Markov Switching Autoregressive Conditional Heteroscedasticity (SWARCH) Model to Detect Financial Crisis in Indonesia Based on Import and Export Indicators

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Abstract. A country is said to be a crisis when the financial system is experiencing a disruption that affects systems that cannot function efficiently. The performance efficiency of macroeconomic indicators especially in imports and exports can be used to detect the financial crisis in Indonesia. Based on the import and export indicators from 1987 to 2015, the movement of these indicators can be modelled using SWARCH three states. The results showed that SWARCH (3,1) model was able to detect the crisis that occurred in Indonesia in 1997 and 2008. Using this model, it can be concluded that Indonesia is prone to financial crisis in 2016.

1. Introduction
Each country has different natural potentials that are not available in other countries. This condition caused a country will need products that are not available in the country but available in other countries. Therefore, the country is trading with other countries, so that there are import and export activities. High imports and low exports may indicate a crisis in the country. Indonesia experienced the worst crisis that occurred in the middle of July 1997. So that it needs to hold a system of financial crisis detection. According to Kaminsky et al. [5], there are 15 indicators that can be used to detect crises such as import and export.

Some volatility models that ever introduced by experts are autoregressive conditional heteroscedasticity (ARCH), generalized autoregressive conditional heteroscedasticity (GARCH), and exponential generalized autoregressive conditional heteroscedasticity (EGARCH). In the volatility model the condition changes that occur in the data are ignored, but in the Markov model switching changes the condition is considered as an unobserved variable called state. Later Hamilton and Susmel [3] introduced the Markov switching ARCH (SWARCH) model. The model is able to explain the state changes and illustrate the data volatility well. The SWARCH model has been applied by some researchers, e.g. Chang et al. [1] uses SWARCH model assuming three states. The results show that SWARCH (3,2) model can identify crisis on stock market and Korean Won exchange rate crisis per US Dollar.

This study determines the appropriate model for the movement of import and export indicators. The model is used to detect early financial crisis in 2016. Furthermore, it is determined the relation of conditions of import and export indicators in detecting financial crisis in Indonesia.
2. ARMA Model
The ARMA model consists of two components, the autoregressive (AR) model with the p order and the moving average (MA) model with the q order (Tsay [7]). The ARMA model can be written as

\[ r_t = \sum_{i=1}^{p} \phi_i r_{t-i} + \alpha_t - \sum_{i=1}^{q} \theta_i a_{t-i}, \]

where \( r_t \) is the value of log return at time \( t \), \( \phi \) is parameter of AR model, \( \theta \) is parameter of MA model, and \( a_t \) is the residue of ARMA model at time \( t \).

3. Volatility Model
Some models of volatility that ever introduced by experts are ARCH, GARCH and EGARCH.

3.1. ARCH Model
The ARCH(m) model can be written as follows

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

where \( \alpha_0 > 0, \alpha_i \geq 0, m \) is the order of the ARCH model and \( \sigma_t^2 \) is the residual variance of the ARMA model.

3.2. GARCH Model
The GARCH(p, q) model can be written as follows

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

where \( \beta_j \geq 0 \) and \( (p, q) \) is the order of the GARCH model.

3.3. EGARCH Model
The EGARCH(r, s) model can be written as follows

\[ \log \sigma_t^2 = \alpha_0 + \sum_{i=1}^{r} \alpha_i \left( \frac{a_{t-i}}{\sqrt{\sigma_{t-i}^2}} - \frac{2}{\pi} \right) + \sum_{j=1}^{s} \beta_j \log \sigma_{t-j}^2 + \sum_{i=1}^{s} \gamma_j \frac{a_{t-i}}{\sqrt{\sigma_{t-i}^2}}, \]

where \( \gamma_j \geq 0 \) and \( (r, s) \) is the order of the EGARCH model.

4. SWARCH Model
According to Hamilton and Susmel [3], the SWARCH model can be written as

\[ r_t = \mu_s + \alpha_t a_t = \sigma_t \varepsilon_t, \]

\[ \sigma_{t+s}^2 = \alpha_0 s_t + \sum_{i=1}^{m} \alpha_i s_{t-i}, \]

where \( \varepsilon_t \sim N(0,1) \), and \( s_t = \{1,2, ..., k\} \). The equation is said to be a SWARCH process with \( k \) state and \( m \) order and can be denoted as \( a_t \sim SWARCH(k, m) \).

5. Filtered Probability
Filtered probability is the probability of a state in the t-period based on observational data until the t-period (Sopipan et al. [6]). According to Hermosillo and Hesse [4], the value of filtered probability of more than 0.6 is in state 3 with high volatility or can be said to occur the crisis in that data period. The value of filtered probability between 0.4 and 0.6 is in state 2 with medium volatility or can be interpreted as prone to crisis. While the filtered probability value less than 0.4 is in state 1 with low
volatility or stable condition. According to Hamilton [2], filtered probability in state 3 can be written as

\[ P_r[s_t=3|\psi_t] = 1 - P_r[s_t=1|\psi_t] - P_r[s_t=2|\psi_t], \]

where \( \psi_t \) is an \( \alpha_t \) set until time \( t \), \( P_r[s_t=1|\psi_t] \) is filtered probability at state 1 and \( P_r[s_t=2|\psi_t] \) is filtered probability at state 2.

6. Detection of Crisis

To detect the crisis can be seen from the value of filtered probability at state 3 in the period of the data. According to Sopipan et al. [6], filtered probability forecasting can be written as

\[ \text{Pr}(s_t = j|\psi_t) = \sum_{i=1}^{3} p_{ij} \text{Pr}(s_{t-1} = i|\psi_{t-1}), \]

where \( p_{ij} \) is the transition probability from state \( i \) to state \( j \) and \( \text{Pr}(s_{t-1} = i|\psi_{t-1}) \) is filtered probability at state \( i \) and time \( t-1 \).

7. Research Methods

The data used in this research are monthly data of import and export from 1987 to 2015 that obtained from International Financial Statistics (IFS) CD-ROM issued by IMF and Bank Indonesia (BI). The steps of data analysis are

(1) Creating a data plot and then testing the stationary of data using a Dickey Fuller (ADF) augmented test.

(2) If the data are not stationary then it is transformed using log return.

(3) Create an Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plot of log return data to determine the appropriate ARMA model.

(4) Testing the effect of heteroscedasticity by using Lagrange multiplier test.

(5) Establishing an appropriate volatility model and combining volatility model with Markov Switching assuming three states.

(6) Calculating the value of filtered probability at state 3 to detect crisis.

(7) Forecasting the crisis conditions for one year ahead and determining the relation of conditions of import and export indicators.

8. Result and Discussion

Plot of import and export data can be seen in Figure 1 and Figure 2.

Figure 1 and Figure 2 show that the data fluctuates from time to time. This indicates that the data is not stationary, so that required data transformation using log return. Plot of log return of import and export can be seen in Figure 3 and Figure 4.
Figure 3 and Figure 4 show that the data are stationary and evidenced by an ADF test value of 0.001 less than α = 0.05. Since the log return of import and export data are stationary, it can be modeled using the ARMA model.

8.1. Establishment of ARMA Model
The result of ARMA model parameter estimation based on the plot of ACF and PACF got the appropriate model for the import indicator that is ARMA (2,0) which can be written as

\[ r_t = -0.552200 r_{t-1} - 0.287786 r_{t-2} + \alpha_t \]

For the export indicator, it is obtained ARMA(1,0) model which can be written as

\[ r_t = -0.328037 r_{t-1} + \alpha_t \]

Based on the Lagrange multiplier test, it is obtained probability value for imports of 0.0388 and exports of 0.0007, with both probabilities smaller than 0.05. This shows that the residue of ARMA model contains heteroscedasticity effect, so the volatility model is used.

8.2. Formation of Volatility Model
Volatility models include ARCH, GARCH, and EGARCH. The results of ARCH model parameter estimation for the import data are presented in Table 1 and for export data are presented in Table 2.

| Parameter | \( ARCH(1) \) | Prob. | \( ARCH(2) \) | Prob. |
|-----------|----------------|-------|----------------|-------|
| \( \alpha_0 \) | 0.010293 | 0.0000 | 0.010024 | 0.0000 |
| \( \alpha_1 \) | 0.289039 | 0.0042 | 0.283806 | 0.0057 |
| \( \alpha_2 \) | - | - | 0.023753 | 0.7427 |
| \( AIC \) | -1.442103 | - | -1.437041 | - |
| \( SC \) | -1.397541 | - | -1.381337 | - |

The corresponding model to the import data is ARCH (1) which can be written as

\[ \sigma_t^2 = 0.010293 + 0.289039 \sigma_{t-1}^2 \]

Table 2. The result of ARCH Model Parameter Estimation for Export Data

| Parameter | \( ARCH(1) \) | Prob. | \( ARCH(2) \) | Prob. | \( ARCH(3) \) | Prob. |
|-----------|----------------|-------|----------------|-------|----------------|-------|
| \( \alpha_0 \) | 0.005780 | 0.0000 | 0.005018 | 0.0000 | 0.005098 | 0.0000 |
| \( \alpha_1 \) | 0.196269 | 0.0129 | 0.178101 | 0.0297 | 0.178505 | 0.0295 |
| \( \alpha_2 \) | - | - | 0.113774 | 0.0371 | 0.113503 | 0.0373 |
| \( \alpha_3 \) | - | - | - | - | 0.001399 | 0.9771 |
| \( AIC \) | -2.116821 | - | -2.122922 | - | -2.117146 | - |
| \( SC \) | -2.083471 | - | -2.078455 | - | -2.061561 | - |

The corresponding model to the export data is ARCH (1) which can be written as...
\[ \sigma_t^2 = 0.010293 + 0.289039 \, a_{t-1}^2 , \]

where \( a_{t-1}^2 \) is the quadratic residue at time \( t-1 \). Furthermore, the GARCH model is estimated and obtained that GARCH model has insignificant parameter. So the GARCH model is unusable, and the EGARCH model also can not be used. Therefore the volatility model used is ARCH (1) model.

A diagnostic test was then performed on the residual ARCH(1) model. Based on the Ljung-Box test, it is obtained the probability value more than 0.05. This indicates that the residual ARCH(1) model does not contain autocorrelation. From the result of Lagrange multiplier and Kolmogorov-Smirnov test, it is obtained probability value for imports of 0.8734 and 0.101 and probability for export of 0.4512 and 0.558, the probability value is greater than 0.05. Thus it can be concluded that the residual ARCH(1) model does not contain heteroscedasticity and normal distributed.

8.3. Formation of Combined Models of Volatility and Markov Switching
The volatility model that can be used is ARCH, so the SWARCH model is formed. The SWARCH (3,1) estimation model for import data can be written as

\[ r_t = \begin{cases} 0.000022 & \text{for state 1} \\ 0.000026 & \text{for state 2} \\ 0.000019 & \text{for state 3} \end{cases} . \]

The value shows the average log return data on state 1 of 0.000022, state 2 of 0.000026, and state 3 of 0.000019. The heteroscedasticity model of SWARCH (3,1) is

\[ \sigma_t^2 = \begin{cases} 0.009127 + 0.009127 \, a_{t-1}^2 & \text{for state 1} \\ 0.009127 + 0.009127 \, a_{t-1}^2 & \text{for state 2} \\ 0.009127 + 0.009127 \, a_{t-1}^2 & \text{for state 3} \end{cases} . \]

While the probability of change from one state to another is explained by a transition probability matrix written as

\[ P = \begin{pmatrix} 0.000022 & 0.499999 & 0.099881 \\ 0.000026 & 0.499999 & 0.099881 \\ 0.000019 & 0.000026 & 0.800238 \end{pmatrix} . \]

The value indicates the probability of changing state from low to high of 0.999999, the probability of survival in the medium state is equal to the change of state from medium to low by 0.499999, and the probability to survive in a high state of 0.800238.

Furthermore SWARCH(3,1) model for export data can be written as

\[ r_t = \begin{cases} 0.000025 & \text{for state 1} \\ 0.000018 & \text{for state 2} \\ 0.000027 & \text{for state 3} \end{cases} . \]

The heteroscedasticity model of SWARCH (3,1) for export data is

\[ \sigma_t^2 = \begin{cases} 0.237830 + 0.226953 \, a_{t-1}^2 & \text{for state 1} \\ 0.229286 + 0.226953 \, a_{t-1}^2 & \text{for state 2} \\ 0.231370 + 0.226953 \, a_{t-1}^2 & \text{for state 3} \end{cases} . \]

The probability of change from one state to another can be explained by the transition probability matrix written as

\[ P = \begin{pmatrix} 0.000000 & 0.000000 & 0.453617 \\ 0.000000 & 0.000000 & 0.453617 \\ 0.999999 & 0.999999 & 0.992766 \end{pmatrix} . \]

8.4. Filtered Probability
Signal of financial crisis can be seen from filtered probability value at state 3. Plot of filtered probability of import data on period of January 1987 until December 2015 is presented in Figure 5. While the plot of filtered probability of export data on period of January 1987 to December 2015 is presented in Figure 6. In Figure 5 there are 44 months and in Figure 6 there are 28 months that have filtered probability value more than 0.6 so it indicates that indicator is in high volatility condition.
8.5. Forecasting

Forecasting of filtered probability based on import and export indicator is presented in Table 3.

Table 3. Forecasting of Filtered Probability of Import and Export Indicators in 2016

| Month    | Import  | Export  |
|----------|---------|---------|
| January  | 0.581679| 0.573237|
| February | 0.474497| 0.479944|
| March    | 0.542282| 0.564582|
| April    | 0.562576| 0.487791|
| May      | 0.568615| 0.557458|
| June     | 0.570374| 0.494254|
| July     | 0.570848| 0.551595|
| August   | 0.570937| 0.499573|
| September| 0.570911| 0.546769|
| October  | 0.570849| 0.503951|
| November | 0.570776| 0.542797|
| December | 0.570701| 0.507555|

Table 3 shows the value of filtered probability between 0.4 and 0.6. Therefore it can be concluded that Indonesia is prone to financial crisis in 2016 based on import and export indicators.

To determine the correlation of indicator condition used chi square test for independence. Since the value of \( T = 22,70742 > \chi^2_{(0.95,4)} = 9.488 \) and \( p\)-value = 0.000 less than \( \alpha = 0.05 \), it can be concluded that there is a condition relationship between import and export indicators in detecting financial crisis in Indonesia.

9. Conclusion

The appropriate model for the movement of import and export indicators from 1987 to 2015 is SWARCH (3,1). The SWARCH (3,1) model is able to provide information that 2016 is prone to financial crisis in Indonesia. There is a relationship of import and export indicators in detecting financial crisis in Indonesia.
References
[1] Chang K, Cho K Y and Hong M 2010 J. of Economic Research 15 249-272.
[2] Hamilton J D 1989 Econometrica 57 357-384.
[3] Hamilton J D and Susmel R 1994 J. of Econometrics 64 307-333.
[4] Hermosillo B G and Hesse H 2009 Global Market Condition and Systematic risk: IMF IMF Working Paper.
[5] Kaminsky G, Lizondo S and Reinhart C 1998 Leading Indicators of Currency Crises IMF Staff Papers 45.
[6] Sopipan N, Sattayatham P and Premanode B 2012 J. of Mathematical Finance 2 121-131.
[7] Tsay R S 2005 Analysis of Financial Time Series (Canada: John Wiley and Sons).