
| 304 | 12 | 29 | .705 | 296 | 281 | 317 |
| 305 | 105 | 107 | .840 | 0 | 0 | 313 |
| 306 | 9 | 125 | .982 | 273 | 297 | 316 |
| 307 | 2 | 20 | 1.139 | 299 | 292 | 315 |
| 308 | 3 | 95 | 1.304 | 300 | 0 | 316 |
| 309 | 4 | 85 | 1.520 | 294 | 298 | 314 |
| 310 | 15 | 16 | 1.850 | 295 | 303 | 312 |
| 311 | 92 | 226 | 2.299 | 0 | 0 | 318 |
| 312 | 1 | 15 | 3.192 | 290 | 310 | 319 |
| 313 | 104 | 105 | 4.224 | 0 | 305 | 318 |
| 314 | 4 | 8 | 5.261 | 309 | 301 | 317 |
| 315 | 2 | 10 | 6.401 | 307 | 302 | 320 |
| 316 | 3 | 9 | 8.597 | 308 | 306 | 320 |
| 317 | 4 | 12 | 11.473 | 314 | 304 | 319 |
| 318 | 92 | 104 | 21.039 | 311 | 313 | 321 |
| 319 | 1 | 4 | 36.692 | 312 | 317 | 322 |
| 320 | 2 | 3 | 55.313 | 315 | 316 | 321 |
| 321 | 2 | 92 | 145.499 | 320 | 318 | 322 |
| 322 | 1 | 2 | 322.000 | 319 | 321 | 0 |

Table 2: Results of cluster analysis of dollar exchange rates to rupiah.

| Stage | Cluster Combined | | Coefficients | Stage Cluster First Appears | | Next Stage |
|---|---|---|---|---|---|---|
| | Cluster 1 | Cluster 2 | | Cluster 1 | Cluster 2 | |
| 301 | 96 | 107 | .264 | 290 | 0 | 306 |
| 302 | 123 | 144 | .300 | 276 | 292 | 307 |
| 303 | 111 | 122 | .345 | 272 | 296 | 310 |
| 304 | 95 | 110 | .410 | 284 | 293 | 316 |
| 305 | 101 | 103 | .475 | 288 | 0 | 313 |
| 306 | 96 | 118 | .554 | 301 | 0 | 314 |
| 307 | 113 | 123 | .657 | 285 | 302 | 311 |
| 308 | 93 | 109 | .761 | 279 | 300 | 312 |
| 309 | 1 | 12 | .889 | 289 | 297 | 317 |
| 310 | 91 | 111 | 1.191 | 294 | 303 | 316 |
| 311 | 113 | 133 | 1.662 | 307 | 298 | 317 |
| 312 | 92 | 93 | 2.164 | 299 | 308 | 318 |
| 313 | 99 | 101 | 2.709 | 295 | 305 | 320 |
| 314 | 96 | 108 | 3.661 | 306 | 291 | 318 |
| 315 | 97 | 98 | 5.264 | 0 | 0 | 320 |
| 316 | 91 | 95 | 6.948 | 310 | 304 | 319 |
| 317 | 1 | 113 | 9.769 | 309 | 311 | 319 |
| 318 | 92 | 96 | 15.356 | 312 | 314 | 321 |
| 319 | 1 | 91 | 28.075 | 317 | 316 | 321 |
| 320 | 97 | 99 | 55.778 | 315 | 313 | 322 |
| 321 | 1 | 92 | 122.281 | 319 | 318 | 322 |
| 322 | 1 | 97 | 322.000 | 321 | 320 | 0 |

## 4.5 Form of Markov Switching and Volatility Models

In the Markov model, switching condition changes are considered as an unobservable random variable called state. To model changes in these conditions can be formed transition probability matrix. The conditions intended in this study are conditions of low and high volatility. The transition probability matrix for the ICI indicator is written as follows

$$P = \begin{pmatrix} 0.98389655 & 0.05777095 \\ 0.01610345 & 0.94222905 \end{pmatrix}$$

Based on the P transition probability matrix, the probability value to survive in low volatility is 0.98389655 and high volatility is 0.94222905. While the probability transition matrix for the dollar exchange rates to rupiah indicator is written as follows

$$Q = \begin{pmatrix} 0.95802949 & 0.009195131 & 0.009823464 \\ 0.02465327 & 0.980435796 & 0.013257485 \\ 0.01731724 & 0.010369073 & 0.976919050 \end{pmatrix}$$

Based on the Q transition probability matrix obtained the probability value to withstand low volatility of 0.95802949, the probability value to withstand moderate volatility of 0.980435796 and the probability value to withstand high volatility of 0.976919050.

The best combination of volatility and Markov switching models for ICI indicators using equation (3) is SWARCH (2, 1) with conditional averages and conditional variances for each state are

$$\mu_{S_t} = \begin{cases} 0.00019137, \text{for } state\ 1, \\ -0.00025328, \text{for } state\ 2, \end{cases}$$

and

$$\sigma^2_{t,S_t} = \begin{cases} 0.00324169, \text{for } state\ 1 \\ 0.28938583, \text{for } state\ 2 \end{cases}$$

The best model for the dollar exchange rates to rupiah indicator is SWARCH (3, 3) with conditional averages and conditional variances for each state respectively

$$\mu_{S_t} = \begin{cases} 0.00009063, \text{for } state\ 1 \\ -0.00000063, \text{for } state\ 2 \\ 0.00001288, \text{for } state\ 3 \end{cases}$$

and

$$\sigma^2_{t,S_t} = \begin{cases} 0.00007556, \text{for } state\ 1, \\ 0.00000265, \text{for } state\ 2, \\ 0.00000018, \text{for } state\ 3. \end{cases}$$

### 4.6 Determination of Crisis

Figure 2 shows the plot of smoothed probability from the SWARCH (2,1) model for the ICI indicator that calculated using equation (4).

If the value of smoothed probability is less than 0.4708 so the condition is stable, while the crisis is when the smoothed probability value is more than 0.4708. From figure 2, it can be seen that in March to June 1990, August 1990 to October 1991, July 1997 to August 2000, and July 2008 to April 2009 were detected to be a crisis.

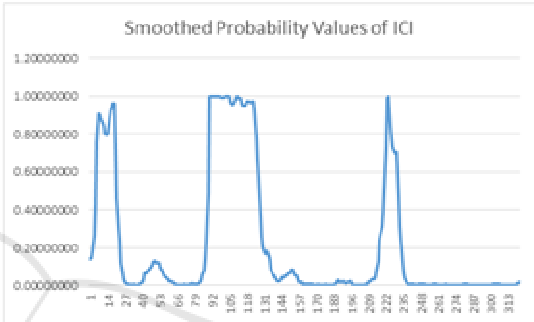


Figure 2: Smoothed probability for ICI.

Figure 2 shows the value of the smoothed probability of the dollar (US) exchange rates to rupiah. The crisis occurs when the value of the smoothed probability is greater than 0.9024 and prone to the crisis if the value of smoothed probability is between 0.4086 and 0.9024, while the state is stable if the value of smoothed probability is less than 0.4086. Based on this limit, the crisis was detected in July 1997 to October 2000, March 2001 to September 2001, and October 2008 to April 2009.

## 5 CONCLUSIONS

Based on the results and discussion, it was obtained findings as follows:

1. The ICI and dollar exchange rates to rupiah indicators can be modeled by SWARCH (2,1) and SWARCH (3, 3), and can capture the crisis that occurred in 1997, 1998 and 2008.
2. Indicator of the dollar (US) exchange rates to rupiah is more sensitive than ICI to explain crisis conditions in accordance with facts.

## REFERENCES


Hamilton, J. D. and Susmel, R., 1994. Autoregressive conditional heteroscedasticity and changes in regime. *Journal of Econometrics,* vol. 64, pp. 307 – 333.

Henry, O. T., 2007. Between the rock and a hard place: regime switching in the relationship between short-term interest rates and equity returns in the UK. *Research Paper Number 1019,* Department of Economics, the University of Melbourne.

Kim, C. J. and Nelson, C. R., 1999. *State space models with regime switching, classical, and Gibs sampling approaches with applications*. MIT Press.

Sugiyanto, Zukhronah, E. and Aini, N. A., 2017. Models for financial crisis detection in Indonesia based on bank deposits, real exchange rates and terms of trade indicators. *Journal of Physics: Conf. Series* 943(012024), pp. 1 – 6.

Sugiyanto, Zukhronah, E. and Setianingrum, M., 2018. The detection of financial crisis using combination of volatility and Markov switching models based on real output, domestic credit per GDP, and ICI indicators. *Journal of Physics: Conf. Series* 1025(012115), pp.1 – 6.

Tsay, R.S., 2002. *Analysis of financial time series*. John Wiley and Sons, Canada.