Financial crisis prediction in Indonesia using combined of volatility and Markov switching models based on real interest rate on deposit and nominal exchange rate indicators

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Abstract. The financial crisis has happened Indonesia 1997 and 2008. The crisis had brought the disadvantages impact on the economy of Indonesia. To anticipate the impact of the crisis, an early detection system that can detect some signs of a financial crisis is needed so that the government as a decision maker in maintain the stability of the economy. The crisis occurred due to high volatility and structural changes in macroeconomic indicators. One of model that can be used to captured signals crisis is a combination of volatility and Markov switching. Fluctuations can be explained using volatility model, while some changes in conditions are explained through Markov switching. This study uses indicators of the real interest rate on deposit and nominal exchange rate to detect signals crisis in Indonesia. The results showed that the MS-ARCH(2,1) models of the real interest rate on deposit could only explain the crisis that occurred in 1997 and the MS-GARCH(3,1,1) models of nominal exchange rate could explain the crisis that occurred in 1997 and 2008. Based on the predicted value of smoothed probability, it shows that from July 2019 to June 2020, there are no signals of financial crisis in Indonesia.

1. Introduction
Indonesia has experienced two major crisis in 1997 and 2008. The financial crisis in 1997 is begun with the decline of the Bath Thailand exchange rate, while the crisis in 2008 is begun with bad credit in property sector in America. The impact of the financial crisis was the disruption of economic stability in Indonesia. To anticipate impact of crisis, an early warning system is needed to anticipate future crises. The early detection system for a financial crisis in Indonesia can be observed through several indicators. Kaminsky et al. [1], develop a crisis early detection system by observing 15 indicators when a crisis occurs. The indicators are real interest rate on deposit and nominal exchange rate.

Banks are financial business institutions that collect funds from the public. One of the bank’s products in collecting customer’s funds is deposits. Customers who have bank deposits are entitled to receive service fees. The real interest rate on deposit is obtained from reduction between the deposit interest rate and inflation. Bank Indonesia as the central bank has the authority to set the interest rate. The high difference between domestic interest rate on central bank and interest rate on foreign will affect the nominal exchange rate.
Time series data are indicated to contain effect of heteroscedasticity so that it can use the volatility model. Hamilton [2] introduces the Markov switching (MS) that can solve the problem of changing data time series condition. Hamilton and Susmel [3] introduced MS-autoregressive conditional heteroscedasticity (ARCH) models used to describe volatility stock prices. Chang et al. [4] identify the MS-ARCH models the global financial crisis and accurate state in Korea with the assumption of three states. Gray [5] applies MS-generalized autoregressive conditional heteroscedasticity (GARCH) models to United States interest rate data.

Sugiyanto et al. [6] conducted research about detection of financial crisis based on Indonesia Composite Index, domestic credit/ Gross Domestic Product, and real output indicators in Indonesia from 1990 to 2016. Based on three indicators, the financial crisis can be detected in 1997-1998 and 2008 by applying the MS-ARCH(3,1) models. Sugiyanto et al. [7] uses the difference real BI rate and real Fed rate, the real interest rate on deposit, and the difference between interest rate on deposit and lending indicators to detect crisis in Indonesia. The result show that the MS-GARCH(3,1,1) models can detect crisis in the middle 1997 to 1998. This paper detects and predicts the financial crisis in Indonesia using Markov switching and volatility models based on real interest rate on deposit and nominal exchange rate indicators.

2. Materials
Stationarity requirements must fulfill in time series data. The time series data stationarity can be apply using ADF (Augmented Dickey Fuller) test. One way to stationarity data is to use log return transformation. The log return transformation can be given as follows
\[ r_t = \ln \frac{Y_t}{Y_{t-1}} \]
where \( Y_t \) denotes the data at time \( t \) and \( Y_{t-1} \) denotes the data at time \( (t-1) \).

2.1. Autoregressive moving average (ARMA) model
The model of ARMA using stationary data consists components AR with orde \( p \) and MA with orde \( q \). According to Tsay [8], the model of ARMA\( (p,q) \) can be formulated as
\[ r_t = \phi_0 + \sum_{i=1}^{p} \phi_i r_{t-i} + a_t - \sum_{i=1}^{q} \theta_i a_{t-i}, \]
where \( \phi_0 \) is the constant, \( \phi_i \) is parameter of AR model, \( a_t \) is the residual at time \( t \), and \( \theta_i \) is parameter of MA model.

2.2. Volatility model
The volatility model is used if the residual of ARMA model contain heteroscedasticity effect. Variance modelling of residual can use the ARCH model. In the ARCH model the function of past residuals is expressed as conditional variance. The model of ARCH\( (m) \) formulation as
\[ \sigma_i^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}, \]
where \( \sigma_i^2 \) is variance at time \( t \), \( \alpha_0 \) is constant, \( \alpha_i \) is parameters of ARCH, and \( m \) is order of ARCH model. The GARCH model is a development the model of ARCH. The model of GARCH\( (m,s) \) can be formulated as
\[ \sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2, \]
where \( \beta_j \) denotes parameters of GARCH model and \( s \) denotes order of GARCH model (Tsay [8]).
2.3. Markov switching model
Markov switching model is an alternative to developing time series data models that explain changing conditions. Changes in conditions that occur are considered as unobservable variables called states. The conditional mean Markov switching model is formulated as

\[ r_t = \mu_{s_t} + \tilde{r}_t, \]  

(4)

where \( r_t \) is observable variable, \( \mu_{s_t} \) denotes mean model that depend on the state and \( \tilde{r}_t \) is following the ARMA\((p,0)\) process (Hamilton and Susmel [3]). According to Hamilton [2] the Markov switching model of equation (4) of the time series process for the state at the time \( t \) can be formulated as

\[ r_t - \mu_{s_t} = \sum_{i=1}^{p} \phi_i r_{t-i} + a_t, \]  

(5)

The \( s_t \) variable follows Markov chain’s first order process with \( p_{ij} \) transition probability can be formulated as.

\[ p_{ij} = Pr[s_t = j | s_{t-1} = i] \]  

(6)

and \( p_{ij} \) can be written in the matrix as below

\[ P = \begin{bmatrix} p_{11} & p_{21} & \cdots & p_{1t} \\ p_{12} & p_{22} & \cdots & p_{2t} \\ \vdots & \vdots & \ddots & \vdots \\ p_{1K} & p_{2K} & \cdots & p_{Kt} \end{bmatrix} \]  

(7)

2.4. Combination volatilitas and Markov switching models
According to Hamilton and Susmel [3], the MS-ARCH\((K,m)\) models can be expressed as

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

(8)

and Gray [5], the MS-GARCH\((K,m,s)\) models can be expressed as

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

(9)

where \( s_t \) denotes state at time \( t \) and \( \sigma_{t,s_t}^2 \) denotes the residual variance at period state \( t \).

2.5. Smoothed probability
Based on Kim and Nelson [9], smoothed probability value can be formulated as

\[ Pr(S_t = y|\psi_T) = \sum_{j=1}^{K} Pr(S_t = y, S_{t+1} = j|\psi_T), \]  

(10)

where \( \psi_T \) denotes all information until time \( t \) and \( K \) denotes number of states.
3. Methods
This paper uses real interest rate on deposit and nominal exchange rate indicators. Data is collected monthly starts from January 1990 to June 2019 where training data from January 1990 to June 2018 and testing data from July 2018 to June 2019. Data obtained from International Financial Statistics (IFS). The stages in this paper are as follows.
(1) Plotting the indicators and checking the stationarity of data using ADF test.
(2) Conducting log return transformation if the data are non stationary.
(3) Forming the ARMA model and checking heteroscedasticity effect on the residual model.
(4) Forming the volatility model if there is an heteroscedasticity effect. Then do diagnostic test on the residual of volatility model.
(5) Forming a combination of Markov switching and volatility models.
(6) Calculating smoothed probability values of each indicator.
(7) Determining the limit on smoothed probability values for each indicator.
(8) Predicting financial crisis of Indonesia in the future.

4. Result and discussions
In this section will discuss the prediction of financial crisis based on real interest rate on deposit and nominal exchange rate indicators in Indonesia. The prediction of financial crisis begins with testing the stationarity data, the determination of ARMA estimation models, the volatility models, the Markov switching models, the combined volatility and Markov switching models. So obtained the results prediction and forecast financial crisis in the future.

4.1. Stationarity data
The stationarity of real interest rate on deposit and nominal exchange rate indicators can be identified using time series data plots. Plot of the two indicators showed in figure 1 and figure 2.

Figure 1. Plot of real interest rate on deposit. Figure 2. Plot of nominal exchange rate.

Figure 1 show that the data is indicated an downtrend and figure 2 show that the data is indicated an uptrend. This means that both indicators are non stationary. This is confirmed with an ADF test to see stationarity of data. Probability values of ADF test for real interest rate on deposit and nominal exchange rate indicators are 0.2185 and 0.2662 respectively, where the values is more than the level of significance \( \alpha = 0.05 \) which means non stationary. So, it is needed to transform for both indicators. The data plots of the two indicators after the log return transformation showed in figure 3 and figure 4.
Based on the two pictures above shows that the both indicators are stationary because the data fluctuate around a constant average. This is confirmed by ADF test of the two log return data that obtained each probability values of 0.01. The probability is smaller than level of significance $\alpha = 0.05$ it means stationary. So that the both indicators could be modelled using the model of ARMA.

4.2. ARMA model
The model of ARMA are obtained based on the significant parameters and the smaller Akaike Information Criterion (AIC) value. The model for real interest rate on deposit indicator is ARMA(2,0) which formulation as $r_t = -0.4240r_{t-1} - 0.1995r_{t-2} + a_t$ and based on the indicator of nominal exchange rate indicator is ARMA(2,0) which formulation as $r_t = 0.1380r_{t-1} - 0.1302r_{t-2} + a_t$. Then, a test of the effects of heteroscedasticity is conducted on the residual ARMA models for each indicator. The effect of heteroscedasticity in both models can be tested using Lagrange Multiplier test on the residuals of ARMA(2,0). The probability for both models is obtained of $2.76 \times 10^{-8}$ and $2.12 \times 10^{-5}$ respectively. The values are smaller than the level of significant $\alpha = 0.05$. So that the both ARMA(2,0) model contains heteroscedasticity effect and must be modelled into volatility model.

4.3. Volatility model
The appropriate volatility model for real interest rate on deposit indicator is ARCH(1) which can be written as $\sigma_i^2 = 0.0033 + 2.7922a_{i-1}^2$, while for nominal exchange rate indicator is GARCH(1,1) which can be written as $\sigma_i^2 = 0.0000113 + 1.142a_{i-1}^2 + 0.4796a_{i-2}^2$. Based on the results volatility model, then a diagnostic test on the residual of volatility model. The results of diagnostic test on the residual of volatility model through Ljung-Box test, Lagrange Multiplier test, and Kolmogorov-Smirnov test for the residual volatility model. ARCH(1) model indicate the probability values obtained are 0.14, 0.9136, and 0.8798 respectively, whereas for the GARCH(1,1) model the probability values obtain are 0.131, 0.9951, and 0.6921 respectively. The values more than the level of significance $\alpha = 0.05$, it means that the residuals of ARCH(1) and GARCH(1,1) are no autocorrelation, homogeneous, and normal distribution.

4.4. Combination of volatility and Markov switching models
Changes in these conditions are described in conditions of high volatility and low volatility. The combined model for the real interest rate on deposit indicator is MS-ARCH(2,1) with the assumption
two states. To model change in conditions matrix of transition probability for real interest rate on deposit indicator can be written as.

\[
P_1 = \begin{pmatrix}
0.8436 & 0.1564 \\
0.2263 & 0.7737
\end{pmatrix}
\]

Based on \( P_1 \) the state probability to stick out in low volatility is 0.8436 and the state probability to stick out in high volatility is 0.7737. Whereas for the nominal exchange rate, it uses the combined MS-GARCH(3,1,1) assumption three states. The three states consist of states with high, medium, and low volatility. Nominal exchange rate indicator have a matrix of transition probability is as follows.

\[
P_2 = \begin{pmatrix}
0.979801 & 0.015664 & 0.009127 \\
0.000833 & 0.949128 & 0.013638 \\
0.019366 & 0.035207 & 0.977235
\end{pmatrix}
\]

From the matrix of transition probability \( P_2 \) the state probability to stick out in low volatility is 0.979801, medium volatility is 0.949128 and high volatility is 0.977235.

The mean and variance MS-ARCH(2,1) each state respectively are

\[
\mu_{1,t} = \begin{cases} 
-0.00194975 & \text{for state 1} \\
0.00007914 & \text{for state 2}
\end{cases}
\]

\[
\sigma^2_{1,t} = \begin{cases} 
0.00238786 & \text{for state 1} \\
0.01009811 & \text{for state 2}
\end{cases}
\]

Whereas the mean and variance MS-GARCH(3,1,1) each state respectively are

\[
\mu_{2,t} = \begin{cases} 
0.000003, & \text{for state 1} \\
0.000008, & \text{for state 2} \\
0.000001, & \text{for state 3}
\end{cases}
\]

\[
\sigma^2_{2,t} = \begin{cases} 
0.000001, & \text{for state 1} \\
0.000077, & \text{for state 2} \\
0.00000005, & \text{for state 3}
\end{cases}
\]

4.5. Smoothed probability

The financial crisis can be detected by looking at the value of smoothed probability for each indicator. Smoothed probability plot showed in figure 5 and figure 6.

![Figure 5. Smoothed probability for real interest rate on deposit.](image1)

![Figure 6. Smoothed probability for nominal exchange rate.](image2)

Hermosillo and Hesse [10] state that the value limit of the smoothed probability in a crisis-prone state is between 0.4 and 0.6, while in crisis state if more than 0.6. However, each indicator has different characteristics so that each indicator can have different conditions. The determination of the limit smoothed probability based on the actual situation in Indonesia. The limit obtained from the lowest smoothed probability during crisis and then used to predict the crisis from July 2019 to June 2020 in Indonesia. Figure 5, the financial condition experience crisis if the smoothed probability value more than 0.92 and a noncrisis condition if less than 0.92. Based on this limits, the crisis of 1997 could be
detected in August 1997 to October 1998. Figure 6, a crisis will occur if the nominal exchange rate indicator has a smoothed probability value more than 0.97. The crisis that occurred from August 1997 to January 1999, from June 1999 to January 2000, from May 2000 to September 2000, from April 2001 to September 2001, and from October 2008 to January 2009.

Table 1 is the forecast and actual smoothed probability of the two indicators. Condition of forecast and actual produce noncrisis conditions.

### Table 1. Actual and forecast of smoothed probability.

| Month        | Real interest rate on deposit | Nominal exchange rate |
|--------------|-------------------------------|-----------------------|
|              | Forecast | Condition | Actual | Condition | Forecast | Condition | Actual | Condition |
| July 2018    | 0.02070  | Noncrisis | 0.00090 | Noncrisis | 0.02246  | Noncrisis | 0.00014 | Noncrisis |
| August 2018  | 0.03467  | Noncrisis | 0.00160 | Noncrisis | 0.03687  | Noncrisis | 0.00022 | Noncrisis |
| September 2018 | 0.04610 | Noncrisis | 0.00139 | Noncrisis | 0.05057  | Noncrisis | 0.00028 | Noncrisis |
| October 2018 | 0.05546  | Noncrisis | 0.00062 | Noncrisis | 0.06358  | Noncrisis | 0.00102 | Noncrisis |
| November 2018 | 0.06312 | Noncrisis | 0.00057 | Noncrisis | 0.07595  | Noncrisis | 0.00450 | Noncrisis |
| December 2018 | 0.06940 | Noncrisis | 0.00056 | Noncrisis | 0.08770  | Noncrisis | 0.00136 | Noncrisis |
| January 2019  | 0.07454  | Noncrisis | 0.00080 | Noncrisis | 0.09888  | Noncrisis | 0.00093 | Noncrisis |
| February 2019 | 0.07875 | Noncrisis | 0.00103 | Noncrisis | 0.10951  | Noncrisis | 0.00021 | Noncrisis |
| March 2019    | 0.08219  | Noncrisis | 0.00060 | Noncrisis | 0.11962  | Noncrisis | 0.00013 | Noncrisis |
| April 2019    | 0.08501  | Noncrisis | 0.00068 | Noncrisis | 0.12924  | Noncrisis | 0.00018 | Noncrisis |
| May 2019      | 0.08732  | Noncrisis | 0.00107 | Noncrisis | 0.13840  | Noncrisis | 0.00065 | Noncrisis |
| June 2019     | 0.08921  | Noncrisis | 0.00287 | Noncrisis | 0.14712  | Noncrisis | 0.00337 | Noncrisis |

Table 1 shows that the smoothed probability value in the column actual and forecast for real interest rate on deposit indicator smaller than 0.92 which means that there is noncrisis condition. While in the column actual and forecast for nominal exchange rate indicator smaller than 0.97 which means that there is noncrisis condition. So it can be concluded that the two indicators show the noncrisis conditions between the forecast and actual smoothed probability are the same. Therefore, the combined models are appropriate to detect crisis for the next month.

### 4.6. The financial crisis prediction in Indonesia

Table 2 is the value prediction real interest rate on deposit and nominal exchange rate indicators for the next year.

### Table 2. The prediction of smoothed probability.

| Month        | Real interest rate on deposit | Nominal exchange rate |
|--------------|-------------------------------|-----------------------|
|              | Prediction | Condition | Prediction | Condition |
| July 2019    | 0.02007 | Noncrisis | 0.01850 | Noncrisis |
| August 2019  | 0.03415 | Noncrisis | 0.03287 | Noncrisis |
| September 2019 | 0.04567 | Noncrisis | 0.04653 | Noncrisis |
| October 2019 | 0.05511 | Noncrisis | 0.05952 | Noncrisis |
| November 2019 | 0.06284 | Noncrisis | 0.07188 | Noncrisis |
| December 2019 | 0.06917 | Noncrisis | 0.08363 | Noncrisis |
| January 2020 | 0.07435 | Noncrisis | 0.09483 | Noncrisis |
| February 2020 | 0.07859 | Noncrisis | 0.10548 | Noncrisis |
| March 2020   | 0.08206 | Noncrisis | 0.11563 | Noncrisis |
| April 2020   | 0.08491 | Noncrisis | 0.12531 | Noncrisis |
| May 2020     | 0.08723 | Noncrisis | 0.13453 | Noncrisis |
| June 2020    | 0.08914 | Noncrisis | 0.14332 | Noncrisis |
Based on table 2, it shows that the results prediction of smoothed probability for the both indicators smaller than the limit smoothed probability 0.92 and 0.97. So, it can be concluded that based on smoothed probability prediction from July 2019 to June 2020 Indonesia will not experience the financial crisis.

Then a data simulation in June 2019 shown in figure 7 and figure 8.

![Figure 7. Smoothed probability for real interest rate on deposit data simulation](image)

![Figure 8. Smoothed probability for nominal exchange rate data simulation.](image)

Figure 7 shows a simulation for real interest rate on deposit indicator in June 2019 will experience a crisis if the data has decreases by 6% from Mei 2019. While figure 8 show simulation for nominal exchange rate indicator in June 2019 will experience a crisis if the data has increases by 10% from Mei 2019.

5. Conclusion
The result this paper showed that the real interest rate on deposit indicator MS-ARCH(2,1) can only detect crisis signal in 1998 and nominal exchange rate indicator MS-GARCH(3,1,1) can detect crisis signals in 1998 and 2008. The prediction of smoothed probability values, it shows that there are no symptoms of financial crisis in the July 2019 to June 2020 in Indonesia. Current research focuses on the prediction of a univariate crisis model. The recommendation for further researcher can use a multivariate model and use other indicators.

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