The detection of financial crisis using combination of volatility and markov switching models based on real output, domestic credit per GDP, and ICI indicators

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Abstract. Open economic system has not only provided ease for every country to interact with each other, but also make it easier to transmitted the crisis. Financial crisis that hit Indonesia in 1997-1998 and 2008 severely impacted the economy, thus a method to detect crisis is required. According to Kamisky et al. [6], crisis can be detected based on several financial indicators such as real output, domestic credit per Gross Domestic Product (GDP), and Indonesia Composite Index (ICI). This research aims to determine the appropriate combination of volatility and Markov switching model to detect financial crisis in Indonesia based on the indicators. Volatility model used for modeling the unconstant-variance of ARMA. Markov switching is an alternative model of time series data with changed conditions in the data, or called state. In this research, we are using three assumption of states namely low volatility state, medium volatility state and high volatility state. The data of each indicator were taken from 1990 until 2016. The result of the study show that MS-ARCH(3,1) can be used to detect the financial crisis that hit Indonesia in 1997-1998 and 2008 based on real output, domestic credit per GDP, and ICI indicators.

1. Introduction

Open economic system has given challenges to developing countries such in Indonesia with more integrated financial sectors. But in the other hand, its transmission across countries seems easier to occur. Crisis has occurred in 1997 when Thailand currency fell significantly and spread to other countries. In 2008, the serial of crisis reoccurred when United States create instability in global economy and spread quickly throughout the world. Crisis is an instability of a financial system in the economic order. To maintain financial system stability, there must be a monitoring strategy for dealing with crisis so the recovery efforts can be done as early as possible. As stated by Kaminsky et al. [6], to detect a crisis there were 15 indicators that can be used, including real output, domestic credit per gross domestic product (GDP), and Indonesia Composite Index (ICI) indicators.

Bank and capital market become indicator of the financial system that increase every year because expansion of capital market and growth of banking sector is connected. The connection occurs when transaction in capital market conducted through the banking system. As result of significant investment, bank place quality enhancement in provisioning funds and will accelerating economic growth. Real output, credit domestic per GDP, and ICI indicators have the accountability of shock in
economic stability. As an anticipation, Hamilton and Susmel [2] introduce Markov switching autoregressive conditional heteroscedasticity (MS-ARCH) model which is a combination of volatility and Markov switching as an alternative to modeling time series data that focus on fluctuation and changes in regime of data. Furthermore, in this research the combination of volatility and Markov switching models is used to detect financial crisis in Indonesia based on real output, domestic credit per GDP, and ICI indicators.

2. Materials and Methods

2.1. Autoregressive Moving Average (ARMA(p,q))

ARMA(p,q) model is usually used as a linear time-series models for conditional mean. Mostly, an ARMA(p,q) model combines from AR(p) and MA(q). A time series \( r_t \) follows an ARMA(p,q) models if it satisfies

\[
r_t = \varphi_0 + \varphi_1 r_{t-1} + \cdots + \varphi_p r_{t-p} + \theta_0 \epsilon_{t} + \theta_1 \epsilon_{t-1} + \cdots + \theta_q \epsilon_{t-q},
\]

where \( r_t \) is a transformations series at time-\( t \), \( \varphi_0 \) is constant, \( \varphi_p \) is parameter of AR, \( \theta_q \) is parameter of MA and \( \{\epsilon_t\} \) is white noise series. The concept of ARMA model is highly relevant in volatility modeling (Tsay [7]).

2.2. Volatility Models

2.2.1. Autoregressive Conditional Heteroscedasticity (ARCH(m)). The process \( \{\epsilon_t\} \) follow ARCH(m) model if

\[
a_t = \sigma_t \epsilon_t \quad \text{for} \quad \epsilon_t \sim N(0,1) \quad \text{and} \quad a_t | \psi_{t-1} \sim N(0, \sigma_t^2)
\]

\[
\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2,
\]

where \( \psi_{t-1} \) denote the information at time \( (t - 1) \), \( m \) is ARCH order, \( \alpha_0 \) is constant, \( \alpha_i \) is parameter of ARCH, \( \sigma_t^2 \) is conditional variance at time \( t \), and \( \{\epsilon_t\} \) is a sequence of independent and identically distributed random variables with mean zero and variance 1 (Tsay [7]).

2.2.2. Generalized Autoregressive Conditional Heteroscedasticity (GARCH(m,s)). The ARCH model is often requires many parameters to adequately describe the volatility process of a data. Bollerslev [1] extended high order of ARCH by including the lags of conditional variance to GARCH(m,s) model. The process \( \{a_t\} \) follow GARCH(m,s) model if

\[
a_t = \sigma_t \epsilon_t \quad \text{for} \quad \epsilon_t \sim N(0,1) \quad \text{and} \quad a_t | \psi_{t-1} \sim N(0, \sigma_t^2)
\]

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

If \( \beta_j = 0 \), for all \( j \), then GARCH(m,s) reduces to an ARCH(m) model.

2.2.3. Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH(m,s)). To overcome some weakness of the GARCH model in handling financial time series, Henry [3] propose the exponential GARCH (EGARCH) model. In particular, to allow for asymmetric effect between positive and negative of financial data. The alternative form for the EGARCH(m,s) model is

\[
\ln \sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i |a_{t-i}| + \gamma_i \ln \sigma_{t-i}^2 + \sum_{j=1}^{s} \beta_j \ln \sigma_{t-j}^2.
\]

Here a positive \( a_{t-i} \) contributes \( \alpha_i (1 + \gamma_i) | \epsilon_{t-i} | \) to log volatility and a negative \( a_{t-i} \) gives \( \alpha_i (1 - \gamma_i) | \epsilon_{t-i} | \), where \( | \epsilon_{t-i} | = a_{t-i} / \sigma_{t-i} \). The \( \gamma_i \) parameter signifies the leverage effect of \( a_{t-i} \) (Tsay [7]).
2.3. Combination of Markov Switching-ARCH (MS-ARCH)

Hamilton and Susmel [2] extended $y_t$ as a vector of observed variable and let $s_t$ denote an unobserved random variable satisfy the first order Markov chain that can take on the value $1, 2, \ldots, or T$. The variable $s_t$ is regarded as the state or regime that the process is in at date $t$ and $s_t$ governs that parameters of the conditional distribution of $y_t$. The MS-ARCH model with only three regimes can be represented as follows.

$$ r_t = \mu_{st} + a_t, \quad a_t = \sigma_{st} \varepsilon_t $$

$$ \sigma_{st}^2 = \sigma_{0st}^2 + \sum_{i=1}^{m} \alpha_{iit} \sigma_{st-i}^2 $$

where $s_t = 1, 2, or 3$, $\mu_{st}$ is the conditional mean and $\sigma_{st}^2$ is the conditional volatility under regime $s_t$ on $\psi_{t-1}$.

The unobserved random variable $s_t$ is governed by a first order Markov chain with constant transition probability given by

$$ P[s_t = j | s_{t-1} = i] = p_{ij}, \quad \sum_{j=1}^{3} p_{ij} = 1, \text{ for } i, j = 1, 2, 3. $$

In matrix notation, $P$ can be defined by

$$ P = \begin{pmatrix}
    p_{11} & p_{12} & p_{13} \\
    p_{21} & p_{22} & p_{23} \\
    p_{31} & p_{32} & p_{33}
\end{pmatrix}. $$

2.4. Smoothed Probability

Kim and Nelson [5] describe smoothed probability ($\Pr(S_t = j | \psi_T)$) as the regime probability based on all information in the sample. Smoothed probability can be represented as,

$$ \Pr(S_t = j | \psi_T) = \sum_{k=1}^{3} \Pr(S_t = j, S_{t+1} = k | \psi_T), $$

where $\psi_T$ is all of the information until time $T$. Based on Hermosillo and Hesse [4] 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. Data

This Research studied about crisis identification using real output, domestic credit per GDP and ICI indicators. The data used for represent real output indicator is Gross Domestic Product by industrial origin at 2010. Then for domestic credit per GDP used comparison of growth rate domestic credit to growth rate GDP. While ICI indicator used monthly data of ICI. Length of the ICI data was different from the other, because we use quarterly data for real output and domestic credit per GDP. The data was obtained from Bank Indonesia (BI) and Badan Pusat Statistik (BPS) from 1990 until 2016. Software R is used to calculate and estimate models. Plot of real output, domestic credit per GDP, and ICI indicators can be seen in Figure 1.
Figure 1 indicates fluctuation of real output, domestic credit per GDP, and ICI indicator that make the data was not stationary. Stationarity of data can be checked using Augmented Dickey Fuller test (ADF test). We obtained probability value of ADF are 0.99, 0.01, and 0.6934 so we conclude that real output and ICI was not stationary, while domestic credit indicator per GDP was stationary.

According to Tsay [7] financial indicators tend to fluctuate in all time so its needed transformation for the data. The most suitable transformation for real output and ICI indicators is log return, while for domestic credit per GDP is difference. We use difference transformation on domestic credit per GDP because the data for this indicator is growth rate which values are not always positive. After that, we check the stationarity of the data transformation using ADF test and obtain probability values are 0.07, 0.01, and 0.01 so the data transformation of the real output, domestic credit per GDP and the ICI indicators has been stationary.

4. Result

4.1. Establishment of ARMA(p,0) Model

The ARMA (p,0) model can be identified using the PACF plot of data transformation for each indicator. Based on the real output indicator, we obtained the appropriate significant model is ARMA (2,0) and written as $r_t = -0.009374 + 1.241895 r_{t-1} - 0.441199 r_{t-2} + a_t$. The appropriate model for domestic credit per GDP indicator is ARMA(2,0) and written as $r_t = -0.67142 r_{t-1} - 0.28761 r_{t-2} + a_t$. The appropriate model on ICI indicator is ARMA(1,0) and written as $r_t = -0.21427 r_{t-1} + a_t$. Lagrange Multiplier (LM) test used to see the heteroscedasticity effect on the residues ARMA model for the indicators. Based on LM test we obtained probability values are 0.0377, 0.02751, and 0.005048 so there was a heteroscedasticity effect on residues of ARMA model for each indicator.

4.2. Establishment of Volatility Model

The results of estimation for real output indicator obtained the best volatility model is ARCH(1) and written as $\sigma_t^2 = 0.00008596 + 1.109 a_{t-1}^2$. On the domestic credit per GDP indicator obtained the best volatility model is ARCH(1) and written as $\sigma_t^2 = 0.19489 + 3.28323 a_{t-1}^2$. According to ICI indicator obtained the best volatility model is ARCH(1) and written as $\sigma_t^2 = 0.0053319 + 0.1560969 a_{t-1}^2$. After obtain the best volatility model it is necessary to do diagnostic test on the standardize residues for each indicator. Depend on the Ljung-Box statistics, probability value are 0.9202, 0.2873, and 0.7157 which means there is no autocorrelation on model residues. Based on the LM test obtained probability value are 0.8109, 0.7197, and 0.06634 which means there is no heteroscedasticity effect on model residues. Based on the Kolmogorov-Smirnov test obtained probability are 0.8119, 0.9999, and 0.8903 which means of residues normally distributed. Based on the diagnostic tests concluded that ARCH(1) model is able to used to estimate real output, domestic credit per GDP and the ICI indicators.
4.3. Establishment of MS-ARCH Model

The changes condition in Markov switching model namely 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 real output indicator transition probability matrix can be written as follows

\[
P_1 = \begin{pmatrix}
0.515937122 & 0.0223787 & 0.54879769 \\
0.003576516 & 0.8336659 & 0.04255742 \\
0.480486361 & 0.1439554 & 0.40864489
\end{pmatrix}.
\]

Based on \( P_1 \) obtained that the probability to survive on low volatility state is 0.515937122. Probability changes from low to medium volatility state is 0.003576516. Probability changes from low to high volatility state is 0.480486361. Probability changes from medium to low volatility state is 0.0223787. Probability survive in medium volatility state is 0.8336659. As well as the probability changes from medium to high volatility state is 0.1439554. Probability changes from high to low volatility state is 0.54879769. Probability changes state from high to medium volatility state is 0.04255742. Probability survive in high volatility state is 0.40864489. The matrix of transition probability for domestic credit per GDP and ICI indicators stated in \( P_2 \) and \( P_3 \) as follows

\[
P_2 = \begin{pmatrix}
0.9396306 & 0.08501253 & 3.030069 \times 10^{-6} \\
0.06036927 & 0.81239019 & 0.6766754 \\
1.386951 \times 10^{-7} & 0.10259728 & 0.3233215
\end{pmatrix}
\]

\[
P_3 = \begin{pmatrix}
0.525645121 & 0.003285805 & 0.55573863 \\
0.001600965 & 0.935577221 & 0.03348441 \\
0.472753914 & 0.061136974 & 0.41077695
\end{pmatrix}
\]

The parameter estimates of MS-ARCH(3,1) model can be written as follows

\[
\mu_1,t = \begin{cases}
0.05382, \text{state 1} \\
-0.03494, \text{state 2} \\
0.058869, \text{state 3}
\end{cases}, \quad \sigma_{1,t}^2 = \begin{cases}
0.002654 + 1.196224 \alpha_{t-1}^2, \text{state 1} \\
0.000402 + 0.011055 \alpha_{t-1}^2, \text{state 2} \\
0.000303 + 0.009736 \alpha_{t-1}^2, \text{state 3}
\end{cases}
\]

\[
\mu_2,t = \begin{cases}
0.00558, \text{state 1} \\
0.33157, \text{state 2} \\
-4.19187, \text{state 3}
\end{cases}, \quad \sigma_{2,t}^2 = \begin{cases}
0.000097 + 0.2818711 \alpha_{t-1}^2, \text{state 1} \\
0.1897208 + 0.007305 \alpha_{t-1}^2, \text{state 2} \\
15.1404731 + 2.3359242 \alpha_{t-1}^2, \text{state 3}
\end{cases}
\]

\[
\mu_3,t = \begin{cases}
0.026914455, \text{state 1} \\
-0.021752070, \text{state 2} \\
0.000146013, \text{state 3}
\end{cases}, \quad \sigma_{3,t}^2 = \begin{cases}
0.00000737 + 0.01991329 \alpha_{t-1}^2, \text{state 1} \\
0.00002452 + 0.00133605 \alpha_{t-1}^2, \text{state 2} \\
0.00001257 + 0.00004551 \alpha_{t-1}^2, \text{state 3}
\end{cases}
\]

where \( \mu_{1,t} \) and \( \sigma_{1,t}^2 \) is the conditional mean and variance models MS-ARCH(3,1) for real output indicator, \( \mu_{2,t} \) and \( \sigma_{2,t}^2 \) is the conditional mean and variance models MS-ARCH(3,1) for domestic credit per GDP indicator, and \( \mu_{3,t} \) and \( \sigma_{3,t}^2 \) is the conditional mean and variance models MS-ARCH(3,1) for ICI indicator.

4.4. Detection of Crisis

Crisis detection using MS-ARCH(3,1) can be seen by value of smoothed probability. Figure 2 shows the smoothed probability plots of MS-ARCH (3.1) model by real output, domestic credit per GDP, and ICI indicators.
Figure 2. (a) Smoothed Probability of Real Output (b) Smoothed Probability of Domestic Credit per GDP (c) Smoothed Probability of ICI

Crisis condition signed with value of smoothed probability that greater than 0.6 for each indicator as shown in Figure 2. Table 1 showed the crisis period that has been detected based on the value of the smoothed probability greater than 0.6 by real output, domestic credit per GDP, and ICI indicators.

| Year | Real Output | Domestic Credit per GDP | ICI |
|------|-------------|-------------------------|-----|
| 1990 | Sept-Dec    |                         |     |
| 1991 | Jan-Sept    |                         |     |
| 1997 | Q4          | Q4                      | Aug-Des |
| 1998 | Q1, Q2, Q4  | Q1, Q4                  | Jan-Des |
| 1999 | Q3          |                         | Jan-Des |
| 2000 |             |                         | Jan-Aug |
| 2008 |             |                         | Aug-Dec |
| 2009 |             |                         | Jan-Apr |

*note: Q means quarter

5. Conclusions
The results of study showed that MS-ARCH(3,1) can be used to detect the financial crisis in Indonesia. Based on real output, domestic credit per GDP, and ICI indicators financial crisis can be detect on 1997-1998 and 2008.

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