Predicting currency crisis in Indonesia based on real output and Indonesia Composite Index (ICI) indicators

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Abstract. The currency crisis that occurred in the middle of 1997, 1998 and 4\textsuperscript{th} quarter of 2008 was caused by disturbances in the currency system. When there is disturbance in the system then the cause indicators will experience fluctuations and changes in conditions. High fluctuation can be modeled using volatility model, while the changes in condition can be modeled using Markov switching model. Therefore, combination of volatility and Markov switching models is very appropriate to explain the crisis. In this paper, we use real output and ICI indicators on the period of January 1990 until December 2016 to explain the crisis as well as to forecast the possibility of an impending crisis. The results show that the appropriate model is ARCH (1) and Markov switching with 3 states, called SWARCH (3,1) model. This model can catch the crisis that happened in 1998 and 1999 for real output indicator. Meanwhile ICI indicator can explain the crisis in August to December 1997, 1998 and September to December 2008. Based on SWARCH (3,1) model, it can be predicted that Indonesia does not experience currency crisis in one year later.

1. Introduction
The open economic system has given challenges to developing countries like Indonesia, by increasing the integration of the country's financial sector. But on the other hand it can facilitate the spread of crises between countries, as happened in 1997 when the value of the Thai currency fell sharply and the impact spread to various countries. Disruptions in the financial system in economic rules can cause a currency crisis. Currency crises can be detected through banking and capital market performance. Real output indicator represents performance in the banking sector, while the Indonesia Composite Index (ICI) indicator is performance in the capital market sector.

The banking system facilitates the development of capital market and investment growth. The higher the investment, the greater the savings and the opportunity to provide funds which will ultimately accelerate economic growth, but have a vulnerability to financial stability shocks. This causes real output and ICI indicators to fluctuate and change conditions. Indicators that experience fluctuations can be explained by the volatility model, while indicators that experience changes in conditions can be explained by the Markov switching model.

The autoregressive conditional heteroscedasticity (ARCH) model was introduced by [1], to model the variance of inflation data in the UK from 1958 to 1977 and obtained a more realistic prediction of variance. Bollerslev [2] introduced generalized autoregressive conditional heteroscedasticity (GARCH) to model US GNP data from 1948 to 1983. In some cases the GARCH model is less able to explain the leverage effect. Chen [3] explained that leverage effect is a situation where volatility experiences a bad news and good news periodically so as to produce an asymmetric effect on
volatility. Nelson [4] introduced the exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model which could explain the leverage effect and applied to the weighted market index daily return data from 1962 to 1987.

Hamilton [5] introduced the Markov switching (MS) model as a time series data model that contained changes in conditions. Hamilton and Susmel [6] combined the MS and ARCH models to produce the Markov switching autoregressive conditional heteroscedasticity (SWARCH) model. They applied SWARCH model on U.S gross national product (GNP) data from 1952 to 1984, the model can explain the state changes that occur in the U.S GNP data economic variables. Chang et al. [7] used the SWARCH model to identify stock market and exchange rate volatility in Korea and the global financial crisis. Sugiyanto et al. [8] through output real, domestic credit per gross domestic product (GDP), and ICI indicators detect the financial crisis using combination of volatility and Markov switching models. Sugiyanto et al. [9] also explained the financial crisis using the MS-GARCH model through banking indicators. The financial crisis model can also be explained through the bank deposit indicator, the real exchange rate and terms of trade using a combination of Markov switching and volatility models [10]. Using data from 1990 to 2016 of the bank deposits, real exchange rate, and trade of terms indicators, Sugiyanto et al. [11] has predicted that 2017 will not be a financial crisis in Indonesia. This research discusses currency crises that might occur in Indonesia through real output and ICI indicators using a combination of Markov switching and volatility models.

2. Materials and Methods

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

Financial data fluctuates from time to time, therefore changes in data to the form of log returns are used to be the data are stationary. The log return at time t can be written $r_t = \ln \left( \frac{P_t}{P_{t-1}} \right)$ with $r_t$ is the log return at time t, $P_t$ is the value of data at time t. The ARMA model (p, q) is a combination of the AR (p) and MA (q) models which can be stated as

$$ r_t = \phi_1 r_{t-1} + \phi_2 r_{t-2} + \ldots + \phi_p r_{t-p} + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots + \theta_q e_{t-q} $$

With $e_t$ is the residue of the ARMA model (p, q) at time t, p is the order of AR, $\phi_p$ is the parameter of AR, and q is the order of MA, $\theta_q$ is the parameter of MA.

2.2. Volatility models

Volatility refers to the spread of all possible outcomes from unobservable variables. Statistically, volatility is often measured as a sample standard deviation. Standard deviation is more convenient and intuitive when we think about volatility because it has the same unit of measure as the mean. Although volatility cannot be observed directly but has several characteristics: (1) there is a volatility group that maybe high for a certain period of time and low for another period, (2) volatility involves time to time continuously, (3) volatility does not deviate to infinity, this means that volatility is often stationary, (4) volatility seems to react differently to large increases or large decreases. Some volatility models are proposed specifically to correct weaknesses that already exist because of their inability to capture the characteristics mentioned earlier.

2.2.1. Autoregressive Conditional Heteroscedasticity (ARCH)

Engle [1] introduced the ARCH model as residual variance model. The conditional variance $\sigma_t^2$ is used as a function of past residues. Given $\psi_t$ is the set of all information for $e_t$ from the past time to the time t where $e_t$ is the residual of ARMA (p, q) at time t. The $e_t$ process can be modelled as

$$ e_t = \epsilon_t \sigma_t, \text{ where } \epsilon_t \sim N(0,1), $$

And $\sigma_t^2 = E(\epsilon_t^2 | \psi_{t-1})$ is the conditional variance of the residue at time t and $\sigma_t^2 = E(\epsilon_t^2 | \psi_{t-1})$.

In general the process $\{e_t\}$ is called ARCH (q) if

$$ \epsilon_t | \psi_{t-1} \sim N(0, \sigma_t^2), $$

with $\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2$, where $\alpha_0 > 0$, $\alpha_i \geq 0$ for $i > 0$. 

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2.2.2. Generalized Autoregressive Conditional Heteroscedasticity (GARCH).
Although an ARCH model is simple, many parameters often require to adequately describe the volatility process of a data. Bollerslev [2] designed 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

\[
a_t = \sigma_t \varepsilon_t \quad \text{for} \quad \varepsilon_t \sim N(0,1)
\]

and

\[
a_t \mid \psi_{t-1} \sim N(0, \sigma_t^2)
\]

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

If \( \beta_j = 0 \), for all \( j \), then GARCH(m,s) reduces to an ARCH(m) model and the \( \alpha_i \) and \( \beta_j \) are referred to as ARCH and GARCH parameters, respectively.

2.2.3. Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH).
The exponential GARCH (EGARCH) model is proposed to overcome the weakness of GARCH model [12]. EGARCH(m,s) model can be stated as

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

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

Here a positive \( a_{t-i} \) contribute \( \alpha_i (1 + \gamma_i) |\varepsilon_{t-i}| \) to log volatility and a negative \( a_{t-i} \) gives \( \alpha_i (1 - \gamma_i) |\varepsilon_{t-i}| \). The \( \gamma_i \) parameter signifies the leverage effect of \( a_{t-i} \) [13].

2.3. Markov Switching-ARCH (SWARCH)
Hamilton and Susmel [6] said that Markov switching model with k state and ARCH(q) model is called SWARCH(k,q) or MS-ARCH(k,q) and can be written as

\[
r_t = \mu_{s_t} + \varepsilon_t,
\]

\[
\varepsilon_t = \sigma_{s_t} u_t, \quad \text{with} \quad u_t \sim N(0,1).
\]

\[
(\varepsilon_t \mid \psi_{t-1}) \sim N(0, \sigma_{s_{t-1}}^2), \quad \text{with}
\]

\[
\sigma_{s_{t} \varepsilon_t}^2 = \alpha_0 s_t + \sum_{i=1}^{q} \alpha_i s_t \varepsilon_{t-i}^2
\]

where \( r_t \) as a vector of observed variable and \( s_t \) denote an unobserved random variable satisfy the first order Markov chain that can take on the value \( 1, 2, \ldots, k \). 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 \( r_t \). The unobserved random variable \( s_t \) are governed by a first order Markov chain with constant transition probability given by

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

In matrix notation, \( P \) can be defined by

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

2.4. Smoothed Probability
Kim and Nelson [14] describe smoothed probability \( P(r(S_t = j|\psi_T)) \) as the regime probability based on all information in the sample. Smoothed probability can be written as,

\[
P(r(S_t = j|\psi_T)) = \sum_{k=1}^{13} Pr(S_t = j, S_{t+1} = k \mid \psi_T),
\]

where \( \psi_T \) is all of the information until time \( T \). Based on Hermosillo and Hesse [15], if the probability of a low-volatility regime has decreased under 0.4 means that the indicator is stable, the probability of a medium-volatility regime (though declining) still remains at around 0.4-0.6 means that the indicators are 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. According to Sopipan et al. [16], prediction of smoothed probability or prediction probability value is defined as

\[
P(S_t = 1|F_T) = p_{11}P(S_t = 1|F_T) + p_{21}P(S_t = 2|F_T) + p_{31}P(S_t = 3|F_T).
\]

2.5. Method

This research is about the identification of crises and forecasting crises in the coming periods using real output and ICI indicators. The real output indicator is quarterly data and ICI indicator is monthly data. Data can be obtained from Bank Indonesia (BI) and the Central Statistics Agency from 1990 to 2016. The model was built using data from 1990 to 2015 year, the data of 2016 year are used to measure model accuracy. Model accuracy is done by comparing the results of forecasting and actual data. Forecasting the currency crisis uses data from 1990 to 2016. The steps of the research are as follows.

1. Create a data plot and stationary test using the Augmented Dickey-Fuller (ADF) test. If the data is not stationary, then change the data using the log return transformation.
2. Create an autocorrelation function (ACF) plot and partial autocorrelation function (PACF) to determine the ARMA model.
3. Test the effect of heteroscedasticity using the Lagrange multiplier test.
4. If there is an effect of heteroscedasticity on the residual of ARMA (p,0) model then the form of the volatility model is the ARCH model.
5. Diagnostic tests include normality, independence and homogeneity of ARMA residues.
6. Combining volatility and Markov switching models with the assumption of three states.
7. Determine the mean and variance of each state.
8. Calculating the value of smoothed probability
9. Determine the condition of a currency crisis based on a predetermined limit.
10. Predict currency crisis in the year of 2017.

3. Results and Discussions

3.1. Data

Plot of real output and ICI indicators can be seen in figure 1. Figure 1 shows that the data is not stationary. Based on the Augmented Dickey Fuller (ADF) test, probability values of each are 0.99 and 0.677, which means the data is not stationary. Using the log return transformation and the ADF test, the probability values of each are 0.089 and 0.01, which means that the transformation of real output and ICI data has been stationary.
3.2. Form of ARMA(p,0) model
The ARMA (p, q) model can be determined using the autocorrelation function (ACF) and the partial
autocorrelation function (PACF) plot of the transformation data. Based on real output indicator, the
best model has been obtained is ARMA (2.0) and can be stated as
\[ r_{1t} = 0.009354 + 1.242332 r_{t-1} - 0.441591 r_{t-2} + a_t. \]
The best model for the ICI indicator is ARMA (1.0) and can be stated as
\[ r_{2t} = 0.21466 r_{t-1} + a_t. \]
The effect of heteroscedasticity can be seen from the Lagrange Multiplier (LM) test. Based on the LM
test obtained the probability value of 0.0377, and 0.005048 so that there is an effect of
heteroscedasticity on the residual of ARMA model for real output and ICI indicators.

3.3. Form of Volatility Model
The best volatility model for real output indicator is ARCH (1) and is stated as
\[ \sigma_{1t}^2 = 0.0000868 + 1.099 a_{t-1}^2. \]
Whereas for ICI indicator, the best volatility model is ARCH (1) and stated as
\[ \sigma_{2t}^2 = 0.0053320 + 0.1560685 a_{t-1}^2. \]

Test diagnostics for autocorrelation on the residue of real output and ICI indicators use Ljung-Box
test. The probability value of Ljung-Box Statistics are 0.05322, and 0.7152 for real output and ICI
indicators respectively. It means that there is no autocorrelation on the residue of model. The
probability value of the LM test is 0.1365, and 0.0665 for real output and ICI indicators, which means
that there is no heteroscedasticity effect on the residue of model. The probability values of the
Kolmogorov-Smirnov test are 0.8317 and 0.8903 for real output and ICI indicators, which means that
the residue is normally distributed. Based on the diagnostic tests, it can be concluded that ARCH(1)
model is able to used to estimate real output and ICI indicators.

3.4. Establishment of SWARCH model
In the Markov switching model, the condition changes are considered as an unobservable random
variable called state. To model changes in these conditions can be formed using transition probability
matrix. The conditions intended in this study are low, medium, and high volatility conditions. The
transition probability matrix for real output indicator is written as
\[
P_1 = \begin{pmatrix}
0.96357 & 0.12550 & 0.03571 \\
0.02335 & 0.87449 & 0.00000 \\
0.01309 & 0.00001 & 0.96429
\end{pmatrix}.
\]
Based on the matrix P1 it is found that the probability of not switching in low volatility conditions is 0.96357. The probability of switching from low to medium volatility is 0.02335. The probability of switching from a low to a high volatility condition is 0.01309. The probability of switching from medium to low volatility is 0.12550. The probability of not switching in a state of medium volatility is 0.87449. The probability of switching from medium to high volatility is 0.00001. The probability of a high to low volatility condition is 0.03571. The probability of changing from high to medium volatility is 0.00000. The probability of not switching in high volatility is 0.96429. The matrix of transition probability for ICI indicator is stated in P2 as follows

\[
P_2 = \begin{pmatrix}
0.93327 & 0.00026 & 0.09311 \\
0.00002 & 0.32277 & 0.10888 \\
0.06671 & 0.67697 & 0.79801
\end{pmatrix}.
\]

The parameter estimates of SWARCH (3,1) model can be presented as follows

\[
\begin{align*}
\mu_{1,t} = \left\{ \begin{array}{ll}
0.0588605, & \text{state 1} \\
-0.023346, & \text{state 2} \\
0.013088, & \text{state 3}
\end{array} \right. \\
\sigma^2_{1,t} = \left\{ \begin{array}{ll}
0.00309175 + 0.2812762, & \text{state 1} \\
0.00154558 + 0.00764797, & \text{state 2} \\
0.00276082 + 0.1308897, & \text{state 3}
\end{array} \right.
\end{align*}
\]

\[
\begin{align*}
\mu_{2,t} = \left\{ \begin{array}{ll}
-0.017479, & \text{state 1} \\
-0.012911, & \text{state 2} \\
0.030234, & \text{state 3}
\end{array} \right. \\
\sigma^2_{2,t} = \left\{ \begin{array}{ll}
(1.77523 \times 10^{-7}) + 0.01366622 \alpha_{t-1}, & \text{state 1} \\
(1.23249 \times 10^{-5}) + 0.0002627676 \alpha_{t-1}, & \text{state 2} \\
(3.00545 \times 10^{-6}) + 0.049833251 \alpha_{t-1}, & \text{state 3}
\end{array} \right.
\end{align*}
\]

where \( \mu_{1,t} \) and \( \sigma^2_{1,t} \) is the conditional mean and variance of SWARCH(3,1) model for real output indicator, and \( \mu_{2,t} \) and \( \sigma^2_{2,t} \) is the conditional mean and variance of SWARCH(3,1) model for ICI indicator.

3.5. Crisis Detection

Detection of crisis using SWARCH (3,1) can be seen by smoothed probability value. Figure 2 shows the smoothed probability plots of SWARCH (3,1) model for real output and ICI indicators.

![Figure 2](image)

**Figure 2.** (a) Smoothed probability of real output (b) Smoothed probability of ICI

Crisis condition signed by the value of smoothed probability that more 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 smoothed probability which more than 0.6 for real output and ICI indicators.
Table 1. Crisis detection based on smoothed probability

| Year | Real output | ICI   |
|------|-------------|-------|
| 1997 | Aug-Dec     |       |
| 1998 | Q1,Q2,Q3,Q4 | Jan-Dec|
| 1999 | Q1,Q2,Q3,Q4 | Jan-Dec|
| 2000 | Jan-Jun     |       |
| 2008 | Sep-Dec     |       |
| 2009 | Jan-Apr     |       |

Table 2 showed the comparison of prediction and actual smoothed probability value for real output and ICI from January to December 2016.

Table 2. Comparison of prediction and actual smoothed probability value

| Periods | Real output | ICI |
|---------|-------------|-----|
| Month   | Prediction  | Actual | Prediction | Actual |
| Jan     | 0.01563     | 0.00140 | 0.01563 | 0.00140 |
| Feb     | Q1          | 0.00220 | 0.00041 | 0.00236 | 0.00143 |
| Mar     |             | 0.03171 | 0.00135 | 0.03171 | 0.00135 |
| Apr     |             | 0.03950 | 0.00143 | 0.03950 | 0.00143 |
| May     | Q2          | 0.00562 | 0.00059 | 0.04684 | 0.00141 |
| Jun     |             | 0.05371 | 0.00159 | 0.05371 | 0.00159 |
| Jul     |             | 0.06013 | 0.00155 | 0.06013 | 0.00155 |
| Aug     | Q3          | 0.01004 | 0.00063 | 0.06613 | 0.00201 |
| Sept    |             | 0.07172 | 0.00301 | 0.07172 | 0.00301 |
| Oct     |             | 0.07694 | 0.00562 | 0.07694 | 0.00562 |
| Nov     | Q4          | 0.01524 | 0.00308 | 0.08181 | 0.01065 |
| Dec     |             | 0.08636 | 0.01843 | 0.08636 | 0.01843 |

Table 2 showed the prediction smoothed probability value are not different with actual smoothed probability so it can be concluded that SWARCH (3,1) model for two indicators can be used to detect the currency crisis in Indonesia. Table 3 is prediction smoothed probability for real output and ICI indicators in January until December 2017.

Table 3. Prediction smoothed probability for real output and ICI on 2017

| Periods | Prediction probability |
|---------|------------------------|
| Month   | Real Output | ICI |
| Jan     | Q1          | 0.07325 | 0.01551 |
| Feb     |             | 0.03038 | 0.03038 |
| Mar     |             | 0.04396 | 0.04396 |
| Apr     |             | 0.05647 | 0.05647 |
| May     | Q2          | 0.14289 | 0.06798 |
| Jun     |             | 0.07858 | 0.07858 |
| Jul     |             | 0.08834 | 0.08834 |
| Aug     | Q3          | 0.19913 | 0.09732 |
| Sept    |             | 0.10559 | 0.10559 |
| Okt     |             | 0.11321 | 0.11321 |
Table 3 showed that prediction smoothed probability for two indicators are less than 0.4, so it can be concluded that currency crisis did not hit Indonesia in 2017.

4. Conclusion
According to the results and discussion, it can be concluded that the currency crisis model for real output and ICI indicators is SWARCH (3,1). Based on the value of smoothed probability of SWARCH (3,1) model, it can be predicted that in 2017 the currency crisis did not hit Indonesia.

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