Detection method of financial crisis in Indonesia using MSGARCH models based on banking condition indicators

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Abstract. Financial crisis has hit Indonesia for several times resulting the needs for an early detection system to minimize the impact. One of many methods that can be used to detect the crisis is to model the crisis indicators using combination of volatility and Markov switching models [5]. There are some indicators that can be used to detect financial crisis. Three of them are the difference between interest rate on deposit and lending, the real interest rate on deposit, and the difference between real BI rate and real Fed rate which can be referred as banking condition indicators. Volatility model used to overcome the conditional variance that change over time. Combination of volatility and Markov switching models used to detect condition change on the data. The smoothed probability from the combined models can be used to detect the crisis. This research resulted that the best combined volatility and Markov switching models for the three indicators are MS-GARCH(3,1,1) models with three states assumption. Crises in mid of 1997 until 1998 has successfully detected with a certain range of smoothed probability value for the three indicators.

Keywords: detection, crisis, MS-GARCH, banking, interest rate.

1. Introduction
Financial crisis is a condition where a country’s finance worsen. It can be seen from drastic rise of inflation rate, exchange rate’s fall, and other economical activity decline. Financial crisis has hit Indonesia for several time. One of them was the 1997’s crisis that caused severe impact on Indonesia’s economic. Even Indonesia has to bear the international debt to overcome the 1997’s crisis until now. Detection methods of financial crisis must be developed to anticipate another crisis.

Kaminsky [3] developed a detection method of financial crisis by monitoring several crisis indicators that tend to exhibit some unusual behavior in the periods preceding a crisis. There are some indicators that can be used in detecting financial crisis. Three of them are the difference between interest rate on deposit and lending, the real interest rate on deposit, and the difference between real BI rate and real Fed rate which can be referred as banking condition indicators.

Lending rate is a rate of interest that given by a bank to customers who lend money from the bank. Deposit rate is a rate of interest that given by a bank to customers who save their money in the bank. Real interest rate on deposit is deposit rate that has been reduced by inflation rate in its country. Real BI rate is central bank policy rate in Indonesia that has been reduced by inflation rate in Indonesia. Real Fed rate is central bank policy rate in America that has been reduced by inflation rate in America.
Banking condition indicators indicate the existence of heteroscedasticity effect causing a need to use volatility model. The volatility model obtained later will be combined with the Markov switching model using three state assumption to overcome the difference between stable, prone, and crisis condition for each indicators. The alternative way to detect crisis is using smoothed probability on certain state obtained from the combination models. Detection method of financial crisis using combination of volatility and Markov switching method has been researched by Mwamba and Majadibodu [5]. They identify currency crisis in South Africa using MS-GARCH model based on foreign exchange.

Based on the previous research, we are interested in detecting financial crisis using combination of volatility and Markov switching model based on the difference between interest rate on deposit and lending, the real interest rate on deposit, and the difference between real BI rate and real Fed rate. In the next section, we present theoretical basis of combined volatility and Markov switching models. The research methodology is given in Section 3. In Section 4 we apply the combination of volatility and Markov switching models to the difference between interest rate on deposit and lending, the real interest rate on deposit, and the difference between real BI rate and real Fed rate. The conclusion is given in Section 5.

2. Combination of volatility and Markov Switching Model

In general, time series data divided into two categories, that are stationary and non-stationary. Stationerity of data can be tested with augmented Dickey-Fuller (ADF) test. Non-stationary time series data can be transformed into stationary data using log return transformation. Let $Z_t$ denotes the data at time $t$ and $r_t$ denotes the log return of the data, the log return transformation can be written as $r_t = \ln\left(\frac{Z_t}{Z_{t-1}}\right)$ (Tsay [6]).

2.1. Mean Model

The autoregressive moving average (ARMA) Model with $(p,q)$ order of the log return data $r_t$ can be written as

$$r_t = \theta_0 + \sum_{i=1}^{p} \theta_i r_{t-i} - \sum_{j=1}^{q} \theta_j a_{t-j} + a_t$$

where $\theta_0$ denotes the constanta, $p$ denotes the autoregressive (AR) order, $\theta_{1,2,...,p}$ denotes the AR parameters, $q$ denotes the moving average (MA) order, $\theta_{1,2,...,q}$ denotes the MA parameters, and $a_t$ denotes the model residual at time $t$. The highest MA order determined by ACF plot which cut off after the $p^{th}$ lag while AR order determined by PACF plot which cut off after the $q^{th}$ lag. The heterocedasticity effect of ARMA model can be tested with lagrange multiplier (LM) test. (Tsay[6]).

2.2. Volatility Model

ARMA model residual which contain heteroscedasticity effect can be modelled with volatility model. The residual $a_t$ can be written as

$$a_t = \sigma_t \epsilon_t$$

where $\epsilon_t$ denotes the standardized residual, $\sigma_t^2$ denotes the variance at time $t$, and $F_{t-1}$ denotes information at time $t-1$ (Tsay[6]).

2.2.1. Autoregressive Conditional Heteroscedasticity (ARCH) Model. The ARCH($m$) model can be written as

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2$$
where $\alpha_0$ denotes the model constant, $m$ denotes the ARCH order, and $\alpha_{1,2,\ldots,m}$ denotes the ARCH parameters. The highest order of ARCH determined by PACF plot of ARMA squared residual which cut off after the $m^{th}$ lag (Tsay[6]).

2.2.2. Generalized ARCH (GARCH) Model. The GARCH($m,s$) model can be written as

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

where $s$ denotes the GARCH order and $\beta_{1,2,\ldots,s}$ denotes the GARCH parameters. The GARCH model can allow much more flexible lag structure than ARCH model (Tsay[6]).

2.2.3. Exponential GARCH (EGARCH) Model. Leverage effect found on the GARCH model can be resolved by using EGARCH model. The EGARCH($m,s$) model can be written as

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

where $\gamma_{1,2,\ldots,m}$ denotes the EGARCH parameters (Tsay[6]).

2.3. Markov Switching Model. Based on Hamilton and Susmel [2], Markov switching model for conditional mean can be written as

$$r_t = \mu_{s_t} + \tilde{r}_t$$

where $\mu_{s_t}$ denotes the mean on state at time $t$ and $\tilde{r}_t$ follows the ARMA process.

2.4. Combination of Volatility and Markov Switching Models.

2.4.1. Markov Switching ARCH (SWARCH) Model. Based on Hamilton and Susmel [2], the SWARCH($K, m$) model can be written as

$$\sigma_{t,s}^2 = \alpha_{0,s} + \sum_{i=1}^{m} \alpha_{i,s} \sigma_{t-i}^2$$

where $K$ denotes the state assumption and $s_t$ denotes state at time $t$.

2.4.2. Markov Switching GARCH (MS-GARCH) Model. Based on Gray [1], the MS-GARCH($K,m,s$) model can be written as

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

where $K$ denotes the state assumption and $s_t$ denotes state at time $t$.

2.5. Smoothed Probability.

Based on Kuan [4], the smoothed probability can be written as

$$P(s_t = i|Z^T; \theta) = \sum_{s_{t+1}=1}^{S} P(s_{t+1} = i|Z^T; \theta) P(s_t = i|s_{t+1} = i, Z^T; \theta).$$

2.6. Crisis Detection

Crisis detection can be determined by smoothed probability from combination of volatility and Markov switching model. Mwamba and Majadibodu [5] which use the two state assumption, set the crisis limit when the smoothed probability is higher than 0.5. But, there is no condition to decide the smoothed probability limit of crisis. Which is why, the smoothed probability limit of crisis determined with consideration of actual past crisis. In Indonesia’s case, the crisis happened from mid 1997 until 1998.
3. Model Application
The difference between interest rate on deposit and lending, the real interest rate on deposit, and the difference between real BI rate and real Fed rate data from January 1990 until December 2016 was obtained from International Financial Statistic (IFS). The data was analyzed with R software.

3.1. Data Plotting and Transformation
Data plot for the three indicators can be seen in Figure 1. Data 1 denotes the difference between interest rate on deposit and lending, Data 2 denotes the real interest rate on deposit, and Data 3 denotes the difference between real BI rate and real Fed rate.

![Figure 1. (a) Data 1 plot, (b) data 2 plot, and (c) data 3 plot.](image)

Figure 1(a), (b), and (c) indicate nonstationary data structure where the data fluctuate not around their mean. After testing the stationarity of the data with ADF test, the p-value obtained for data 1 is 0.1042; for data 2 is 0.1028; and for data 3 is 0.1467 which are greater than the significance level that is $\alpha = 0.05$. This means data 1, data 2, and data 3 is not stationary. Hence, the data transformed with log return transformation and again their stationarity tested with ADF test. The p-value obtained for data 1, data 2, and data 3 is less than 0.01 which are less than the significance level that is $\alpha = 0.05$. This means data 1, data 2, and data 3 are stationary.

3.2. Mean Model Estimation.
The log return data which are stationary then modelled with ARMA model. The highest possible order of ARMA model can be seen from ACF and PACF plots. ACF an PACF plots of data 1 can be seen in figure 2.

![Figure 2. (a) ACF plot and (b) PACF plot for the log return of data 1.](image)

The ACF and PACF plots from Figure 2 show that both ACF and PACF plots were cut off after the first lag. So the possible ARMA model for data 1 is ARMA(1,1), ARMA(1,0), and ARMA(0,1). But the best model which has lowest AIC value and all of its parameter was significant is ARMA(1,0). ARMA(1,0) model for data 1 can be written as $r_t = 0.15042r_{t-1} + \alpha_t$. With the same method as data 1, the best mean model obtained for data 2 and data 3 is also ARMA(1,0). ARMA(1,0) model for data 2 can be written as $r_t = 0.132376r_{t-1} + \alpha_t$. ARMA(1,0) model for data 3 can be written as $r_t = 0.34296r_{t-1} + \alpha_t$. 
To see whether there is heteroscedasticity in ARMA(1,0) for the three data or not, their residuals tested with Lagrange multiplier (LM) test. The p-value of LM test for data 1, data 2, and data 3 consecutively are $2.2 \times 10^{-10}$, $8.616 \times 10^{-10}$, and $1.021 \times 10^{-14}$ which is less than significance level that is $\alpha = 0.05$. This means the ARMA(1,0) for data 1, data 2, and data 3 has heteroscedasticity effect.

### 3.3. Volatility Model Estimation.

To resolve the heteroscedasticity effect, volatility model was used. The highest possible order of ARCH model can be seen from PACF plot from ARMA(1,0) squared residuals. The PACF plot shows that the plot was cut off after the first lag, but the fourth lag and the fifth lag rise above the confidence band. The best ARCH model for data 1 which has all significant parameter is ARCH(1).

The higher order of this model have some insignificant parameter. But this model can’t explain the rise of the forth and fifth lag, so the GARCH model was also used. The GARCH(1,1) for data 1 has all significant parameter and smaller AIC value than ARCH(1) so the best model to use is GARCH(1,1).

A GARCH(1,1) model for data 1 can be written as $\sigma_t^2 = 0.00001402 + 0.2282a_{t-1}^2 + 0.7096a_{t-1}^2$. Residual from this model then tested with sign bias test to see the need to model the volatility with EGARCH model. The p-value obtained is 0.858045 which is greater than the significance level ($\alpha = 0.05$). This indicates no leverage effect in the GARCH(1,1) model so there is no need to model the volatility with EGARCH model.

With the same method as data 1, the best volatility model for data 2 and data 3 are also GARCH(1,1) which can consecutively be written as $\sigma_t^2 = 0.0001075 + 0.1752a_{t-1}^2 + 0.7792a_{t-1}^2$ and $\sigma_t^2 = 0.0001078 + 0.4543a_{t-1}^2 + 0.6245a_{t-1}^2$.

### 3.4. MS-GARCH Estimation.

To detect the influence of volatility level difference to the stable, prone, and crisis condition, the GARCH(1,1) model can be combined with Markov switching model into MS-GARCH model with three state assumption. Those three state consist of low volatility state, mide volatility state, and high volatility state. Transition matrices obtained for data 1, data 2, and data 3 consecutively are written as $P_1$, $P_2$, and $P_3$.

$$P_1 = \begin{pmatrix}
0.991318 & 0.130750 & 0.991341 \\
0.004339 & 0.868635 & 0.007935 \\
0.004343 & 0.000615 & 0.000724
\end{pmatrix},

P_2 = \begin{pmatrix}
0.99108 & 0.86306 & 0.000000 \\
0.00007 & 0.13661 & 0.08384364 \\
0.00885 & 0.00033 & 0.9161563
\end{pmatrix},

P_3 = \begin{pmatrix}
0.9880748 & 0.1450943 & 0.1140314 \\
1.98 \times 10^{-12} & 0.8549056 & 0.00000057 \\
0.1119252 & 0.00000001 & 0.8859680
\end{pmatrix}$$

Based on $P_1$, the probability that volatility in state 3 now will be moved to state 1 next time is 0.991341 which means the high volatility is easy to overcome. While the probability that volatility in state 2 now will be moved to state 2 next time is 0.868635 which means the mid volatility is hard to overcome. Model MS-GARCH(3,1,1) obtained for data 1, data 2, and data 3 can be written consecutively as follow.

$$\mu_{t1} = \begin{cases}
-0.000189656, \text{ state 1} \\
0.007220047, \text{ state 2}, \sigma_{t1}^2 \\
-0.003733029, \text{ state 3}
\end{cases}

\mu_{t2} = \begin{cases}
-0.000202154, \text{ state 1} \\
-0.002334698, \text{ state 2}, \sigma_{t2}^2 \\
0.000855913, \text{ state 3}
\end{cases}

\mu_{t3} = \begin{cases}
-0.000155594, \text{ state 1} \\
0.003390033, \text{ state 2}, \sigma_{t3}^2 \\
0.000762704, \text{ state 3}
\end{cases}$$

where $\mu_t$ donates the conditional mean model and $\sigma_t^2$ donates the conditional volatility model.
3.5. Crisis Detection.
The smoothed probability obtained from MS-GARCH (3,1,1) model for data 1, data 2, and data 3, can be seen at Figure 3.

Figure 3. The smoothed probability of (a) data 1, (b) data 2, and (c) data 3.

Crisis limit for data 1 set when the smoothed probability is higher than 0.1 in state 2 and prone limit set when the smoothed probability is between 0.04 and 0.1 in state 2. Crisis limit for data 2 set when the smoothed probability is higher than 0.6 in state 3 and prone limit set when the smoothed probability is between 0.4 and 0.6 in state 3. Crisis limit for data 1 set when the smoothed probability is higher than 0.6 in state 3 and prone limit set when the smoothed probability is between 0.4 and 0.6 in state 3. This limit has successfully detect the actual crisis in mid 1997 until 1998 with details in Table 1.

| Data  | 1997            | 1998            | 1999            |
|-------|-----------------|-----------------|-----------------|
| Data 1| September       | June, July,     | January - May   |
|       |                 | September - December |                |
| Data 2| August – October, December | January - December | January - March, April - October |
| Data 3| September - November | January - August, October - December | January - August |

The crisis detected at 1999 is the result of crisis aftermath from 1998. There are some crisis detected in that year although in actual it iss considered that there was no crisis in 1999.

4. Conclusion
The combination of volatility and Markov switcing models for the difference between interest rate on deposit and lending, the real interest rate on deposit, and the difference between real BI rate and real Fed rate are MS-GARCH(3,1,1) with three state asumption. The smoothed probability obtained from the three indicators have successfully detect the actual crisis.

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