Prediction of currency crisis in Indonesia using combined volatility and Markov regime switching models based on lending interest rate / deposit interest rate indicator

Sugiyanto\(^1\), E Zukhronah\(^2\) and I Slamet\(^3\)

\(^{1,2,3}\)Department of Statistics, Faculty of Mathematics and Natural Sciences, Universitas Sebelas Maret, Ir. Sutami Street 36 Keningan, Surakarta, Central Java, Indonesia

Email: sugiyanto61@staff.uns.ac.id, etikzukhronah@staff.uns.ac.id, isnandarslamet@staff.uns.ac.id

Abstract. In mid of 1997, a currency crisis had a severe impact on the economy in Indonesia. Based on this situation, it is necessary to build an early warning system to anticipate the crisis events. The crisis occurred due to some macro-economic indicators fluctuated very high and the change of regime. Combined volatility and Markov regime switching models suited to explain the crisis. In this article it was used indicator of lending interest rate / deposit interest rate from 1990 to 2018. The results showed that MRS-GARCH (3,1,1) model can explain the crisis. Based on this model, it can be predicted that in 2019 there was no sign of a currency crisis in Indonesia.

1. Introduction
Currency crisis that occurred in Thailand have an impact on the currency crisis in Indonesia. Currency crisis that occurred in middle 1997 led to the prolonged economic crisis and a very severe impact on the economy in Indonesia. Based on that condition, it needs an early warning system of a currency crisis that can be prevented to avoid a prolonged crisis.

Autoregressive conditional heteroscedasticity (ARCH) model was introduced by Engle [1] which was used to model the variance of inflation data in the UK from 1958 to 1977 and obtained the prediction variance data that was more realistic. Bollerslev [2] introduced a generalized autoregressive conditional heteroscedasticity (GARCH) to model the data of US GNP from 1948 to 1983. In some cases, GARCH less able to explain the effect of leverage. Chen [3] explains that the leverage effect is a situation where the volatility experienced bad news and good news on a regular basis to produce asymmetric effects on volatility.

Hamilton [4] introduced a model Markov regime switching (MRS) as time series model that contains a regime change. Hamilton and Susmel [5] combines the MRS and ARCH models to generate Markov regime switching autoregressive conditional heteroscedasticity (MRS-ARCH) model. They apply the MRS-ARCH models to the data of US gross national product (GNP) from 1952 to 1984. Chang [6] used MRS-ARCH model to identify the volatility of the stock market and the exchange rate in Korea and the global financial crisis. Sugiyanto [7] detected financial crisis using a combination of volatility and Markov switching models through real output, domestic credit per gross domestic product (GDP), and ICI indicators. Sugiyanto [8] also describes the financial crisis using MS-GARCH
models through banking indicators. This article discusses currency crisis that may happened in Indonesia through indicator of lending interest rate/deposit interest rate using a combination of volatility and Markov regime switching models.

2. Material and methods

2.1. Material

ARMA (p, 0) model is equal to the AR (p) model. Model AR (p) can be written as follows

\[ r_t = \phi_0 + \phi_1 r_{t-1} + \cdots + \phi_p r_{t-p} + \epsilon_t, \]

where \( r_t \) is the log return at time \( t \), \( \epsilon_t \) is the residue of an AR (p) model, and \( \phi_0, \phi_1, \ldots, \phi_p \) is the parameters of AR(p) model.

According to Engle [1], ARCH(m) model can be written as follows

\[ \sigma_t^2 = \sigma_0 + \sum_{i=1}^{m} \alpha_i \epsilon_{t-i}^2, \]

\[ \alpha_0 > 0, \alpha_i \geq 0, \text{for } i > 0, \sigma_t^2 = E(\epsilon_t^2 | \psi_{t-1}) \text{ is the residue of conditional variance at time } t, \text{and } \psi_t \text{ is all of information set up to time } t. \]

According to Tsay [9], GARCH (m, s) model can be written as follows

\[ \sigma_t^2 = \alpha_0 + \sum_{i=0}^{m} \alpha_i \sigma_{t-i}^2 + \sum_{j=0}^{s} \beta_j \sigma_{t-j}. \]

Clustering has a variety of purposes related to the grouping or segmenting a set of objects into subsets, or clusters, so that the object relationships in one cluster closer than different clusters. The core of the cluster analysis is classifying objects based on the degree of similarity (or dissimilarity). There are two main methods of clustering that are hierarchical clustering and k-means clustering [10].

Dynamic time warping (DTW) is designed to reflect the greatest similarity between the series by calculating the minimum distance between them. DTW distance of two time series can be calculated using the method of dynamic program based on a matrix of accumulated distance. After getting the best number of clusters, the next step is to seek Markov regime switching model using the number of state equal to the number of best cluster.

Markov regime switching is an alternative modelling of time series that can explain regime change [4]. The regime change can be viewed as an unobservable random variable. According to Hamilton and Susmel [5], Markov regime switching autoregressive conditional heteroscedasticity model can be written as follows

\[ r_t = \mu_{s_t} + a_t, \quad a_t = \sigma_t \epsilon_t, \]

\[ \sigma_{t,s_t}^2 = \alpha_{0,s_t} + \sum_{i=1}^{m} \alpha_{i,s_t} a_{t-i}^2 + \sum_{j=1}^{s} \beta_{j,s_t} \sigma_{t-j}^2, \] (1)

\[ \sigma_{t,s_t}^2 = \alpha_{0,s_t} + \sum_{i=1}^{m} \alpha_{i,s_t} a_{t-i}^2 + \sum_{j=1}^{s} \beta_{j,s_t} \sigma_{t-j}^2, \] (2)

Equation (1) and (2) are the MRS-GARCH model with the regime \( k \) and order (m, s). Based on Gray [11], Markov regime switching generalized autoregressive conditional heteroscedasticity model can be written as follows

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

where \( r_t \) is a vector of observation variables and \( s_t \) demonstrated an unobservable random variables that satisfies the first order of Markov chain with values \( 1,2,\ldots,T \). Variables \( s_t \) is considered a regime that the process occurs at the time \( t \) and \( s_t \) is arranges the first order of Markov chain. Conditional distribution parameters and unobservable random variables with constant transition probabilities are given by

\[ P[s_t = j | s_{t-1} = i] = p_{ij}, \quad \sum_{j=1}^{T} p_{ij} = 1, \text{ for } i,j = 1,2,\ldots,T. \]
In matrix notation, $P$ can be defined by

$$
P = \begin{pmatrix}
P_{11} & P_{12} & \cdots & P_{1T} \\
P_{21} & P_{22} & \cdots & P_{2T} \\
\vdots & \vdots & \ddots & \vdots \\
P_{T1} & P_{T2} & \cdots & P_{TT}
\end{pmatrix},
$$

Based on Kim and Nelson [12], the smoothed probability values $(Pr(S_t = i|\psi_T)), t = 1,2, ..., T, t = 1,2, ..., T$ can be written as follows,

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

Based on Sopipan et al. [13], the smoothed probability values at time $T + 1$ can be predicted using

$$
Pr(S_{t+1} = i|\psi_T) = p_{i1} Pr(S_t = 1|\psi_T) + p_{i2} Pr(S_t = 2|\psi_T) + \cdots + p_{ij} Pr(S_t = j|\psi_T),
$$

where $p_{ij}$ shows the elements of the transition matrix $P_{ij}$. Short-term crisis signal can be seen from the number of predicted of smoothed probabilities values.

2.2. Method

The monthly data on lending interest rate / deposit interest rate from January 1990 to October 2018 were taken from International Financial Statistics (IFS). Data in January 1990 until December 2017 were used to build the model and the data in January 2018 to October 2018 were used as a data testing. The steps in this study are as follows.

1. Creating plot data and testing the stationarity of data using the Augmented Dickey Fuller (ADF) test. If the data is not stationary then performed data transformations using the log returns.
2. Make ARMA model and perform diagnostic test best models ARMA.
3. Clustering the volatility uses Dynamic Time Warping (DTW) distance and testing the heteroscedasticity of the residue ARMA using Lagrange multiplier test.
4. If there is any residual heteroscedasticity on the ARMA model, so it is identified the volatility models. Furthermore, it is done the diagnostic test (autocorrelation, heteroscedasticity and normality).
5. Perform the modeling using a combined of volatility and Markov regime switching models.
6. Calculate the smoothed probability value of each data lending interest rate / deposit interest rate.
7. If the smoothed probability value of the data lending interest rate / deposit interest rate is more than 0.921 then it can be predicted that there is currency crisis.
8. Predicting the currency crisis for the future year.

3. Result and discussions

Plot the data lending interest rate / deposit interest rates can be seen in Figure 1.
Figure 1. Plot indicator of lending interest rate / deposit interest rate

Figure 1 shows the data contains a trend which indicates that the data is not stationary. In addition, the stationary data can also be seen from the ADF test. Based on the ADF test, probability value is greater than 0.05, which means that the data is not stationary so that the necessary transformation of log returns. Plot of log return lending interest rate / deposit interest rates can be seen in Figure 2.

![Figure 1](image1.png)

Figure 2. Plot of log returns of lending interest rate / deposit interest rate

Figure 2 shows that the log return data does not contain trend that indicates that data is stationary. The stationary of data can be shown by the ADF test. Based on the ADF test, probability value is less than 0.05, which means that the data is already stationary. Then, ACF and PACF are plotted to determine the order of ARMA model. Based on the value of AIC, the best model is ARMA (1.0) for the lending interest rate / deposit interest rate. ARMA (1.0) model can be written as follows

\[ r_t = 0.49647r_{t-1} + \epsilon_t \]

where \( r_t \) is the log return of lending interest rate / deposit interest rate at time \( t \), and \( \epsilon_t \) is the residuals at time \( t \). Plot of residue ARMA(1.0) model can be seen in Figure 3.

![Figure 2](image2.png)

Figure 3. Plot of residue ARMA (1.0) model.

Figure 3 shows that residues ARMA(1.0) model shaped leptokurtic. Leptokurtic curve indicates a range of different values, so it needs to cluster. Clustering analysis for the time series data is using DTW distance. Based on the results of clustering, the number of cluster corresponding to the lending interest rate / deposit interest rate is 3.

![Figure 3](image3.png)
Furthermore, it tests the heteroscedasticity of residue ARMA(1.0) model. Based on Lagrange multiplier test, probability value is less than 0.05. This means that the residue ARMA model contains heteroscedasticity. To handle the heteroscedasticity it is used volatility model. Volatility model for lending interest rate / deposit interest rate is GARCH (1,1), which can be written as follows

$$\sigma_t^2 = 0.0009936 + 0.2307a_{t-1}^2 + 0.6676\sigma_{t-1}^2,$$

where $\sigma_t^2$ is the variance at time $t$, and $a_{t-1}$ is the residual at time $t-1$.

Furthermore, the diagnostic test of residue GARCH (1,1) model is done. Based on the Ljung-Box test, probability value is greater than 0.05, which means that the volatility model does not contain any residual autocorrelation. A probability value of Lagrange multiplier test is greater than 0.05, which means that residual of volatility model has already homogeneous. A probability value of the Kolmogorov-Smirnov test is greater than 0.05, which means that residual of volatility model is a normal distribution.

Regime is a change in conditions that occur in the Markov regime switching model. Regime is assumed to follow a first order of Markov chain for the lending interest rate / deposit interest rate with the transition probabilities $p_{ij}$ where $i, j = 1, 2, 3$. Based on that condition, Markov regime switching generalized autoregressive heteroscedasticity MRS-GARCH (3,1,1) model is a GARCH (1,1) model which has 3 regime, the regime 1,2,3 sequence illustrates the volatility of low, medium, and high. A regime has the possibility to survive in the same regime or the regime moved to another regime for the next time. The probability of regime change can be seen from transition probability matrix. Transition probability matrix of 3 regimes for lending interest rate / deposit interest rate is as follows.

$$P = \begin{pmatrix} 0.92741666 & 0.05977186 & 0.01281148 \\ 0.06156000 & 0.91671889 & 0.02172111 \\ 0.05040072 & 0.06298390 & 0.88661539 \end{pmatrix}.$$ 

The average and variance of each regime is

$$\mu_{2t} = \begin{cases} -0.01983988, & \text{for regime 1} \\ 0.00597216, & \text{for regime 2} \\ 0.08691729, & \text{for regime 3} \end{cases}, \quad \sigma_{2t}^2 = \begin{cases} 0.00117972, & \text{for regime 1} \\ 0.00014220, & \text{for regime 2} \\ 0.09117983, & \text{for regime 3} \end{cases}.$$

To detect a crisis, it can be seen from the lowest smoothed probability at the time of crisis in Indonesia (1997-1998). Based on lending interest rate / deposit interest rate indicator, the crises occurs when the smoothed probability value is more than 0.921. Plot of smoothed probability value for the lending interest rate / deposit interest rates can be seen in Figure 4.

**Figure 4.** Smoothed probability value of lending interest rate / deposit interest rate.

Figure 4 shows that there are 34 smoothed probability value that greater than 0.921. Lending interest rate / deposit interest rate indicator can detect the crisis in June - August 1991, September 1997 - November 1999, August to September 2003, June-July 2014. Based on this result, it can be concluded that the MRS-GARCH (3, 1, 1) model can detect a crisis. Furthermore, the prediction and actual of smoothed probabilities and prediction of crisis conditions can be determined using the model, as shown in Table 1.
Table 1. Comparison of prediction and actual smoothed probability for lending interest rate / deposit interest rate

| Periods      | Prediction of smoothed probability | Prediction crisis condition | Actual of smoothed probability | Actual crisis condition |
|--------------|------------------------------------|----------------------------|--------------------------------|-------------------------|
| January 2018 | 0.034088                           | stable                     | 0.001878                       | stable                  |
| February 2018| 0.048773                           | stable                     | 0.001040                       | stable                  |
| March 2018   | 0.061255                           | stable                     | 0.000888                       | stable                  |
| April 218    | 0.071790                           | stable                     | 0.001205                       | stable                  |
| May 2018     | 0.080669                           | stable                     | 0.002025                       | stable                  |
| June 2018    | 0.088110                           | stable                     | 0.004041                       | stable                  |
| July 2018    | 0.094321                           | stable                     | 0.003915                       | stable                  |
| August 2018  | 0.099477                           | stable                     | 0.003899                       | stable                  |
| September 2018| 0.103729                           | stable                     | 0.005469                       | stable                  |
| October 2018 | 0.107206                           | stable                     | 0.015909                       | stable                  |

Based on Table 1, it can be concluded that the actual and prediction of crisis situation is the same. This means that the model is very good to predict the financial crisis on one year ahead.

The monthly data from 1990 to 2018 can be calculated to predict the smoothed probability value and the crisis conditions as shown in Table 2.

Table 2. Smoothed probability value and prediction of crisis condition for lending interest rate / deposit interest rate.

| Periods        | Smoothed probability predictions | Prediction crisis condition |
|----------------|----------------------------------|----------------------------|
| November 2018  | 0.026513                         | stable                     |
| December 2018  | 0.036354                         | stable                     |
| January 2019   | 0.045441                         | stable                     |
| February 2019  | 0.053797                         | stable                     |
| March 2019     | 0.061452                         | stable                     |
| April 2109     | 0.068441                         | stable                     |
| May 2019       | 0.074805                         | stable                     |
| June 2019      | 0.080582                         | stable                     |
| July 2019      | 0.085816                         | stable                     |
| August 2019    | 0.090547                         | stable                     |
| September 2019 | 0.094814                         | stable                     |
| October 2019   | 0.098657                         | stable                     |
| November 2019  | 0.102111                         | stable                     |
| December 2019  | 0.105212                         | stable                     |

Table 2 shows the prediction of some future period from November 2018 to December 2019 based on indicators of lending interest rate / deposit interest rate. There are no signs of crisis on currency in Indonesia. However, the question is when it will be in crisis? Based on simulation results, when the indicator has decreased or the increase of 14% is possible to experience a crisis as the result of smoothed probability in Figure 5.
Figure 5. Smoothed probability of lending interest rate / deposit interest rate with a 14% increase or decrease

4. Conclusion
The model for lending interest rate / deposit interest rate indicator is the MRS-GARCH (3,1,1). Based on the model, it can be predicted that in 2019 in Indonesia there is no sign of a currency crisis

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