The application of combined Markov regime switching and volatility model in detecting early financial crisis in Indonesia

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Abstract. The financial crisis had occurred in Indonesia in the middle of 1997 to 1998 which caused the economy of Indonesia was down suddenly. Because the crisis occurred suddenly and even unexpectedly, the Indonesian government was not ready to deal with it. Therefore, the Indonesian government needs a system that can detect crisis signals; so that, such a financial crisis can be avoided. Export and import indicators have high fluctuation and regime-changing during a crisis so that they also can be used to detect crisis signals. The volatility model is able to explain the volatility which included in the indicators, while the Markov regime switching model can explain the regime-changing. Furthermore, a method that can be used to detect a crisis is the combination of Markov regime switching and volatility model. The value of smoothed probability obtained from the combination of those models is able to detect the financial crisis in Indonesia. The results show that export and import indicators can be modelled successively using MRS-GARCH (2,1,1) and MRS-ARCH (2,1). The results obtained from the prediction of those two models show that there is no financial crisis signal in Indonesia for a year later.

1. Introduction
Indonesia had experienced the financial crisis in the middle of 1997 until 1998, while Indonesia’s economic condition looks far from a crisis with low inflation, high international reserves, and good banking condition. The crisis was started with the impairment of Thailand’s currency. This impairment caused by the low international reserves of Thailand so they couldn’t maintain their currency with the dollar. Finally, Thailand’s government decided to float the value of its currency. This friction aimed to increase the export revenues, but in fact, it had the crisis transmitting effect to other countries including Indonesia. The situation in Indonesia became worse when the economic downturn was followed by political conditions that were not conducive. Furthermore, the global financial crisis impact (2008) was also felt in Indonesia. The crisis was caused by the United States of America which experienced a housing credit crisis (subprime mortgage).

Kaminsky et al. [1] declared that there were 15 indicators that are able to predict the financial crisis and two of them used in this research, those are export and import. The total of services and goods sold from one country to another is called exports, while imports are goods or services purchased from one country to another country. The indicators used in this research have the heteroscedasticity effect so that
it is smaller precise if it is modelled by using a model of stationary time series as the model of autoregressive moving average (ARMA). The more suitable model to use is the volatility model.

Engle [2] said that an approach to the volatility model is autoregressive conditional heteroscedasticity (ARCH) then Bollerslev et al. [3], introduced the ARCH model generalization, namely the generalized autoregressive conditional heteroscedasticity (GARCH). This model was first applied to the United States Gross National Product data (1948-1983) and the GARCH (1,2) model was more accurate and efficient compared to the ARCH (8) model. Hamilton and Susmel [4], introduced a model that is able to explain the changes in volatility and it was first applied to stock price data. This model was known as Markov switching autoregressive conditional heteroscedasticity (MS-ARCH).

Financial crisis detection based on the combination of Markov switching and volatility model was implemented by Chang et al. [5], which applied the MS-ARCH model to recognize the global financial crisis in Korea. Sugiyanto et al. [6], researched the early financial crisis detection in Indonesia based on indicators of real exchange rates, bank deposits, and trade terms using the MS-ARCH model. Sugiyanto and Hidayah [7], researched the prediction of Indonesia’s financial crisis based on indicators of lending interest rate/deposit interest rate and the real interest rate on deposits by applying the MRS-GARCH model. This research discusses the early detection of the financial crisis in Indonesia based on export and import indicators using the combination of Markov regime switching and volatility model.

2. Materials
2.1. The model of autoregressive moving average (ARMA)
The model of ARMA is a stationary time series model that identifies regression equations using past values or a combination of past values with past residuals. According to Cryer [8], the ARMA model contains two components, namely the autoregressive (AR) model and the moving average (MA) model where p and q successively is the order of the AR model and the order of the MA model. ARMA (p,q) model is the AR (p) model. Tsay [9] said that the AR (p) model can be denoted as

$$r_t = \varphi_1 r_{t-1} + \varphi_2 r_{t-2} + \cdots + \varphi_p r_{t-p} + \varepsilon_t$$

(1)

with $r_t$ is log return at t time, $\varphi_1, \varphi_2, \ldots, \varphi_p$ are the AR model parameters, and $\varepsilon_t$ is the AR model residual.

2.2. The model of Volatility
The model of volatility is able to solve the heteroscedasticity effects in the ARMA model residuals.

2.2.1. The model of autoregressive conditional heteroscedasticity (ARCH). Tsay [9] said that the model of ARCH (m) can be denoted as

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \ldots + \alpha_m a_{t-m}^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2$$

(2)

with $m$ is the ARCH model order, $\alpha_0$ is ARCH model constant, $\alpha_i$ is ARCH model parameter, and $\sigma_t^2$ is residual of variance at t period.

2.2.2. The model of generalized autoregressive conditional heteroscedasticity (GARCH). Tsay [9] said that the model of GARCH (m,s) can be denoted as

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \ldots + \alpha_m a_{t-m}^2 + \beta_1 \sigma_{t-1}^2 + \ldots + \beta_s \sigma_{t-s}^2$$

(3)

with $\beta_j$ is the GARCH model parameter.

2.3. The combination of Markov regime switching and volatility model
2.3.1. Markov regime switching-ARCH (MRS-ARCH). According to Hamilton and Susmel [4], the MRS-ARCH (K,m) model can be denoted as
\[ \sigma_{i,t}^2 = \alpha_0 + \sum_{j=1}^{m} \alpha_j \sigma_{i-1}^2 + \sum_{j=1}^{s} \beta_j \sigma_{j-1}^2 \]  

with \( K \) is the regime numbers, \( m \) is the ARCH model order, and \( \sigma_{i,t}^2 \) is the variance residuals in regime at \( t \) time.

### 2.3.2. Markov regime switching-GARCH (MRS-GARCH).

According to Gray [10], the MRS-GARCH (\( K,m,s \)) model can be denoted as

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

with \( m \) and \( s \) are the order of the GARCH model.

### 2.4. Transition probability matrix

The MRS-ARCH and MRS-GARCH model contain \( s_t \) index that shows the random variable which unobserved and fulfilled the first-order of the Markov chain. The \( s_t \) variable is the regime in which the process is at \( t \) time and it sets the Markov chain’s first-order. The conditional distribution parameters from the random variable which unobserved with constant transition probability can be denoted as

\[ P(s_t = j | s_{t-1} = i) = p_{ij}^T, \quad \sum_{j=1}^{T} p_{ij} = 1, \quad i, j = 1,2, ..., T. \]  

\( P \) can be denoted in matrix notation like below matrix

\[
P = \begin{pmatrix}
p_{11} & p_{12} & \cdots & p_{1T} 
p_{21} & p_{22} & \cdots & p_{2T} 
\vdots & \vdots & \ddots & \vdots 
p_{T1} & p_{T2} & \cdots & p_{TT}
\end{pmatrix}
\]

### 2.5. Smoothed probability

According to Kim and Nelson [11], the smoothed probability can be denoted as

\[
P(S_i = t | \Psi_T) = \sum_{j=1}^{K} P(S_i = j | \Psi_T) P(S_i = i | S_{i+1} = K, \Psi_T),
\]

with \( \Psi_T \) is a set of entire information in the observations data up to \( T \) time.

According to Guidolin and Pedio [12], the prediction value of smoothed probability at \( t+1 \) time is able to be denoted as

\[
P(S_{i+1} = i | \Psi_T) = \sum_{j=1}^{K} p_{ij}^T P(S_i = j | \Psi_T),
\]

with \( P(S_{i+1} = i | \Psi_T) \) is the value of smoothed probability at \( t \) time for the \( j \)th regime and \( p_{ij}^T \) is the transition probability of regime. The short-term signal of a crisis on an indicator can be predicted by looking at the predicted value of smoothed probability.

### 3. Research Methods

Export and Import data used in this research were secondary data obtained from the International Monetary Fund (IMF) website. Those are monthly data from January 1990 to 2019. The data from
January 1990 to June 2018 were used as training data while the data from July 2018 to June 2019 were used as testing data. The stages below are carried out in this research.

1. Plotting the data then doing the Augmented Dickey-Fuller (ADF) test to see the data stationary. If the data are not stationary, then doing the log return transformation to the data.
2. Estimating the ARMA model and testing the model significance partially.
3. Testing the heteroscedasticity effect on residuals of the ARMA model.
4. Clustering the volatility from residuals of the ARMA model using agglomerative hierarchical clustering with the distance is using the dynamic time warping (DTW) method to obtain the regime numbers.
5. Identifying the appropriate volatility model.
6. Doing the diagnostic tests to the residuals of volatility model (normality, autocorrelation, and heteroscedasticity test).
7. Creating the combination of Markov regime switching and volatility model by using the cluster optimal number as the regime.
8. Determining the financial crisis condition using the value of smoothed probability.
9. Comparing the value of smoothed probability with its prediction from testing data to see the model accuracy.
10. Predicting the financial crisis signal on July 2019-June 2020.

4. Result and discussion
The results obtained from this research will be explained in this part which include the data plot and stationary testing, the ARMA model, the diagnostic testing, the volatility model, the combined Markov regime switching and volatility model, financial crisis detection, and financial crisis prediction.

The important step that has to be done before determining the appropriate model is defining the type of data pattern. The plots of export and import data are presented in Figure 1 and Figure 2.

![Figure 1](image.png)  
**Figure 1.** The plot of export data.  
![Figure 2](image.png)  
**Figure 2.** The plot of import data.

Figure 1 and Figure 2 show that export and import data have a trend pattern or the data are not stationary. ADF test can be used to see the stationary of data. Based on the ADF test, the probability value for each indicator is 0.2828 and 0.5068 which bigger than 0.05 so it implies that the data are not stationary. Because the data are not stationary so the data will be transformed using log return transformation.

The plots of the data after having transformation are presented in Figure 3 and Figure 4.
The number of clusters obtained based on clustering analysis is two clusters for each series data. The appropriate ARMA model for export and import is ARMA (2,0). Those models are chosen from the minimum Akaike Information Criterion (AIC) value which can be written successively as

\[ r_t = 0.011843 - 0.253841 r_{t-1} - 0.098624 r_{t-2} + \varepsilon_t \]

\[ r_t = 0.0126885 - 0.4876726 r_{t-1} - 0.1784015 r_{t-2} + \varepsilon_t \]

The normal curves of residual plots from the model of ARMA (2,0) for each indicator is presented in Figure 5 and Figure 6.

Figure 3 and Figure 4 show that the plot of the data after having transformation have been stationary because the data fluctuations are around a constant average value and not depends on the time and the variance fluctuations. Moreover, the probability value based on the ADF test is 0.01 which smaller than 0.05, so it can be concluded that the export and import data after having transformation have been stationary. After that, the partial autocorrelation function (PACF) and autocorrelation function (ACF) plots will be used to specify the ARMA model. The appropriate ARMA model for export and import is ARMA (2,0). Those models are chosen from the minimum Akaike Information Criterion (AIC) value which can be written successively as

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\[ r_t = 0.0126885 - 0.4876726 r_{t-1} - 0.1784015 r_{t-2} + \varepsilon_t \]
ARMA model contain the heteroscedasticity effects. Therefore, the volatility model will be used to overcome the heteroscedasticity effects. The appropriate volatility model for the export indicator is GARCH (1,1) which can be formulated as

$$\sigma_t^2 = 0.0026235 + 0.3300943 \sigma_{t-1}^2 + 0.4762425 \sigma_{t-1}^2$$

while the appropriate volatility model for the import indicator is ARCH (1) which can be formulated as

$$\sigma_t^2 = 0.013462 + 0.407339 a_{t-1}^2$$

After the volatility model obtained, the diagnostic tests will be carried out. The normality test is carried out using the Kolmogorov-Smirnov test and the result points out that probability value is bigger than 0.05 for those volatility models so it implies that the model residual is normally distributed. Autocorrelation test is carried out by using the Ljung-Box test, the result points out that the probability value is bigger than 0.05 accordingly there is no autocorrelation between the residuals. After that, the heteroscedasticity test is carried out, the result points out that the probability value is bigger than 0.05 for those models accordingly the residuals have been homogenous or there is no heteroscedasticity effect in the residuals.

The regime-changing can be identified from the matrix of transition probability. The regimes referred to in this research are high and low volatilities. The regime is deemed to pursue the Markov chain first order with transition probability $p_{ij}$ where $i, j = 1, 2$ for export and import indicators. Therefore, MRS-GARCH (2,1,1) for export indicator and MRS-ARCH (2,1) for import indicator has two regimes where regime 1 and regime 2 successively describe the low and high volatility. The matrix of transition probability with two regimes for export indicator can be written as

$$P_1 = \begin{pmatrix} 0.9846 & 0.0154 \\ 0.1405 & 0.8595 \end{pmatrix}$$

from the matrix of transition probability above, the probability to stay on the low and high volatility successively is 0.9846 and 0.8595. While the probability to move from high to low volatility and the otherwise successively is 0.1405 and 0.0154.

The mean and variance for every regime in export data are

$$\mu_{1,i} = \begin{cases} 0.00002568, \text{ for regime 1} \\ 0.00010057, \text{ for regime 2} \end{cases} \qquad \sigma_{1,i}^2 = \begin{cases} 0.00002365, \text{ for regime 1} \\ 0.000015733, \text{ for regime 2} \end{cases}$$

The matrix of transition probability with two regimes for import indicator can be written as

$$P_2 = \begin{pmatrix} 0.9939 & 0.0061 \\ 0.0245 & 0.9755 \end{pmatrix}$$

from the matrix of transition probability above, the probability to stay on the low and high volatility successively is 0.9939 and 0.9755. While the probability to move from high to low volatility and the otherwise successively is 0.0245 and 0.0061.

The mean and variance for every regime in import data are

$$\mu_{2,i} = \begin{cases} 0.00002971, \text{ for regime 1} \\ 0.00005199, \text{ for regime 2} \end{cases} \qquad \sigma_{2,i}^2 = \begin{cases} 0.00004767, \text{ for regime 1} \\ 0.00013768, \text{ for regime 2} \end{cases}$$

The crisis detection can be carried out by using the minimum value of smoothed probability when the crisis happened in Indonesia (1997 and 2008) and the result shows that the financial crisis happened when the smoothed probability is bigger than 0.82 for export and 0.98 for import indicators. Smoothed probability plots for export and import indicators are presented in Figure 7 and Figure 8.
Based on Figure 7, it can be viewed that there are 24 values of smoothed probability bigger than 0.82 and from Figure 8, it can be viewed that there are 27 values of smoothed probability bigger than 0.98. The export indicator can detect the crisis from August 1992 – October 1992, December 1997-June 1999, and July 2016- August 2016. Whereas the import indicator can detect the crisis on July 1997-September 1999. Therefore, it can be concluded that MRS-GARCH (2,1,1) for export and MRS-ARCH (2,1) for import can detect the crisis in Indonesia from 1997 to 1998.

Based on the smoothed probability obtained from those indicators, it can be seen that the import indicator can detect the crisis faster than export. This is because the real crisis was started in July 1997, while the export indicator gave the crisis signals from December 1997 and import indicator can detect the crisis from August 1992 and then July 1997. Moreover, the smoothed probability values from imports show that its value increased slowly from September 1996 to July 1997 when the crisis detected. While the smoothed value of export indicator increased suddenly by 62 percent from September to December 1997. Although those indicators can detect the crisis in 1997, they cannot detect the crisis occurred in 2008.

The export indicator only needs three months to return to the non-crisis conditions, while the import indicator took two years to return to the non-crisis conditions. This was because many businessmen want to pursue the income from export.

After that, counting the smoothed probability prediction values. The prediction results of smoothed probability in the next period are presented in Table 1 and Table 2.

| Period    | Prediction | Crisis condition | Actual       | Crisis condition |
|-----------|------------|------------------|--------------|-----------------|
| July ’18  | 0.202719   | Non-crisis       | 0.029116     | Non-crisis      |
| August ’18| 0.300768   | Non-crisis       | 0.028564     | Non-crisis      |
| September ‘18 | 0.38353 | Non-crisis       | 0.011433     | Non-crisis      |
| October ‘18| 0.45339    | Non-crisis       | 0.006123     | Non-crisis      |
| November ’18| 0.512358  | Non-crisis       | 0.004935     | Non-crisis      |
| December ‘18| 0.562132  | Non-crisis       | 0.006127     | Non-crisis      |
| January ’19 | 0.604147   | Non-crisis       | 0.006173     | Non-crisis      |
| February ’19| 0.639611   | Non-crisis       | 0.009303     | Non-crisis      |
| March ’19  | 0.669546   | Non-crisis       | 0.017059     | Non-crisis      |
| April ’19  | 0.694814   | Non-crisis       | 0.024688     | Non-crisis      |
| May ’19    | 0.716143   | Non-crisis       | 0.040208     | Non-crisis      |
| June ’19   | 0.734147   | Non-crisis       | 0.086206     | Non-crisis      |
Table 2. The values of prediction and actual from the smoothed probability for import data.

| Period    | Prediction | Crisis condition | Actual | Crisis condition |
|-----------|------------|------------------|--------|------------------|
| July ‘18  | 0.250124   | Non-crisis       | 0.357716 | Non-crisis       |
| August ‘18| 0.248570   | Non-crisis       | 0.359216 | Non-crisis       |
| September ‘18 | 0.247064 | Non-crisis       | 0.362779 | Non-crisis       |
| October ‘18| 0.245603   | Non-crisis       | 0.372755 | Non-crisis       |
| November ‘18| 0.244188   | Non-crisis       | 0.386744 | Non-crisis       |
| December ‘18| 0.242816  | Non-crisis       | 0.413770 | Non-crisis       |
| January ‘19| 0.241486   | Non-crisis       | 0.446591 | Non-crisis       |
| February ‘19| 0.240196  | Non-crisis       | 0.483226 | Non-crisis       |
| March ‘19  | 0.238946   | Non-crisis       | 0.491267 | Non-crisis       |
| April ‘19  | 0.237734   | Non-crisis       | 0.502927 | Non-crisis       |
| May ‘19    | 0.236560   | Non-crisis       | 0.516310 | Non-crisis       |
| June ‘19   | 0.235421   | Non-crisis       | 0.543147 | Non-crisis       |

Table 1 and Table 2 above show that the crisis conditions on actual and prediction are the same. Therefore, those combined models are appropriate to detect the financial crisis for a year later.

The prediction of the financial crisis for a year later is able to be identified from the smoothed probability prediction values. The smoothed probability prediction values for export and import indicators are presented in Table 3.

Table 3. The smoothed probability prediction values for export and import.

| Period    | Export     | Crisis condition | Import    | Crisis condition |
|-----------|------------|------------------|-----------|------------------|
| July ‘19  | 0.086588   | Non-crisis       | 0.533547  | Non-crisis       |
| August ‘19| 0.086919   | Non-crisis       | 0.524247  | Non-crisis       |
| September ‘19 | 0.087205 | Non-crisis       | 0.515238  | Non-crisis       |
| October ‘19| 0.087452   | Non-crisis       | 0.506511  | Non-crisis       |
| November ‘19| 0.087665  | Non-crisis       | 0.498057  | Non-crisis       |
| December ‘19| 0.087850  | Non-crisis       | 0.489868  | Non-crisis       |
| January ‘20 | 0.088009 | Non-crisis       | 0.481935  | Non-crisis       |
| February ‘20| 0.088147  | Non-crisis       | 0.474251  | Non-crisis       |
| March ‘20  | 0.088266   | Non-crisis       | 0.466807  | Non-crisis       |
| April ‘20  | 0.088369   | Non-crisis       | 0.459595  | Non-crisis       |
| May ‘20    | 0.088458   | Non-crisis       | 0.452610  | Non-crisis       |
| June ‘20   | 0.088535   | Non-crisis       | 0.445843  | Non-crisis       |

Table 3 shows that all the smoothed probability values are smaller than 0.82 and 0.98, so it can be concluded that based on export and import indicators, Indonesia will not experience the financial crisis from July 2019 to June 2020.

5. Conclusion
The appropriate models based on export and import indicators are MRS-GARCH (2,1,1) and MRS-ARCH (2,1). Those indicators can detect the signals of the financial crisis in 1997 but both of them cannot detect the signals of the financial crisis in 2008. Indonesia will not experience the financial crisis from July 2019 to June 2020 based on the prediction result from those combined models. As explained before, indicators used in this research are export and import which using univariate time series method; so that the recommendation for the further researcher is the researcher can use the other crisis indicators or multivariate time series method to detect the financial crisis.
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