Models for financial crisis detection in Indonesia based on bank deposits, real exchange rate and terms of trade indicators

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Abstract. Several times Indonesia has experienced to face a financial crisis, but the crisis occurred in 1997 had a tremendous impact on the economy and national stability. The impact of the crisis fall the exchange rate of rupiah against the dollar so it is needed the financial crisis detection system. Some data of bank deposits, real exchange rate and terms of trade indicators are used in this paper. Data taken from January 1990 until December 2016 are used to form the models with three state. Combination of volatility and Markov switching models are used to model the data. The result suggests that the appropriate model for bank deposit and terms of trade is SWARCH (3,1), and for real exchange rates is SWARCH (3,2).

1. Introduction
Impaired financial system stability can lead to financial crisis. In order to maintain this stability, it is necessary to monitor the indicators that contribute to the occurrence of the crisis. Financial crisis that hit Asia on the middle of 1997 is begun by the falling of Baht Thailand. The crisis is also happened in Indonesia that have seriously effect on the economic stability. Detection of crisis in a country could be seen through many indicators. According to Kaminsky et al. [1], there are 15 indicator that can be used to detect the crisis, three of them are bank deposits, real exchange rates, and terms of trade.

Monthly data of bank deposits, real exchange rates, and terms of trade are a time series data that are indicated having heteroschedasticity and condition changes. To overcome this condition, it is used a combination of volatility and Markov switching models. Such models include SWARCH (switching autoregressive conditional heteroscedasticity), MS-GARCH (Markov switching generalized autoregressive conditional heteroscedasticity), and MS-EGARCH (Markov switching exponential generalized autoregressive conditional heteroscedasticity). SWARCH model is introduced by Hamilton and Susmel [2]. Some researchers have conducted research on the detection of financial crisis that occurred in a country using the combination of volatility and Markov switching models. Chang et al. [3] used SWARCH model to identify the stock volatility foreign and global financial crisis in Korea based on real exchange rate on the period of January 4th 2000 to March 31st 2010 with three states assumption.

Gray [4] introduced the MS-GARCH model that have the same characteristics with SWARCH but involve more simple parameters, to model the rate data of the United States from January 1970 to April 1994. Mwamba and Majadibodu [5] identify a currency crisis on South Africa based on indicators of foreign currency using the MS-GARCH (1,1) model.
Henry [6] modeled short-term rates data in the UK on period of January 2\textsuperscript{nd} 1980 until August 29\textsuperscript{th} 2007 using the MS-EGARCH model. The result shows that the model MS-EGARCH able to capture the volatility asymmetries and changing conditions on the data. Shojaei [7] investigated the influence of oil price crisis in Tehran Stock Exchange. The model used is the MS-EGARCH (1,1) with two states, namely a low state (recession) and high state (expansion).

2. Experimental Details

2.1. Autoregressive (AR) Model
AR model is usually used as a linear time series models. AR model has an orde called p that can be determined by partial autocorrelation function (PACF) plot. Model AR(p) can be written as

$$r_t = \phi_1 r_{t-1} + \phi_2 r_{t-2} + \cdots + \phi_p r_{t-p} + \alpha_t,$$

where $r_t$ is log return series at time-$t$, $\Phi_p$ is parameter of AR model (Tsay [8]).

2.2. Volatility Model

2.2.1. ARCH Model. Residue of AR model containing heteroscedasticity effect can be modeled using a volatility model where the residue can be expressed as

$$\alpha_t = \alpha_t \varepsilon_t \; \text{for} \; \varepsilon_t \sim N(0,1) \; \text{and} \; \alpha_t \mid F_{t-1} \sim N(0, \sigma_{t}^2),$$

where $F_{t-1}$ is set of all the information in time $t-1$. Model ARCH(m) can be written as

$$\sigma_{t}^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i \varepsilon_{t-i}^2,$$

where $m$ is the order of ARCH model, $\alpha_0$ is a constant, $\alpha_i$ is a parameter of the ARCH model, and $\sigma_{t}^2$ is the residual variance to the time-$t$ (Tsay [8]).

2.2.2. GARCH Model. High order of ARCH model can be overcome using a GARCH(m,s) which can be written as

$$\sigma_{t}^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2,$$

where $\beta_j$ is parameter of GARCH model (Tsay [8]).

2.2.3. EGARCH Model. Leverage problem on GARCH effect can be overcome by the model EGARCH (m, s) which can be written as

$$\ln(\sigma_{t}^2) = \alpha_0 + \sum_{i=1}^{m} \alpha_i \left( \frac{\alpha_{t-i}}{\sigma_{t-i}^2} \right) - \frac{2}{\sqrt{\pi}} + \sum_{i=1}^{m} \gamma_i \frac{\alpha_{t-i}}{\sigma_{t-i}^2} + \sum_{j=1}^{s} \beta_j \ln(\sigma_{t-j}^2),$$

where $\gamma$ is a parameter Leverage effect (Tsay [8]).
2.3. **SWARCH Model**

According to Hamilton and Susmel [2], Markov switching model for the average conditional can be written as

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

where \( r_t \) is the log return at time \( t \), \( \tilde{r}_t \) is following the process of AR (p) with an average of zero, and \( \mu_{s_t} \) is the average of state at time \( t \). While SWARCH model can be written as

\[ r_t = \mu_{s_t} + \alpha_t + \sigma_{t,s_t} \epsilon_t \]

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

where \( \mu_{s_t} \) is the conditional average on a state and \( \sigma_{t,s_t}^2 \) is a variance of residue in a state at time \( t \).

2.4. **Smoothed Probability**

According to Kuan [9], smoothed probability value is defined as

\[ P(s_t = i | Z^T; \theta) = \sum_{s_t=1}^{3} P(s_{t+1} = i | Z^T; \theta) P(s_t = i | s_{t+1} = i, Z^T; \theta) \]

Based on Hermosillo and Hesse [10] while the probability of a low-volatility regime has decrease under 0.4 means that the indicator is stabil, the probability of a medium-volatility regime (though declining) still remains at around 0.4-0.6 means that the indicators is prone condition, and if the probability of a high-volatility regime has increased to over 0.6 means that the indicators on a crisis condition.

3. **Research Method**

The research used data of bank deposits, real exchange rate, and terms of trade from January 1990 to December 2016 that were obtained from Bank Indonesia and World Bank. The steps of the research are as follows.

1) Create a data plot and then test the stationary of data. If the data are not stationary then transform the data using log return.

2) Make a plot of partial autocorrelation function (PACF) of log return data then form the AR model.

3) Test the effects of heteroscedasticity on the residue of AR model using Lagrange multiplier test.

4) If there is the effects of heteroscedasticity on the residue of AR model, estimates the parameter of ARCH model.

5) Establish the combination of volatility and Markov switching models with the assumption of a three states.

6) Determine the conditions of the crisis based on the smoothed probability.

4. **Results and Discussion**

4.1. **Data**

Plot data of bank deposits, real exchange rate, and terms of trade can be seen in Figure 1.

![Figure 1](a) Bank Deposits Indicator (b) Real Exchange Rate Indicator (c) Terms of Trade Indicator
Figure 1 indicates that the data are not stationary in mean and variance. It is proven by ADF test with probability values for each data are 0.9322, 0.4678, and 0.3247 respectively. Then, the data were transformed using log return. Based on ADF test for log return data, the probability value is 0.01 where it is less than $\alpha = 0.05$ so it can be concluded that the data are stationary. The next step is to form an AR model.

### 4.2. Establishment of AR Model

AR model can be identified from PACF plot of log return data. Based on bank deposits, it was obtained an AR(1) model i.e. $\tau_1 = 0.22527 \tau_{t-1} + \epsilon_t$. Meanwhile for real exchange rate, it was obtained an AR(3) model i.e. $\tau_1 = 0.41724 \tau_{t-1} - 0.17960 \tau_{t-2} + 0.14351 \tau_{t-3} + \epsilon_t$ and for terms of trade, it was obtained an AR(2) model i.e. $\tau_1 = -0.61933 \tau_{t-1} - 0.31982 \tau_{t-2} + \epsilon_t$.

Based on Lagrange multiplier test on the residue of model, it was obtained the each probability of bank deposits, real exchange rate, and terms of trade as $0.003321$, $7.752 \times 10^{-13}$, and $0.0002142$ respectively. All of probability values are less than 0.05, it means that there are the effect of heteroscedasticity on the residue. To overcome this condition, it was used ARCH model.

### 4.3. Establishment of ARCH Model

For bank deposits, the best model is ARCH(1) which can be written as

$$\sigma^2_t = 0.0003955 + 0.5610426 a^2_{t-1}. $$

Meanwhile, the best model for real exchange rate is ARCH(2) which can be written as

$$\sigma^2_t = 1.515 \times 10^{-4} + 1.834 a^2_{t-1} + 0.03617 a^2_{t-2}, $$

and the best model for terms of trade is ARCH(1) which can be written as

$$\sigma^2_t = 0.0074505 + 0.2724708 a^2_{t-1}. $$

Ljung-Box test results the probability values each of bank deposits, real exchange rate and terms of trade as 0.1007, 0.2514, and 0.8663 respectively. These values are more than 0.05, so it can be concluded that the residue of ARCH models do not contain autocorrelation. Based on the Kolmogorov Smirnov test, the probability values of each indicators are 0.4969, 0.7335, and 0.972. These values are more than 0.05, so it can be concluded that the residue of ARCH models are normally distributed. Based on Lagrange multiplier test, the probability values of each indicators are 0.9241, 0.7629, and 0.2167. These values are more than 0.05, so it can be concluded that the residue of ARCH models do not contain the effect of heteroscedasticity. Based on these tests, it can be concluded that the ARCH models are the appropriate models. To model the changes of condition, it is used Markov switching model.

### 4.4. Establishment of SWARCH Model

The condition changes in Markov switching model are called states. The condition of intended in this research is low, medium and high volatility. States can be formed by transition probability. The transition probability can be formed as a matrix notation and usually called as matrix of transition probability, for bank deposits indicator transition probability matrix can be written as the following

$$P_1 = \begin{bmatrix}
0.42029 & 0.943161 & 0.057943 \\
0.573877 & 0.000863 & 0.582474 \\
0.005834 & 0.055976 & 0.359583
\end{bmatrix}. $$

Based on $P_1$ obtained that the probability to survive on low volatility state is 0.42029. Probability of transition from low to medium volatility state is 0.573877. Probability of transition from low to high volatility state is 0.005834. Probability of transition from medium to low volatility state is 0.943161. Probability survive in medium volatility state is 0.000863. As well as the probability of transition from medium to high volatility state is 0.055976. Probability of transition from high to low volatility state is 0.582474. Probability of transition from high to medium volatility state is 0.359583. The matrix of transition probability for real exchange rate and terms of trade stated in $P_2$ and $P_3$ as follows.
Based on $P_1$, the parameter estimates of SWARCH(3,1) model for bank deposits can be written as follows:

$\mu_t \begin{cases} 
0.015223, \text{for state 1,} \\
-0.00163, \text{for state 2,} \\
0.048424, \text{for state 3,}
\end{cases}$

$\sigma_t^2 \begin{cases} 
1.911 \times 10^{-6} + 0.010015a_{t-1}^2, \text{for state 1,} \\
0.0001058 + 0.371051a_{t-1}^2, \text{for state 2,} \\
7.722 \times 10^{-5} + 0.8681867a_{t-1}^2, \text{for state 3,}
\end{cases}$

Based on $P_2$, the parameter estimates of SWARCH(3,2) model for real exchange rate can be written as follows:

$\mu_t \begin{cases} 
0.004737, \text{for state 1,} \\
0.003718, \text{for state 2,} \\
0.026658, \text{for state 3,}
\end{cases}$

$\sigma_t^2 \begin{cases} 
3.133 \times 10^{-6} + 0.4102282a_{t-1}^2 + 0.031234a_{t-2}^2, \text{for state 1,} \\
4.052 \times 10^{-6} + 0.137679a_{t-1}^2 + 0.001046a_{t-2}^2, \text{for state 2,} \\
1.221 \times 10^{-5} + 0.007305a_{t-1}^2 + 0.013346a_{t-2}^2, \text{for state 3,}
\end{cases}$

Based on $P_3$, the parameter estimates of SWARCH(3,1) model for terms of trade can be written as follows:

$\mu_t \begin{cases} 
-0.00152, \text{for state 1,} \\
-0.00289, \text{for state 2,} \\
0.008067, \text{for state 3,}
\end{cases}$

$\sigma_t^2 \begin{cases} 
6.57 \times 10^{-6} + 0.224834a_{t-1}^2, \text{for state 1,} \\
3.536 \times 10^{-6} + 0.050367a_{t-1}^2, \text{for state 2,} \\
7.489 \times 10^{-5} + 1.542798a_{t-1}^2, \text{for state 3,}
\end{cases}$

where $\mu_t$ and $\sigma_t^2$ is the conditional mean and variance of SWARCH model.

4.5. Crisis Detection

Crisis detection using SWARCH(3,1) and SWARCH(3,2) can be seen by value of smoothed probability. Figure 2 show the smoothed probability plots of SWARCH (3,1) modeled by bank deposits and terms of trade while SWARCH(3,2) modeled by real exchange rate.

Figure 2. (a) Smoothed Probability of bank deposits (b) Smoothed Probability of real exchange rate (c)
Smoothed Probability of terms of trade.

Crisis condition signed with value of smoothed probability that greater than 0.6 for bank deposits and real exchange rate indicators, that greater than 0.8 for terms of trade indicators as shown in Figure 2. Table 1 showed the crisis period that has been detected on 1997, 1998, and 2008 based on the value of the smoothed probability that greater than 0.6 by bank deposits and real exchange rate, that greater than 0.8 by terms of trade.

| Year | Bank Deposits | Real Exchange Rate | Terms of Trade |
|------|---------------|--------------------|-----------------|
| 1997 | December      | July, August, September, October, November, December | January, August, September, December |
| 1998 | January, May, June, August, October | January-December | February, March, April, June, August |
| 2008 | October, November, December | February, April |

Table 1. showed that smoothed probability for real exchange rate and terms of trade can detect the financial crisis that hit Indonesia in 1997, 1998, and 2008. That smoothed probability for bank deposits can not detect the financial crisis that hit Indonesia in 2008.

5. Conclusion

The results of this research are bank deposit and terms of trade can be modelled by SWARCH(3,1) while real exchange rate can be modelled by SWARCH(3,2) that can be used to detect the financial crisis in Indonesia in 1997, 1998, and 2008.

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