Prediction of Indonesian financial crisis using Markov regime switching autoregressive conditional heteroscedasticity models based on bank deposits and lending/deposit interest rate indicators

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Abstract. The financial crisis that occurred in middle of 1997 made Indonesia to become one of the countries which had the worst and the longest affected in term of its rate of recovery. This event made us aware of the importance of creating an early warning system for the financial crisis. The crisis occurred due to several macroeconomic indicators experiencing very high fluctuation and changes in the structure of the condition (regime). The combination of volatility and Markov regime switching models is a type of model that can explain the fluctuation and changes in such condition. The indicators of bank deposit and lending/deposit interest rate in January 1990 to June 2019 were used to construct the combined model. The results of this research showed that the MRS-ARCH(2,1) model for the bank deposit and lending/deposit interest rate indicators can explain the conditions of the financial crisis that occurred. The predicted value of the MRS-ARCH(2,1) model shows that from July 2019 to June 2020 there were no signs of a financial crisis in Indonesia.

1. Introduction
The devaluation of the Thai Bath currency in middle 1997 caused financial crisis in Asia. The crisis then spread to several countries in Asia such as Indonesia, Hong Kong, Laos, South Korea and Malaysia. Indonesia is one of the worst affected countries and has the longest recovery period due to the financial crisis. Based on these events, an early warning system becomes very important to detect financial crises. Banking indicators such as bank deposits and lending/deposit interest rate can detect financial crisis. These banking indicators have changing condition and high fluctuation. Volatility models can be used to explain high volatility, whereas Markov regime switching model can be used to explain changing condition.

Engle [1] introduced ARCH model, this model was used to estimate the average and variation of annual inflation data in United Kingdom from 1958-1977. Prediction of variance from ARCH model is more realistic. Generalized autoregressive conditional heteroscedasticity (GARCH) was introduced by Bollerslev [2] to estimate model for United States gross national product data from 1948-1983. The GARCH model are less able to clarify the effects of leverage in some cases. According to Chen [3], the leverage effect is a condition where volatility experiences face good and bad news periodically so that it generates asymmetrical effect on volatility.
According to Hamilton [4], Markov regime switching (MRS) is a time series model that explains changing conditions. Based on Hamilton and Susmel [5], a combination between MRS and ARCH model was implemented on the United States GNP data from 1952-1984 and this combined model can explain the changing condition of GNP data. Chang [6] identified volatility of exchange rate and stock market in Korea and the global financial crisis using the MRS-ARCH model. Sugiyanto [7] forms a model which can detect financial crisis using a combination of volatility and MRS model based on ICI, real output and domestic credit/GDP indicators. This research discusses the financial crisis that occurred in Indonesia based on bank deposit and lending/deposit interest rate using a combination of volatility and MRS model.

2. Theoretical framework
There are several theories that are in this research to detect and predict financial crisis in Indonesia using a combination of MRS and volatility model.

2.1. Autoregressive Moving Average (ARMA) Model
According to Tsay [8], ARMA \((p, q)\) can be formulated as

\[ r_t = \phi_0 + \phi_1 r_{t-1} + \cdots + \phi_p r_{t-p} + \epsilon_t - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} - \cdots - \theta_q \epsilon_{t-q}, \]

with \( r_t \) is log return data at time \( t \), \( \epsilon_t \) is ARMA residual, \( \phi_0 \) is model constant, \( \phi_1, \ldots, \phi_p \) are parameter of the AR \((p)\), and \( \theta_1, \theta_2, \ldots, \theta_q \) are parameter of the MA \((q)\).

2.2. Volatility Model
Based on Engle [1], Autoregressive Conditional Heteroscedasticity (ARCH) with \( m \) order model can be written by

\[ \alpha_t = \sigma_t \epsilon_t, \]

with \( \epsilon_t \sim N(0,1) \) and \( \alpha_t | \psi_{t-1} \sim N(0, \sigma_t^2) \).

\[ \sigma_t^2 = \alpha_0 + \sum_{i=0}^{m} \alpha_i \epsilon_{t-i}^2, \]

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

If the order of ARCH model was greater than 5, then the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) was formed. Based on Tsay [8], GARCH \((m, s)\) can be written as

\[ \sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \cdots + \alpha_s \epsilon_{t-s}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_m \sigma_{t-m}^2 \]

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

with \( \beta_j \) is the parameter of GARCH model.

2.3. Markov Regime Switching Autoregressive Conditional Heteroscedasticity (MRS-ARCH) Model
According to Hamilton and Susmel [5], MRS-ARCH model with \( k \) optimum state and \( m \) order can be written as

\[ r_t = \mu_s + \sigma_t \epsilon_t, \quad \alpha_t = \sigma_t \epsilon_t, \]

\[ \sigma_{s,t}^2 = \alpha_0 s_t + \sum_{l=1}^{m} \alpha_l s_t \epsilon_{t-l}^2. \]
2.4. Markov Regime Switching Generalized Autoregressive Conditional Heteroscedasticity (MRS-GARCH) model
According to Gray [9], MRS-GARCH model can be written as
\[
\sigma_{t}^2 = \alpha_0 s_t + \sum_{i=1}^{m} \alpha_{i} \sigma_{t-i}^2 + \sum_{j=1}^{s} \beta_{j} s_t \sigma_{t-j}^2,
\]
for \( r_t \) is used to represent a vector of observed variables , \( s_t \) shows unobserved random variables which meet the first order of Markov chain that we can take values from them \( 1, 2, \ldots, T \). Variables \( s_t \) is considered as a regime which its process in the \( t \) and \( s_t \).

2.5. Transition Probability
The parameter of random variables and conditional distribution that are not observed with constant transition probability is written by
\[
P[s_t = j|s_{t-1} = i] = p_{ij},
\]
\[
\sum_{j=1}^{T} p_{ij} = 1, \text{ for } i, j = 1, 2, \ldots, T,
\]
in matrix form, \( P \) can be written as
\[
P = \begin{pmatrix}
p_{11} & p_{21} & \cdots & p_{T1} \\
p_{12} & p_{22} & \cdots & p_{T2} \\
\vdots & \vdots & \ddots & \vdots \\
p_{1T} & p_{2T} & \cdots & p_{TT}
\end{pmatrix}.
\]

2.6. Smoothed probability
According to Kim and Nelson [10], smoothed probability is written by
\[
Pr(S_T = i | \psi_T) = \sum_{s=1}^{T} Pr(S_{t+1} = s | \psi_T) Pr(S_t = i | S_{t+1} = T, \psi_T).
\]
According to Sopipan et al. [11], the predicted value of smoothed probability value at \( T + 1 \) can be obtained with
\[
Pr(S_{t+1} = i | \psi_T) = p_{1i} Pr(S_t = 1 | \psi_T) + p_{2i} Pr(S_t = 2 | \psi_T) + \cdots + p_{ji} Pr(S_t = j | \psi_T),
\]
where \( p_{ji} \) some elements of \( P_{ij} \) transition matrix.

3. Method of research
The data used in this research are monthly data from January 1990 to June 2019 of bank deposits and lending/deposit interest rate indicators. Those data were obtained from the IMF. The data is separated into two parts, from January 1990 to June 2018 used as training data while from July 2018 to June 2019 as testing data. The stages carried out in this research are as follows:
(1) Making a plot of data.
(2) Measuring stationarity of both data using ADF test. If the data were unstationary, transformation was done using log return transformation.
(3) Estimating the ARMA \((p,q)\) model.
(4) Measuring the heteroscedasticity on residual ARMA using the Lagrange multiplier test.
(5) Conducting volatility clustering on the ARMA residual model using Agglomerative Hierarchical Clustering with a distance of Dynamic Time Wrapping (DTW) to determine the number of regimes used.
(6) Estimating volatility model and conducting assumption tests (autocorrelation, normality and heteroscedasticity tests) on the residual of volatility model.
(7) Forming a combination of volatility and MRS model with assumption \( k \) regime which was obtained from optimal number of clusters.
(8) Determining crisis condition based on the smoothed probability.
(9) Comparing predicted and actual value of smoothed probability to determine model accuracy.
(10) Predicting the financial crisis in July 2019-June 2020.

4. Results and discussion

The data is separated into two parts, from January 1990 to June 2018 used as training data while from July 2018 to June 2019 as testing data. The training data is used to estimate the model while the testing data is used to evaluate the model.

4.1. Data and transformed data plot

The plot of data from both indicators shown in Figure 1 and Figure 2.

![Figure 1. data plot of bank deposits.](image1)

![Figure 2. data plot of lending/deposit interest rate.](image2)

Based on figure 1 and figure 2 it can be seen that both data contain trends which indicate that the data were not stationary. Moreover, probability value of ADF test was greater than $\alpha = 0.05$, so both data were not stationary. Therefore, transformation to stationary the data using log return was performed. Log return transformation plot of each indicator shown in figure 3 and figure 4.

![Figure 3. Log return transformation plot of bank deposits.](image3)

![Figure 4. Log return transformation plot of lending/deposit interest rate.](image4)
Figure 3 and figure 4 show that the data of log return fluctuate around zero, indicating that the data were stationary. Moreover, probability value of ADF test was less than $\alpha = 0.05$, so the transformed data were stationary.

4.2. ARMA Model Estimation

The next step was to make an ACF and PACF plot to estimate the ARMA model. ARMA (1,0) for bank deposits and ARMA (1,0) without an intercept for lending/deposit interest rate is the best ARMA model with the smallest AIC. Then, the best model for each indicator are written by

$$r_t = -0.1065345 + 0.0147555 r_{t-1} + \epsilon_t,$$

$$r_t = 0.3509 r_{t-1} + \epsilon_t.$$

4.3. Clustering on the ARMA Residual

The residual plot of ARMA (1,0) and ARMA (1,0) model without intercept shown in the figure 5 and figure 6.

![Figure 5. ARMA residual plot of bank deposits](image)

![Figure 6. ARMA residual plot of lending/deposit interest rate.](image)

Figure 5 and figure 6 show that the residue of ARMA model was leptokurtic so that clustering is necessary to be done. Agglomerative Hierarchical Clustering with Dynamic Time Warping (DTW) distance is used to cluster the residue of ARMA model. The optimal number of clusters was 2 for each indicators.

4.4. Volatility Model Estimation

Furthermore, the residual values of the ARMA(1,0) and ARMA(1,0) without intercept are used to check the effects of heteroscedasticity using Lagrange multiplier (LM) test. The probability value of LM test is smaller than $\alpha = 0.05$, so it can be concluded that the ARMA model residuals contain heteroscedasticity effects. To deal with heterocedasticity, a volatility model is formed. ARCH (1) is the best volatility model for bank deposits, it can be written as

$$\sigma_t^2 = 0.001123 + 1.957a_{t-1}^2,$$

whereas for lending/deposit interest rate, ARCH (1) is also the best volatility model that can be written as

$$\sigma_t^2 = 0.0025483 + 2.6450537a_{t-1}^2.$$
The next step is conduct a diagnostic test on the residues of each volatility model. The probability value of the Ljung-Box test is greater than $\alpha = 0.05$, it means that there is no autocorrelation in the volatility model. According to Kolmogorov-Smirnov test, the probability value is greater than $\alpha = 0.05$, it means that the residual is normally distributed. Then, the probability value of LM test is greater than $\alpha = 0.05$, it means that the residual is homogeneous.

4.5. MRS-ARCH Estimation

The MRS-ARCH (2,1) model for each indicator is the ARCH(1) model which has 2 regimes. The first regime describes low volatility and the second regime describes high volatility. The transition probability matrix with two regimes for bank deposits is

$$
\begin{pmatrix}
0.9581 & 0.0419 \\
0.3672 & 0.6328
\end{pmatrix}
$$

Based on matrix above, it can be concluded that the probability to stay on low volatility of 0.9581 and probability to stay on the high volatility of 0.6328.

The mean and variance for each regime are

- for regime 1: $\mu_{1,t} = 0.00003723$, $\sigma_{1,t} = 0.00000109$
- for regime 2: $\mu_{2,t} = 0.00001011$, $\sigma_{2,t} = 0.00005685$

The mean and variance of each regime are

- for regime 1: $\mu_{1,t} = -0.00000772$, $\sigma_{1,t} = 0.00041333$
- for regime 2: $\mu_{2,t} = 0.00001358$, $\sigma_{2,t} = 0.00001716$

4.6. Crisis Detection

Crisis condition can be determined using minimum value of smoothed probability when the financial crisis happened in Indonesia (on 1997 and 2008). Result shows that the crisis occurred when the smoothed probability value was greater than 0.70 for bank deposits and greater than 0.65 for lending/deposit interest rate. Figure 7 and figure 8 show the smoothed probability plot of each indicator.
Based on figure 7, the value of smoothed probability greater than 0.7 is 28. Based on figure 8, the smoothed probability value greater than 0.65 is 68. Bank deposits indicator detect crises on March 1990 to June 1990, December 1990 to April 1991, December 1991 to April 1992, November 1992, April 1993, November 1997 to January 1998, May 1998 to October 1998, October 1999, January 2004, and January 2018. For lending/deposit interest rate indicator detect crises on September 1990 to October 1991, June 1995 to January 1997, August 1997 to September 1999, October 2001 to April 2002, and August 2008. Therefore, it can be concluded that the MRS-ARCH (2,1) of each indicator can detect crises in Indonesia.

According to the smoothed probability of those indicators, that lending/deposit interest rate indicator can give crisis signal faster than bank deposits indicator. It was caused by the actual crisis condition which began on July 1997, while lending/deposit interest rate indicator gave a sign of crisis condition starting on June 1995 and the bank deposits indicator gave a signal of crisis starting on November 1997.

Next, predict the value of smoothed probability in the testing data. The results of the predicted smoothed probability in the testing data for both indicators are shown in table 1 and 2.
**Table 1.** Comparison between predicted and actual smoothed probability values for bank deposits in the testing data.

| period        | prediction | crisis condition | actual | crisis condition |
|---------------|------------|------------------|--------|------------------|
| July 2018     | 0.064269   | steady           | 0.00454 | steady           |
| August 2018   | 0.079877   | steady           | 0.004114 | steady          |
| September 2018| 0.089099   | steady           | 0.002424 | steady          |
| October 2018  | 0.094549   | steady           | 0.004688 | steady          |
| November 2018 | 0.097769   | steady           | 0.003003 | steady          |
| December 2018 | 0.099672   | steady           | 0.002195 | steady          |
| January 2019  | 0.100796   | steady           | 0.002118 | steady          |
| February 2019 | 0.10146    | steady           | 0.003399 | steady          |
| March 2019    | 0.101853   | steady           | 0.003356 | steady          |
| April 2019    | 0.102085   | steady           | 0.014513 | steady          |
| May 2019      | 0.102222   | steady           | 0.004434 | steady          |
| June 2019     | 0.102303   | steady           | 0.005914 | steady          |

**Table 2.** Comparison between predicted and actual smoothed probability values of lending/deposit interest rate in the testing data.

| period        | prediction | crisis condition | actual  | crisis condition |
|---------------|------------|------------------|---------|------------------|
| July 2018     | 0.02768    | steady           | 0.000594 | steady          |
| August 2018   | 0.047558   | steady           | 0.000635 | steady          |
| September 2018| 0.065264   | steady           | 0.000813 | steady          |
| October 2018  | 0.081038   | steady           | 0.001137 | steady          |
| November 2018 | 0.095088   | steady           | 0.001754 | steady          |
| December 2018 | 0.107605   | steady           | 0.003227 | steady          |
| January 2019  | 0.118754   | steady           | 0.012454 | steady          |
| February 2019 | 0.128686   | steady           | 0.035088 | steady          |
| March 2019    | 0.137534   | steady           | 0.152335 | steady          |
According to Table 1 and 2, it can be seen that the predicted and actual crisis conditions in the testing data are the same. So, both models can predict the actual condition of financial crisis in Indonesia correctly. Next, we can predict the value of smoothed probability of the next period of the two indicators, the predicted results are shown in Table 3.

**Table 3.** Predicted value of smoothed probability of bank deposits and lending/deposit interest rate in the next period.

| period       | bank deposits | crisis condition | lending/deposit interest rate | crisis condition |
|--------------|---------------|------------------|-------------------------------|-----------------|
| July 2019    | 0.04362       | steady           | 0.040466                      | steady          |
| August 2019  | 0.066058      | steady           | 0.056987                      | steady          |
| September 2019 | 0.079411     | steady           | 0.069576                      | steady          |
| October 2019 | 0.087358      | steady           | 0.078927                      | steady          |
| November 2019 | 0.092086     | steady           | 0.085623                      | steady          |
| December 2019 | 0.094901      | steady           | 0.09015                       | steady          |
| January 2020 | 0.096575      | steady           | 0.092914                      | steady          |
| February 2020 | 0.097572      | steady           | 0.094253                      | steady          |
| March 2020   | 0.098165      | steady           | 0.094448                      | steady          |
| April 2020   | 0.098518      | steady           | 0.093735                      | steady          |
| May 2020     | 0.098728      | steady           | 0.092306                      | steady          |
| June 2020    | 0.098853      | steady           | 0.090322                      | steady          |

Based on Table 3, it can be seen that the smoothed probability in June 2019 to June 2020 is less than 0.7 for bank deposits and less than 0.65 for the lending / deposit interest rate. So it can be concluded that in June 2019 until June 2020 there will be no financial crisis in Indonesia or Indonesia's economic conditions will be steady.

**5. Conclusion**

MRS-ARCH (2,1) is the best model based on the indicators of bank deposits and lending/deposit interest rate. Then, based on the result of the predicted smoothed probability of both MRS-ARCH (2,1) model, it was found that in July 2019-June 2020 a financial crisis would not occur in Indonesia.
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