Early detection of the financial crisis in Indonesia, Thailand, and South Korea based on real exchange rates

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Abstract. The 1997 Asian financial crisis and the 2008 global financial crisis had a significant impact on the economies of various countries, including Indonesia, Thailand, and South Korea. Therefore, this study aims to detect early financial crises in these three countries based on real exchange rate indicators. The early detection of financial crises, relevant institutions in applying appropriate policies. Thus, financial crises can be avoided. The real exchange rate indicator contains fluctuations, and changing conditions. As a solution, the volatility models, i.e. autoregressive conditional heteroscedasticity (ARCH) and generalized ARCH (GARCH) explains volatility or fluctuations, and Markov switching (MS) explains changing conditions. The combination of these models yields a smoothed probability value used for detecting financial crises. The real exchange rate of Indonesia, Thailand, and South Korea data against the United States were used from January 1990 to March 2020. The results showed that MS-ARCH(2,1), MS-ARCH(2,1), and MS-GARCH(2,1,1) are for Indonesia, Thailand, and South Korea, respectively. The real exchange rate indicator can detect crises in Indonesia and South Korea in 1997 and 2008. Whereas in Thailand, it was only able to detect crises occurred in the 1997. The prediction results of the smoothed probability showed no signal of the financial crisis in Indonesia, Thailand, and South Korea one year later.

1. Introduction

In 1997 there was an Asian financial crisis. The crisis started on July 2, 1997. At the time, the Thailand government had substantial foreign debts. Then there was an attack from currency speculators against Thailand’s foreign exchange reserves. The Thailand government decided to float its currencies to stimulate export revenue. However, it affected the currencies of other countries. This crisis has had a devastating impact on Indonesia and South Korea. In Indonesia, there was a depreciation of the Rupiah against the USD, from 2,450 in June 1997 to 14,900 in June 1998. In South Korea, there was also depreciation of the Won against the USD, from 867 in February 1997 to 1,702 in January 1998.

The global crisis in 2008 was inevitable. This crisis began from the liquidity failure in the subprime mortgage that occurred in the United States. A subprime mortgage in the United States is the provision of housing loans to borrowers who have no history of borrowing or have a bad history of borrowing. Borrowers like this have the risk of bad credit. The crisis that occurred in the United States then affected to other countries. The countries of Indonesia, Thailand, and South Korea were again feeling the impact of the crisis. In Indonesia, there was another depreciation of the Rupiah against the USD, from 9,419 in December 2007 to 12,151 in November 2008. In Thailand, the impact of the crisis...
was strongest in the manufacturing sector, employment in this sector decreased by around 5-9 percent in Q3 of 2008 and Q1 of 2009 [1]. Meanwhile, in South Korea, 123,371 apartment units were not sold and causing 261 construction companies to go bankrupt [2].

The three countries were severely affected the crisis. Therefore, it is necessary to detect the crisis early to maintain the stability of the economy and the currencies of the three countries. There are fifteen indicators that can signal a crisis [3]. One of them is the real exchange rate indicator that is used in this study. The real exchange rate indicator is a financial time-series data. According to Tsay[4], most of the financial time-series has a heteroscedasticity effect. As a solution, a volatility model is needed. Engle [5] introduced the autoregressive conditional heteroscedasticity (ARCH) model. In the following year, Bollerslev et al. [6] introduced generalized autoregressive conditional heteroscedasticity (GARCH). However, volatility models still have a weakness, it cannot explain changes in conditions from the variance that is not constant. Hamilton [7] introduced a model that can explain changes in structure or a condition. The model is called Markov switching. Then, Hamilton and Sumsel [8] introduced Markov switching autoregressive conditional heteroscedasticity (MS-ARCH) model. This model combines the ARCH Markov switching and volatility models.

Furthermore, MS-ARCH was used to detect the global financial crisis in Korea [9]. MS-ARCH was implemented for early detection of financial crises in Indonesia using indicators of trade terms, bank deposits, and real exchange rates [10]. Sugiyanto and Hidayah [11] used an indicator of the real interest rate on deposit and lending interest rate/deposit interest rate. They then applied the Markov switching autoregressive generalized conditional heteroscedasticity (MS-GARCH) model to predict the Indonesian financial crisis. Based on previous studies, this research aims to detect financial crises in Indonesia, Thailand, and South Korea based on real exchange rate indicators using a combination of volatility and Markov switching models.

2. Materials

2.1. Mean Model

The ARMA$(b,c)$ model is a combination of moving average (MA) models with order $c$ and the autoregressive (AR) model with order $b$ [12]. Tsay [13] writes the AR$(b)$ model as follows:

$$r_t = \phi_1 r_{t-1} + \phi_2 r_{t-2} + \cdots + \phi_b r_{t-b} + \alpha_t.$$  

(1)

Meanwhile, MA$(c)$ model can be formulated as follows:

$$r_t = \alpha_t - \theta_1 \alpha_{t-1} - \theta_2 \alpha_{t-2} - \cdots - \theta_c \alpha_{t-c}.$$  

(2)

An ARMA$(b,c)$ model can be written as follows:

$$r_t = \phi_0 + \sum_{i=1}^{b} \phi_i r_{t-i} + \alpha_t - \sum_{i=1}^{c} \theta_i \alpha_{t-i},$$  

(3)

where $r_t$ is time-series data at time $t$, $\phi_1, \phi_2, \ldots, \phi_b$ is an AR model parameter, $\theta_1, \theta_2, \ldots, \theta_c$ is the MA model parameter, and $\alpha_t$ is the white noise of the residuals model. The highest order MA is determined by the ACF plot, which is cut off after lag $b$. Meanwhile, the highest AR order is determined by the PACF plot, which is cut off after lag $c$.

2.2. Volatility Model

2.2.1. Autoregressive Conditional Heteroscedasticity (ARCH) model. ARCH$(p)$ model can be formulated as follows:

$$\alpha_t = \sigma_t e_t, \quad \sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \cdots + \alpha_p \sigma_{t-p}^2,$$

(4)

where $p$ is an order of ARCH model, $e_t$ is random variable iid with mean 0 and variance 1, $\alpha_t$ is residuals mean model, $\alpha_0$ is model constant, $\alpha_1, \alpha_2, \ldots, \alpha_p$ is the ARCH model parameter, and $\sigma_t^2$ is a conditional variance of residuals at time $t$ [13].

2.2.2. Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. GARCH$(p,q)$ model can be modeled as follows:
\[ a_t = \sigma_t e_t, \]
\[ \sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2, \]
with \( \beta_j \) is the GARCH model parameter [13].

2.3. Combination of Volatility and Markov Switching Model
Markov switching autoregressive conditional heteroscedasticity with order \( K \) and \( p \), MS-ARCH(\( K,p \)), model can be formulated as follows:
\[ \sigma_{t,S_t}^2 = \alpha_0,s_t + \sum_{i=1}^{p} \alpha_i,s_t a_{t-i}^2, \]
where \( K \) is the number of states, \( p \) is the order of the ARCH model, and \( \sigma_{t,S_t}^2 \) is a conditional variance of residuals in the state at time \( t \) [8]. Furthermore, Markov switching autoregressive generalized conditional heteroscedasticity with order \( K, p \) and \( q \), MS-GARCH(\( K,p,q \)), can be modeled as follows:
\[ \sigma_{t,S_t}^2 = \alpha_0,s_t + \sum_{i=1}^{p} \alpha_i,s_t a_{t-i}^2 + \sum_{j=1}^{q} \beta_j,s_t \sigma_{t-j}^2, \]
where \( p \) and \( q \) are the orders of the GARCH model [14].

2.4. Smoothed Probability
Smoothed probability can be written as follows:
\[ P(S_t = i | \psi_T) = \sum_{j=1}^{K} P(S_{t+1} = j | \psi_T) P(S_t = i | S_{t+1} = j, \psi_T), \]
which \( \psi_T \) is a set of all information up to time \( T \) [15]. The following is a smoothed probability prediction, according to Guidolin and Pedio [16]:
\[ P(S_{t+1} = i | \psi_T) = \sum_{j=1}^{K} p_{ij} P(S_t = j | \psi_T), \]
where \( p_{ij} \) is the element of the transition probability matrix and \( P(S_{t+1} = i | \psi_T) \) is the value of the smoothed probability at time \( t \) for the \( i \)th state [16]. A crisis is detected when the smoothed probability value is higher than the predetermined threshold.

3. Research Methods
This research used data on the real exchange rate in Indonesia, Thailand, and South Korea against the United States. The data used in the study were secondary data obtained from the International Monetary Fund. Time-series data were used in the months from January 1990 to March 2020. The training data consisted of data from January 1990 until March 2019 and the testing data consisted of data from April 2019 to March 2020. The procedure for modeling and predicting the financial crisis can be seen in Figure 1 and is explained below.

(1) Plot data of the real exchange rate in three countries.
(2) Identify whether the data is stationary in the mean and variance. If the data is nonstationary, then perform differencing and transformations.
(3) Test the stationarity of data with the Augmented Dickey-Fuller (ADF) test.
(4) Perform the autocorrelation test on data. If there is autocorrelation in the data, it is better to model the data using the mean model.
(5) Determine the appropriate mean model.
(6) Plot kurtosis of residuals each country and clustering the residual mean model to obtain the optimal number of clusters with the Dynamic Time Warping (DTW) method.
(7) Test the effect of heteroscedasticity on residuals of mean model. When a heteroscedasticity effect on the residuals exist, it can be continued to be a volatility model.
(8) Determine the appropriate volatility model.
(9) Perform heteroscedasticity and white noise tests on the residuals volatility model.
(10) Create a combined model of volatility and Markov switching models using the optimal number of clusters as the number of states.
(11) Determine the condition of the financial crisis by using the value of smoothed probability based on a predetermined threshold.
(12) For model accuracy, compare actual value and prediction of smoothed probability.
(13) Predict the financial crisis signals for next year.
Figure 1. A flowchart of the research steps

4. Results
The first step was to plot the data. The real exchange rates for Indonesia, Thailand, and South Korea from January 1990 to March 2020 are depicted in Figure 2(a), Figure 2(b), and Figure 2(c), respectively. The second step was to identify stationary data using the plotted data. Figure 2(a) to Figure 2(c) show that all three series are non-stationary in the mean because there are trends in the series. Figure 2(a) to Figure 2(c) also show the time-dependent variance. Therefore, it is necessary to
find the difference of data to get stationary in the mean and logarithmic transformations to get stationary in the variance. The differentiation and logarithmic transformation for the three countries are shown in Figure 3(a), Figure 3(b), and Figure 3(c), respectively. Based on Figure 3(a) to Figure 3(c), the data are stationary in mean because there are no upward trend in the data plot. Figure 3(a) to Figure 3(c) also show no time-dependent variance. The third step was to test stationarity by using the ADF test on the results of differentiation and transformation. The p-values of the ADF test for three countries were 0.01. Since the p-values are less than $\alpha = 0.05$, it means the difference and transformation data for the three countries are stationary.

![Graphs of exchange rates](image)

**Figure 2.** Real exchange rate of (a) Indonesia, (b) Thailand, and (c) South Korea

After the data were stationary, an autocorrelation test was performed on the transformation and difference result data. The Ljung-Box autocorrelation test was carried out to determine whether or not the mean model should be used. The mean model is needed when there is an autocorrelation in the series. Based on the p-values obtained by Ljung-Box test that were $7.231 \times 10^{-8}$, $1.663 \times 10^{-10}$, and $3.331 \times 10^{-16}$ for Indonesia, Thailand, South Korea, respectively. We can conclude that there are autocorrelation in the series and therefore the mean models are needed.
Figure 3. Result of log transformations and differencing data on real exchange rate of (a) Indonesia, (b) Thailand, and (c) South Korea

Based on the ACF and PACF plots and the smallest AIC value, the best mean model for the Indonesian state was ARMA(2,2), which can be represented as follows:

$$r_t = 0.02293 - 0.33865r_{t-1} - 0.77681r_{t-2} + 0.55841a_{t-1} + 0.88093a_{t-2} + a_t.$$  

Here was the best model for Thailand, namely ARMA(2,3).

$$r_t = 0.0008935 - 0.0795066r_{t-1} - 0.6761604r_{t-2} + 0.5180776a_{t-1} + 0.8496653a_{t-2} + 0.2245864a_{t-3} + a_t.$$  

The best model for South Korea was AR(2), which is written as follows:

$$r_t = 0.001530 + 0.610430r_{t-1} - 0.303682r_{t-2} + a_t.$$  

Based on Figure 4(a), Figure 4(b), and Figure 4(c), there are low and high variance clustering, so it is necessary to cluster the residuals. The Dynamic Time Wrapping (DTW) distance method was the appropriate grouping of time-series data. According to the results of clustering, the optimal number of clusters for each country were two clusters. Variance clustering indicates residuals have a
heteroscedasticity effect. The kurtosis of residuals of each country are shown in Figure 5(a), Figure 5(b), and Figure 5(c) in the form of a leptokurtic curve. A leptokurtic curve indicates not normally distributed on residuals in each country.

**Figure 4.** Residuals plot of (a) Indonesia, (b) Thailand, and (c) South Korea

The next step tested the effect of heteroscedasticity on the residuals of the mean model for each country. If there are a heteroscedasticity effect on the residuals, it can be continued to the volatility model. The Lagrange Multiplier test was used to test the heteroscedasticity effect. Based on the p-values obtained by Lagrange Multiplier test that were 0.003674, < 2.216 × 10⁻¹⁰, and 0.03081 for Indonesia, Thailand, and South Korea, respectively. We can conclude that there are a heteroscedasticity effect on the residuals and therefore the volatility models are needed.
Furthermore, it was necessary to identify a suitable volatility model according to the ACF and PACF plots of the residual mean squared model. Also, to choose the best model, the smallest AIC was chosen. The best volatility models for Indonesia, Thailand, South Korea, respectively, were ARCH(1), ARCH(1), and GARCH(1,1), can be modeled as follows:

\[
\sigma_t^2 = 0.00055 + 1.783a_{t-1}, \\
\sigma_t^2 = 0.0002535 + 0.3635a_{t-1}, \\
\sigma_t^2 = 0.00007425 + 0.3688a_{t-1} + 0.547\sigma_{t-1}^2.
\]

After suitable models were obtained for each country, heteroscedasticity and autocorrelation tests were performed on the residual standardized volatility model. The Ljung-Box test could be used to see whether there was autocorrelation. All three countries have p-values that are more than \(\alpha = 0.05\). So there are no autocorrelation of standardized residuals. Lagrange Multiplier test was used for testing the heteroscedasticity effect. The p-values of the Lagrange Multiplier test in the three countries are more than \(\alpha = 0.05\). It means that there are no heteroscedasticity effect on the standardized residuals. Thus, standardized residuals from the three countries have no heteroscedasticity effect and white noise residuals.

**Figure 5.** Residuals kurtosis of (a) Indonesia, (b) Thailand, and (c) South Korea.
The volatility models of the three countries were then combined with the k-state Markov switching model. The optimal k value was obtained from clustering the mean model residuals. From the previous step, for the three countries, the optimal k was obtained at 2. With k = 2, it means that the financial crisis in three countries can be explained by a crisis (high) and a non-crisis (low) condition. The probability that a state can survive or undergo changes to another state could be seen through the transition probability matrix. The following was the transition probability matrix for Indonesia:

\[
P_1 = \begin{pmatrix}
0.99 & 0.01 \\
0.0387 & 0.9613 \\
\end{pmatrix}.
\]

The probability of the Indonesian state remaining in a low state is 0.99. The change in probability from low to high state is 0.01. Furthermore, the change in probability from high to low state is 0.0387. The probability of the Indonesian state remaining in a high state is 0.9613.

The transition probability matrix from Thailand was as follows:

\[
P_2 = \begin{pmatrix}
0.9968 & 0.0032 \\
0.0711 & 0.9289 \\
\end{pmatrix}.
\]

The probability of the Indonesian state remaining in a low state is 0.9968. The change in probability from low to high state is 0.0032. Furthermore, the change in probability from high to low state is 0.0711. The probability of the Indonesian state remaining in a high state is 0.9289.

South Korea had a probability matrix as follows:

\[
P_3 = \begin{pmatrix}
0.9873 & 0.0127 \\
0.1247 & 0.8753 \\
\end{pmatrix}.
\]

The probability of the Indonesian state remaining in a low state is 0.9873. The change in probability from low to high state is 0.0127. Furthermore, the change in probability from high to low state is 0.1247. The probability of the Indonesian state remaining in a high state is 0.8753.

The following were show the mean and variance for Indonesia, Thailand, and South Korea.

\[
\mu_{1,t} = \begin{cases}
0.0000154, & \text{for state 1} \\
0.0011572, & \text{for state 2}
\end{cases}
\]

\[
\sigma_{1,t} = \begin{cases}
0.0000016, & \text{for state 1} \\
0.0000782, & \text{for state 2}
\end{cases}
\]

\[
\mu_{2,t} = \begin{cases}
-0.00000153, & \text{for state 1} \\
0.000097038, & \text{for state 2}
\end{cases}
\]

\[
\sigma_{2,t} = \begin{cases}
0.0000000572, & \text{for state 1} \\
0.0000276304, & \text{for state 2}
\end{cases}
\]

\[
\mu_{3,t} = \begin{cases}
0.00000188, & \text{for state 1} \\
0.00001982, & \text{for state 2}
\end{cases}
\]

\[
\sigma_{3,t} = \begin{cases}
0.00000015, & \text{for state 1} \\
0.000000772, & \text{for state 2}
\end{cases}
\]

A crisis could be detected by using a smoothed probability value compared to a predetermined threshold. The thresholds was obtained from the smallest probability value when a crisis occurred in each country, were in 1997 and 2008. Then, a crisis occurred when the smoothed probability value was higher than the threshold. For Indonesia, the threshold was 0.97, Thailand was 0.92, and South Korea was 0.9.

Based on Figure 6(a), there are 40 smoothed probability values that are bigger than 0.97. The crisis in Indonesia occurred from June 1997 to October 1999, March to July 2000, February until June 2001, and September 2008. The real exchange rate indicator was signal the crisis in Indonesia in 1997 in July, while in 2008, it was September. Furthermore, for Thailand, based on Figure 6(b), there are 13 smoothed probability values that are bigger than 0.92. The crisis in Thailand occurred from June 1997 to June 1998. In contrast to Indonesia, in Thailand, the signal of the crisis in 1997 was detected a month earlier, in June. This signal was due to the decline in the value of the Thailand currency, which had an impact on other countries. However, the real exchange rate indicator was unable to detect the
2008 crisis in Thailand and could only detect the crisis in 1997. In South Korea, based on Figure 6(c), there are 28 smoothed probability values that are bigger than 0.9. The crisis occurred in October to November 1997, January 1999 to August 2000, and April to September 2008. Crisis detection generated from smoothed probability in Indonesia and South Korea are appropriate with the crisis periods were 1997 and 2008. Therefore, it could be concluded that MS-ARCH(2,1) for Indonesia and MS-GARCH(2,1,1) for South Korea were able to detect crises in 1997 and 2008. However, in Thailand, MS-ARCH(2,1).

Figure 6. Smoothed probability plots of (a) Indonesia, (b) Thailand, and (c) South Korea

Next, calculated the predicted value from smoothed probability for each country. The comparisons between the smoothed probability and actual smoothed probability predictions for Indonesia, Thailand, and South Korea are shown in Table 1, Table 2, and Table 3, respectively.
Table 1. Prediction value from smoothed probability for Indonesia

| Time   | Prediction Smoothed Probability | Information | Actual Smoothed Probability | Information |
|--------|---------------------------------|-------------|-----------------------------|-------------|
| Apr’19 | 0.019632                        | No crisis   | 0.00128585                  | No crisis   |
| May’19 | 0.028676                        | No crisis   | 0.00098695                  | No crisis   |
| Jun’19 | 0.037279                        | No crisis   | 0.00099212                  | No crisis   |
| Jul’19 | 0.045464                        | No crisis   | 0.00219533                  | No crisis   |
| Aug’19 | 0.05325                         | No crisis   | 0.00858335                  | No crisis   |
| Sep’19 | 0.060656                        | No crisis   | 0.01794587                  | No crisis   |
| Oct’19 | 0.067702                        | No crisis   | 0.04806486                  | No crisis   |
| Nov’19 | 0.074405                        | No crisis   | 0.17708582                  | No crisis   |
| Dec’19 | 0.080782                        | No crisis   | 0.31152367                  | No crisis   |
| Jan’20 | 0.086848                        | No crisis   | 0.61130208                  | No crisis   |
| Feb’20 | 0.092618                        | No crisis   | 0.80414082                  | No crisis   |
| Mar’20 | 0.098108                        | No crisis   | 0.77047134                  | No crisis   |

Based on Table 1, the predicted and actual smoothed probability values are less than the Indonesian threshold, which is 0.97. It means a stable condition for Indonesia.

Table 2. Prediction value from smoothed probability for Thailand

| Time   | Prediction Smoothed Probability | Information | Actual Smoothed Probability | Information |
|--------|---------------------------------|-------------|-----------------------------|-------------|
| Apr’19 | 0.007287                        | No crisis   | 7.95 x10^{-5}               | No crisis   |
| May’19 | 0.009946                        | No crisis   | 0.00024287                  | No crisis   |
| Jun’19 | 0.012407                        | No crisis   | 8.99 x10^{-5}               | No crisis   |
| Jul’19 | 0.014685                        | No crisis   | 5.29 x10^{-5}               | No crisis   |
| Aug’19 | 0.016794                        | No crisis   | 5.54 x10^{-5}               | No crisis   |
| Sep’19 | 0.018746                        | No crisis   | 5.68 x10^{-5}               | No crisis   |
| Oct’19 | 0.020553                        | No crisis   | 4.95 x10^{-5}               | No crisis   |
| Nov’19 | 0.022226                        | No crisis   | 6.44 x10^{-5}               | No crisis   |
| Dec’19 | 0.023775                        | No crisis   | 0.00019576                  | No crisis   |
| Jan’20 | 0.025208                        | No crisis   | 0.00113081                  | No crisis   |
| Feb’20 | 0.026535                        | No crisis   | 0.00147732                  | No crisis   |
| Mar’20 | 0.027764                        | No crisis   | 0.00441513                  | No crisis   |

Based on Table 2, the predicted and actual smoothed probability values are less than the threshold for Thailand, which is 0.92. It means a stable condition for Thailand.
Table 3. Prediction value from smoothed probability for South Korea

| Time | Prediction | Information | Actual | Information |
|------|------------|-------------|--------|-------------|
| Apr’19 | 0.098674 | No crisis | 0.26850968 | No crisis |
| May’19 | 0.097816 | No crisis | 0.27841019 | No crisis |
| Jun’19 | 0.097076 | No crisis | 0.26011615 | No crisis |
| Jul’19 | 0.096438 | No crisis | 0.2578578 | No crisis |
| Aug’19 | 0.095887 | No crisis | 0.23712917 | No crisis |
| Sep’19 | 0.095013 | No crisis | 0.20303168 | No crisis |
| Oct’19 | 0.094649 | No crisis | 0.18725573 | No crisis |
| Nov’19 | 0.094345 | No crisis | 0.17523827 | No crisis |
| Dec’19 | 0.094082 | No crisis | 0.15577036 | No crisis |
| Jan’20 | 0.093659 | No crisis | 0.1397176 | No crisis |
| Feb’20 | 0.093855 | No crisis | 0.13298271 | No crisis |
| Mar’20 | 0.093659 | No crisis | 0.13298271 | No crisis |

Based on Table 3, the predicted and actual smoothed probability values are less than the threshold for South Korea, which is 0.9. It means stable conditions for South Korea. Based on Table 1, Table 2, and Table 3, the models have 100% accuracy. Furthermore, the forecasted value of the smoothed probability for the next year was calculated for the three countries. The value of these forecasting results is shown in Table 4. Based on Table 4, Indonesia, Thailand, and South Korea in April 2020 to March 2021 are in a stable condition or will not experience a crisis.

Table 4. Forecast value of smoothed probability for the three countries

| Time | Indonesia | Thailand | South Korea |
|------|-----------|----------|-------------|
|      | Smoothed Probability | Information | Smoothed Probability | Information | Smoothed Probability | Information |
| Apr’20 | 0.73879877 | No crisis | 0.00709106 | No crisis | 0.12710029 | No crisis |
| May’20 | 0.70897904 | No crisis | 0.00957057 | No crisis | 0.12196024 | No crisis |
| Jun’20 | 0.68090377 | No crisis | 0.01186809 | No crisis | 0.11577036 | No crisis |
| Jul’20 | 0.6544709 | No crisis | 0.01396968 | No crisis | 0.11354429 | No crisis |
| Aug’20 | 0.62958435 | No crisis | 0.0159696 | No crisis | 0.1071176 | No crisis |
| Sep’20 | 0.60615366 | No crisis | 0.01779743 | No crisis | 0.101115 | No crisis |
| Oct’20 | 0.58409368 | No crisis | 0.0194911 | No crisis | 0.10450013 | No crisis |
| Nov’20 | 0.5633242 | No crisis | 0.02106045 | No crisis | 0.10221221 | No crisis |
| Dec’20 | 0.54376973 | No crisis | 0.02251461 | No crisis | 0.10021303 | No crisis |
| Jan’21 | 0.5253592 | No crisis | 0.02386204 | No crisis | 0.09846615 | No crisis |
| Feb’21 | 0.50802569 | No crisis | 0.02511057 | No crisis | 0.09693972 | No crisis |
| Mar’21 | 0.49170618 | No crisis | 0.02626745 | No crisis | 0.09560593 | No crisis |
5. Discussion

When the author worked on this article the data was only available until March 2020. The prediction results of the smoothed probability from April 2020 to September 2020 are in accordance with current conditions, namely no crisis occurred. According to Kaminsky et al. [3], a crisis is defined as a situation where there is an attack on a currency which results in a sharp depreciation of exchange rate, or a decrease in foreign exchange reserves, or a combination of both. Table 5 explains the nominal exchange rate of the three countries against the United States from December 2019 to August 2020. Based on Table 5, there have been currency depreciation, but the depreciation is not sharp so it is not called a crisis and in the following months the currencies of the three countries strengthened again.

Table 5. The nominal exchange rate of the three countries against the United States

| Time | Indonesia | Thailand | South Korea |
|------|-----------|----------|-------------|
| Des’19 | 14,017.45 | 30.22   | 1,175.84    |
| Jan’20 | 13,732.23 | 30.43   | 1,164.28    |
| Feb’20 | 13,776.15 | 31.34   | 1,193.79    |
| Mar’20 | 15,194.57 | 32.09   | 1,220.09    |
| Apr’20 | 15,867.43 | 32.64   | 1,225.23    |
| May’20 | 14,906.19 | 32.04   | 1,228.67    |
| Jun’20 | 14,195.96 | 31.16   | 1,210.01    |
| Jul’20 | 14,582.41 | 31.41   | 1,198.90    |
| Aug’20 | 14,724.50 | 31.22   | 1,186.85    |

6. Conclusion

The combination of Markov switching and volatility model could detect the financial crisis in Indonesia, Thailand, and South Korea. The best-combined model based on real exchange rate indicators for Indonesia and Thailand were MS-ARCH(2,1) and South Korea was MS-GARCH(2,1,1). With this combination of models, in Indonesia, crises were detected in July 1997 and September 2008. However, in Thailand, the crisis was only detected in June 1997. Meanwhile, in South Korea, crises were detected in January 1999 and April 2008. The smoothed probability produced accurate results where the predictions were the same as the real condition. Based on the forecast value of smoothed probability, it was estimated that there would be no crisis in the three countries from September 2020 to March 2021. For further research, the multivariate method can be considered to take into account other indicators (see[3]).

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