Early detection models of currency crises in Indonesia based on inflation and interest rates indicators

I F Amri¹, N Chamidah¹ and Sugiyanto²

¹ Department of Mathematics, Faculty of Sciences and Technology, Universitas Airlangga, Jl. Mulyorejo, Surabaya-60115, East Java, Indonesia.
² Department of Statistics, Faculty of Mathematics and Natural Sciences, Universitas Sebelas Maret, Ir. Sutami Street 36 Kentingan, Surakarta, Central Java, Indonesia.

E-mail: nur-c@fst.unair.ac.id

Abstract. The global crisis that occurred in the middle of 1997 showed that the financial crisis had a huge impact on the Indonesian economy. The crisis happened because of several macroeconomic indicators experienced very high fluctuations that were followed by regime changes. The combination of the Markov regime-switching and volatility models are very suitable to explain high fluctuations and regime changes. The inflation and the interest rates indicators, it was obtained that the best model of those indicators was MRS-AR (2,1) and MRS-GARCH (2,2,0), respectively. The MRS-AR (2,1) model can capture crises from August 1997 to December 1998, while the MRS-GARCH (2,2,0) model can capture crises from January to December 1998. The smoothed probability prediction values of the two models, it could be concluded that Indonesia did not experience a currency crisis in 2019.

1. Introduction
The global crisis that occurred in early July 1997 to 1998 was the worst crisis that was very good for the Indonesian economy. As a result of the crisis, Inflation fell to 82.42% in September 1998, and interest rates increased uncontrollably to 90.35% in October 1998. The subprime mortgage crisis in September 2008 in the US has supported several US companies, this improvement also impacts not good on finance in Indonesia, and the Indonesia Stock Exchange closed in October 2008 to prepare the stock market. We need a system to solve future crises based on macroeconomic indicators and other indicators.

Kaminsky and Reinhart[1] developed an early detection system for a currency crisis by observing several indicators that show unusual behavior during a crisis. These indicators include real output, stock prices, foreign exchange reserves, real domestic/foreign interest differentials, excess M1 real balance, M2/foreign exchange reserves, bank deposits, M2 multiplier, domestic credit, real interest rates on deposits, loan interest rate ratios and deposits, real exchange rates, exports, imports, trade exchange rates. Ford et al.[2] uses four indicators, namely market pressure, the ratio of international reserves to the money supply, the real exchange rate, domestic credit growth, in predicting the rupiah crisis. Sugiyanto et al.[3] uses indicators real output, domestic credit, and the composite stock price index (CSPI) to determine the currency crisis in Indonesia, and Sugiyanto et al.[4] uses banking indicators to detect currency crises in Indonesia. This study uses inflation indicators and interest rates to detect currency crises in Indonesia.
Inflation is a process of increasing the prices of general goods and weakening the value of a country’s currency continuously. Rising inflation will reduce exports and the decline in exports has resulted in a reduced flow of foreign currency supply, which has weakened the domestic currency. The sharp decline in the domestic currency produced a currency crisis. While the interest rate is the level of profit that will be received by investors from the use of investment funds based on calculating the economic value at a certain period. Increasing interest rates will bring in investors, but unstable economic conditions cause investors to delay investing, as well as interest rates that are too small. Therefore unusual or abnormal interest rates can cause a crisis.

Monthly inflation and interest rate data are time-series data, and the data have residual variances that change over time so that the Autoregressive Moving Average (ARMA) model is not suitable for use. Therefore, we need a model that can explain the volatility in the data. Engle[5] used an autoregressive conditional heteroscedasticity (ARCH) model as modeling residual variance. Bollerslev[6] used the Generalized ARCH (GARCH), and Nelson[7] used the Exponential-GARCH (EGARCH) model. The EGARCH model can capture residual asymmetry, negative residues (bad information conditions), and positive residues (good information conditions) that cannot be captured by GARCH. However, the ARCH and EGARCH models cannot explain regime change.

Hamilton[8] used the Markov switching model in an autoregressive process to explain regime change. However, this Markov switching model cannot explain data volatility. Hamilton and Susmel[9] used the combination of Markov switching and ARCH (SWARCH) model. The SWARCH model can explain volatility and regime change. Henry[10] used MS-EGARCH model to capture volatility, asymmetry data, and regime change. Sugiyanto et al.[3],[4] used the SWARCH and MS-GARCH models to detect currency crises in Indonesia based on indicators of domestic credit per GDP, real output, banking, and ICI. The results show that the indicators provide a good signal to detect currency crises.

2. Theoretical basis

2.1. ARMA model

According to Tsay[11] the formulated AR (p) model as follows

\[ r_t = \phi_0 + \phi_1 r_{t-1} + \cdots + \phi_p r_{t-p} + \alpha_t, \]

where \( r_t \) is the log return data, \( \alpha_t \) is the residual for AR (p) model, and \( \phi_0, \phi_1, \ldots, \phi_p \) is the parameter for AR (p) model.

2.2. ARCH model

According to Engle [5], ARCH model of order m is as follows

\[ \alpha_t = \sigma_t \epsilon_t, \]

where \( \epsilon_t \sim N(0,1) \) and \( \alpha_t | \psi_{t-1} \sim N(0, \sigma_t^2) \).

\[ \sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \cdots + \alpha_m \sigma_{t-m}^2 = \alpha_0 + \sum_{i=0}^{m} \alpha_i \sigma_{t-i}^2. \]

\( \alpha_0 > 0, \alpha_i \geq 0, \) for \( i > 0 \), \( \sigma_t^2 = E(\alpha_t^2 | \psi_{t-1}) \) is the variance of residual.

2.3. MRS-ARCH

According to Hamilton and Susmel [10] Combined volatility model and Markov regime-switching written as

\[ r_t = \mu_{s_t} + \alpha_t, \quad t = \sigma_t \epsilon_t, \quad \alpha_t = \sigma_t \epsilon_t, \quad \sigma_t^2_{s_t} = \alpha_{0,s_t} + \sum_{i=0}^{m} \alpha_{l,s_t} \sigma_{t-i}^2, \quad \sigma_t^2_{s_t} = \alpha_{0,s_t} + \sum_{i=1}^{m} \alpha_{l,s_t} \sigma_{t-i}^2 + \sum_{j=1}^{k} \beta_{j,s_t} \sigma_{t-j}^2. \]

equation (1) and (2) are a SWARCH process with regime \( k \) and order \( m \). According to Gray[12] equation (1) and (3) is MRS-GARCH(m,s)
2.4. Smoothed probability
According to Kim and Nelson [13], smoothed probability value \( \text{Pr}(S_t = i|\psi_T) \), \( t = 1, 2, \ldots, T \), formulated as
\[
\text{Pr}(S_t = i|\psi_T) = \sum_{s=1}^{T} P_r(S_{t+1} = s|\psi_T) \text{Pr}(S_t = i|S_{t+1} = s, \psi_T),
\]
where \( \psi_T \) is all information in observation data up to time \( T \). According to Sugiyanto [3], crisis conditions are determined from the lowest smoothed probability value when the crisis in 1997. According to Sopipan et al. [14], the smoothed probability prediction can be written as
\[
\text{Pr}(S_{t+1} = j|\psi_T) = \sum_{i=1}^{T} p_{ij} \text{Pr}(S_t = i|\psi_T)
\]
where \( p_{ij} \) denotes the elements of transition matrix \( P_{T \times T} \).

3. Research methods
The monthly data of interest rate and inflation indicators from January 1990 to December 2018 obtained from the Bank of International Settlement (BIS) and Bank Indonesia. The steps in this study are as follows.
1. Create a data plot.
2. Test the stationary of data using the augmented Dickey-Fuller (ADF) test. If the data is not stationary, then transform the data using log return.
3. Make the ARMA model and perform a diagnostic test of the best ARMA model.
4. Test the heteroscedasticity to residual of the ARMA model using a Lagrange multiplier test.
5. Identify the volatility model from heteroscedasticity effect and then use the model.
6. Perform the combined volatility and Markov regime-switching models.
7. Compute the value of smoothed probabilities of each data of the inflation and rate of interest.
8. If the smoothed probability value inflation is more than 0.90, and the interest rate is more than 0.94, then it can be predicted that there is a currency crisis.
9. Forecast the currency crisis for one year ahead.

4. Result and discussions
Plot the interest rates and inflation data seen in Figure 1 and Figure 2, respectively.

![Figure 1. The plot of interest rates data.](image1)

![Figure 2. The plot of inflation data.](image2)

Figures 1 and 2 show interest rates and inflation that have a downward trend. Therefore, the two indicators require transformation, the log return transformation for the interest rate and the differencing for inflation.
Figures 3 and 4 show the transformation data of the two indicators that have been visually stationary. Stationary condition based on the ADF test results with the p-value of each indicator being 0.01, meaning that both of them are less than the significance level of 0.05. The ARMA model parameters (p,q) for interest rates and the ARIMA model parameters (p,d,q) for inflation are estimated. The best model for interest rate and inflation are estimated based on the smallest Akaike Information Criterion (AIC) value. The best models for interest rates and inflation are ARMA (1,0) or AR (1) with an AIC value of -1519.3, and ARIMA (3,1,3) with an AIC value of -1819.5. These models can be written as

\[ r_{1t} = 0.676r_{1(t-1)} + a_{1t} \]  

\[ r_{2t} = 2.600603r_{2(t-1)} - 3.10886r_{2(t-2)} + 2.176018r_{2(t-3)} + 0.667761r_{2(t-4)} + 2.01299a_{2(t-1)} - 2.01297a_{2(t-2)} + 0.999978a_{2(t-3)} + a_{2t} \]

where \( r_{1t} \) is the interest rates transformation at the t-time, \( r_{2t} \) is the inflation transformation at the t-time, \( a_{1t} \) is the AR(1) model error at the t-time, and \( a_{2t} \) is the ARIMA(3,1,3) model error at the t-time. Assumptions of the model, which include normality, non-autocorrelation, and constancy variance (homogeneity) tested as follows. Normality tests are carried out on models (1) and (2) with a p-value for both models of 1, meaning that both models meet assuming normality, because 1 is more than the significance level of 0.05. Non-autocorrelation tests carried out on models (4) and (5), with the p-value of each model being 0.502 and 0.682, meaning that both models met the assumption of non-autocorrelation because the p values of the two models were more than the significance level of 0.05. Homogeneity test on the models (4) and (5) obtained p-values of each model is 0.113 and \( 1.542 \times 10^{-5} \), that’s mean the model (4) had fulfilled homogeneity assumptions because 0.113 was more than a significance level of 0.05 and did not need a volatility model. Model (5) does not meet the
assumption of homogeneity because the p-value of the two models is less than the significance level of 0.05. Hence, it requires a volatility model to overcome the heterogeneity contained in the two indicators. The volatility model for inflation is ARCH(2) written as

$$\sigma_t^2 = (1,605 \times 10^{-4}) + 0.5306a_{2(t-1)}^2 + 0.2306a_{2(t-2)}^2$$  \hspace{0.5cm} (6)

where $\sigma_t^2$ is the variance error of the inflation transformation at the t-time.

Figure 5. Plot comparison of variance error and estimated variance of inflation.

Figure 5 shows model (6) can provide a good estimate of the error variance of inflation. Error variance can be seen from the error variance plot and the variance estimation plot having the same pattern. The error of each model is the difference between the actual variance plot and the variance estimation plot, which looks to have the same pattern as the actual error variance.

Markov regime-switching model is used to overcome changes in conditions in time series data. Before the Markov regime-switching model built, it is important to know the optimal grouping of each indicator. Optimal grouping of each indicator is needed to determine the number of regimes in the Markov regime-switching model. The optimal grouping for the two indicators obtained is two, and the Markov regime-switching model built with two regimes. Regime ($s_t$) is a volatility condition that is fulfilled by a process, with $s_t = 1$ being a regime with low volatility and $s_t = 2$ being a regime with high volatility. The volatility process can survive in the same regime or move from one regime to another from $t$-time to $t + 1$ with transition probability $p_{ij}$ for $i = 1, 2$ and $j = 1, 2$. The two-regime transition probability matrix for interest rates written as

$$P_1 = \begin{pmatrix} 0.966 & 0.034 \\ 0.163 & 0.837 \end{pmatrix}.$$  \hspace{0.5cm} (7)

The transition probability matrix (7) shows the probability of a survival process in a regime with low volatility is 0.966, and the probability of a survival process in a regime with high volatility is 0.837. The two-regime transition probability matrix for inflation indicators is

$$P_2 = \begin{pmatrix} 0.930 & 0.070 \\ 0.010 & 0.990 \end{pmatrix}.$$  \hspace{0.5cm} (8)

The probability transition matrix (8) shows the probability of a survival process in a regime with low volatility is 0.925, and the probability of a survival process in a regime with high volatility is 0.990. Observation of inflation grouped into low volatility has a standard deviation between -0.011 to 0.011, and the others grouped into high volatility.

The Markov regime-switching model built from the generator model. In this research, the generator model used is the ARMA(p,q) model and the volatility model. MRS-AR(2,1) is an AR(1) model with two regimes to cope with changing conditions at the interest rate. MRS-GARCH(2,2,0) is an ARCH(2) model with two regimes to cope with changing conditions and fluctuations with the high volatility that occurs in inflation.
Currency crisis detection in Indonesia is determined based on the smoothed probability value that can explain the movement of values or the change in the structure of the data. The higher of smoothed probability value, the possibility of a currency crisis will also be higher. Detection of the currency crisis in Indonesia in 2019 is determined based on the smoothed probability value of the MRS-AR(2,1), and MRS-GARCH(2,2) models. The condition at the $t$-time is determined as a currency crisis condition if the smoothed probability value at that time is more than the lowest smoothed probability value when Indonesia experiences a currency crisis in the period 1997 to 1998. Indonesia will experience a currency crisis if the smoothed probability value of the MRS-AR(2,1) model is more than 0.90, and the smoothed probability value of the MRS-GARCH(2,2,0) model is more than 0.94.

The smoothed probability value in Figures 6 and 7 used to explain the crisis. Figure 6, the smoothed probability value in August 1997 to December 1998 and September 2008 was more than 0.90 for an indicator of interest rates, meaning Indonesia has experienced a crisis. Figure 7, the smoothed probability value is more than 0.94 in January 1998 to December 1998 for inflation indicators, meaning Indonesia has experienced a crisis. The smoothed probability value will tend to be high if there are high fluctuations in the data, this means that high fluctuations that occur in these indicators can indicate instability and changes in currency conditions in Indonesia.

Table 1 and Table 2 show the comparison of predictions and actual value in detecting the crisis in 2018, respectively based on interest and inflation indicators.
Table 1. Comparison of prediction and actual value based on interest rate.

| Time   | Smoothed Probability Prediction | Detection Currency Crisis | Smoothed Probability Actual | Real Condition Currency Crisis |
|--------|--------------------------------|---------------------------|-----------------------------|--------------------------------|
| Jan-18 | 0.039                          | Not crisis                | 0.002                       | Not crisis                     |
| Feb-18 | 0.065                          | Not crisis                | 0.001                       | Not crisis                     |
| Mar-18 | 0.086                          | Not crisis                | 0.001                       | Not crisis                     |
| Apr-18 | 0.102                          | Not crisis                | 0.001                       | Not crisis                     |
| May-18 | 0.116                          | Not crisis                | 0.001                       | Not crisis                     |
| Jun-18 | 0.127                          | Not crisis                | 0.002                       | Not crisis                     |
| Jul-18 | 0.136                          | Not crisis                | 0.006                       | Not crisis                     |
| Aug-18 | 0.143                          | Not crisis                | 0.003                       | Not crisis                     |
| Sep-18 | 0.148                          | Not crisis                | 0.006                       | Not crisis                     |
| Oct-18 | 0.153                          | Not crisis                | 0.003                       | Not crisis                     |
| Nov-18 | 0.156                          | Not crisis                | 0.004                       | Not crisis                     |
| Dec-18 | 0.159                          | Not crisis                | 0.006                       | Not crisis                     |

The prediction accuracy of the MRS-AR(2,1) model in detecting the 2018 currency crisis based on the interest rate indicator is 100%. The MRS-AR(2,1) model is suitable to be used in predicting currency crisis conditions in Indonesia in 2019 because it has high accuracy in detecting the currency crisis in 2018 and can be detected currency crises that have occurred in Indonesia in 1997 - 1998 and 2008.

Table 2. Comparison of prediction and actual value based on inflation.

| Time   | Smoothed Probability Prediction | Detection Currency Crisis | Smoothed Probability Actual | Real Condition Currency Crisis |
|--------|--------------------------------|---------------------------|-----------------------------|--------------------------------|
| Jan-18 | 0.114                          | Not crisis                | 0.001                       | Not crisis                     |
| Feb-18 | 0.178                          | Not crisis                | 0.001                       | Not crisis                     |
| Mar-18 | 0.237                          | Not crisis                | 0.001                       | Not crisis                     |
| Apr-18 | 0.291                          | Not crisis                | 0.001                       | Not crisis                     |
| May-18 | 0.341                          | Not crisis                | 0.001                       | Not crisis                     |
| Jun-18 | 0.387                          | Not crisis                | 0.001                       | Not crisis                     |
| Jul-18 | 0.429                          | Not crisis                | 0.001                       | Not crisis                     |
| Aug-18 | 0.468                          | Not crisis                | 0.001                       | Not crisis                     |
| Sep-18 | 0.504                          | Not crisis                | 0.001                       | Not crisis                     |
| Oct-18 | 0.537                          | Not crisis                | 0.001                       | Not crisis                     |
| Nov-18 | 0.567                          | Not crisis                | 0.001                       | Not crisis                     |
| Dec-18 | 0.595                          | Not crisis                | 0.003                       | Not crisis                     |

The prediction accuracy of the MRS-GARCH(2,2,0) model in detecting the 2018 currency crisis based on inflation indicators is 100%. The MRS-GARCH(2,2,0) model is suitable to be used in predicting currency crisis conditions in Indonesia in 2019 because it has high accuracy in detecting the
currency crisis in 2018 and can detect currency crises that have occurred in Indonesia in 1997-1998. Furthermore, both models are used to predict the crisis of 2019, as shown in Table 3.

**Table 3.** Currency crisis prediction in Indonesia 2019 based on \((Y_1)\) is interest rates, and \((Y_2)\) is inflation.

| Time   | Smoothed Probability Prediction | Detection Currency Crisis |
|--------|---------------------------------|---------------------------|
|        | \(Y_1\) | \(Y_2\) | \(Y_1\) | \(Y_2\) |
| Jan-19 | 0.037  | 0.018  | Not crisis | Not crisis |
| Feb-19 | 0.062  | 0.031  | Not crisis | Not crisis |
| Mar-19 | 0.082  | 0.042  | Not crisis | Not crisis |
| Apr-19 | 0.098  | 0.052  | Not crisis | Not crisis |
| May-19 | 0.111  | 0.059  | Not crisis | Not crisis |
| Jun-19 | 0.121  | 0.066  | Not crisis | Not crisis |
| Jul-19 | 0.13   | 0.072  | Not crisis | Not crisis |
| Aug-19 | 0.137  | 0.077  | Not crisis | Not crisis |
| Sep-19 | 0.142  | 0.081  | Not crisis | Not crisis |
| Oct-19 | 0.146  | 0.084  | Not crisis | Not crisis |
| Nov-19 | 0.15   | 0.087  | Not crisis | Not crisis |
| Dec-19 | 0.153  | 0.09   | Not crisis | Not crisis |

Table 3 shows, based on inflation and interest rates indicators in Indonesia 2019 to predict the crisis. There is not experiencing a currency crisis in Indonesia. After finding that Indonesia will not experience a crisis in 2019, it is necessary to test the relationship between the two indicators by calculating the chi-square value. Indonesia states the contingency table seen in table 4.

**Table 4.** Indonesia states contingency table from January 1990 to December 2018.

|                | Interest Rates | Total |
|----------------|----------------|-------|
| **Inflation**  |                |       |
| Crisis         | 21             | 26    |
| Not Crisis     | 24             | 298   | 322   |
| **Total**      | 45             | 303   | 348   |

The chi-square table is 3.84 and based on table 4, the calculated chi-square value of 114.84 is higher than 3.84. There are significant differences between variables, or there is influence between one variable with another. For this reason, it is necessary to do a simultaneous analysis using a multivariate model.

5. **Conclusion**

The MRS-AR(2,1) model can explain the 1997 and 2008 crises based on interest rate indicators, while the MRS-GARCH(2,2,0) model can only explain the 1998 crisis based on inflation rate indicators. The smoothed probability prediction of the two models shows that in 2019 Indonesia will not experience a crisis based on indicators of interest rates and inflation. The crisis will not happen because of the influence of one variable with another variable. It is necessary to do significant modeling using multivariate models.
Acknowledgment
Appreciation and thanks the author gave to Mrs. Dr. Nur Chamidah, M.Si, and Mr. Drs. Sugiyanto, M.Si as Supervisor, which has helped this Journal. As well as a thank you to my friend because they are always giving me support.

References
[1] Kaminsky G, Lizondo S and Reinhart C M 1998 Leading indicators of currency crises IMF Staff Papers 45 pp 2-48.
[2] Ford, J L B, Santoso and N J Horwood 2007 Asian currency crisis: do fundamentals still matter? a markov switching approach to causes and timing Department of Economics (England : University of Birmingham)
[3] Sugiyanto, Zukhrornah E and Meganisa S 2018 J. of Phys.: Conf. Series. 1025 012115.
[4] Engle R F 1982 Autoregressive conditional heteroscedasticity with estimation of the variance of United Kingdom inflation. J. of Econometrics. 50 987-1008.
[5] Bollerslev T 1986 On the correlation structure for the generalized autoregressive conditional heteroscedasticity process. J. of Econometrics. 31 307-327.
[6] Hamilton J D 1989 A new approach to the economic analysis of nonstationary time series and the business cycle. J. of Econometrica. 57 pp 357-384.
[7] Hamilton J D and Susmel R 1994 Autoregressive conditional heteroscedasticity and changes in regime. J. of Econometrics. 64 307-333.
[8] Henry O T 2007 Between the rock and a hard place: regime switching in the relationship short-term interest rates and equity return in the UK. Departemen of Economics (Australia: The University of Malbourne)
[9] Tsay R S 2002 Analysis of financial time series (Canada: John Wiley and Sons).
[10] Gray S F 1996 Modeling the conditional distribution of interest rates as a regime-switching process. J. of Financial Economics. 42 27-62.
[11] Kim C J and Nelson C R 1999 State-space models with regime switching: classical and gibbs-sampling approaches with applications (England: The MIT Press).
[12] Sopipan N, Sattayatham P and Premanode B 2012 Forecasting volatility of gold price using markov regime switching and trading strategy. J. of Mathematical Finance. 2 pp 121-131.