COMBINED VOLATILITY AND MARKOV SWITCHING MODELS FOR CURRENCY CRISIS DETECTION IN INDONESIA ON REAL DEPOSIT RATE INDICATORS

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ABSTRACT:

Indonesia experienced its worst currency crisis in the mid-1997 and the global currency crisis in 2008. The impact of these crises had a significant negative effect on the country's economy. Therefore, a system is needed to detect currency crises and prevent their recurrence. One indicator that can be used to detect currency crises is real interest rate savings. A combination of volatility models with Markov switching can be used to detect currency crises. The research results showed that the MS-ARCH(1) model can be used to detect crises in real interest rate savings indicators. Based on these results, it is predicted that the Indonesian economy will remain stable from mid-2022 to 2023.

Keyword: currency crisis; Real deposit interest rate; GARCH; markov switching.

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INTRODUCTION

Currency crisis is a condition where several financial assets suddenly lose a significant portion of their nominal value. In the mid-1997, Indonesia experienced a financial crisis that had a significant impact on the country's economy, caused by the Thai baht currency crisis in the banking sector of Thailand. The financial crisis caused Indonesia's gross domestic product (GDP) growth to plummet by a drastic minus 13%, a 83.2% depreciation of the rupiah, and was followed by banking liquidity difficulties that led to the closure of 16 banks in Indonesia. Considering the past currency crises, a system for detecting currency crises is needed to anticipate future crises. There are 15 indicators that can indicate a currency crisis, one of which is the real deposit interest rate indicator.

Interest rates are a price expressed in percentage form that must be paid by customers to banks or by banks to customers. The increase or decrease in bank interest rates is influenced by the benchmark interest rate (BI Rate). An increase in the benchmark interest rate causes bank interest rates to also increase. The fluctuation of bank interest rates will cause stock prices to decline and have an impact on a country's economy. The data used in this study for the real deposit interest rate indicator is monthly data. This data is a time series data because it is collected, observed, and monitored based on time sequence. The data from the real deposit interest rate indicator changes conditions (state) between non-crisis and crisis conditions.

Engle (1982) introduced the Autoregressive Conditional Heteroscedasticity (ARCH) model to estimate the volatility behavior of data that causes heteroscedasticity effects. However, this model does not consider the existence of condition changes (state) in economic variables caused by currency crises, which leads to significant changes in data values. Hamilton (1994) introduced the Markov Switching (MS) model to model time series data that undergoes condition changes, as an alternative modeling approach for time series data that undergoes condition changes. In this study, the detection of currency crises in Indonesia based on the real deposit interest rate indicator is performed using a combination of Markov Switching and volatility models.

RESEARCH METHOD

The data source used in this study is secondary data obtained from the International Financial Statistics (IFS) database with case studies in Indonesia. The data used is the real deposit rate from January 1990 to July 2022. The data is time series data that fluctuates so that the data is not stationary. In looking at the accuracy of the data, the Augmented Dicky Fuller (ADF) test can be used. According to Brooks (2014) the hypothesis of the ADF test can be written as follows:

$H_0 : \delta = 1$ (data contains root or non-stationary units)

$H_0 : \delta < 1$ (data no root unit or stationary data)

ADF test statistics can be written as follows:

$$ADF_{test} = \frac{\hat{\delta}}{SE(\hat{\delta})}$$

With $\hat{\delta}$ is the estimation of the autoregressive model parameters and $SE(\hat{\delta})$is the standard error of $\hat{\delta}$. The null hypothesis is rejected if $ADF_{test} t_{\alpha,T-m}$ or $p-value < \alpha$, where T is the amount of data and m is the order of the AR model. If after testing the ADF data is not stationary, it can be overcome by transforming the data. One of the data transformations that can be used is the log return transformation. The formula for the log return value at t (r_t) can be written as follows:

$$\begin{aligned} r_t &= ln(1+q_t) \\ &= ln(1+\frac{Z_t - Z_{t-1}}{Z_{t-1}}) \\ &= ln(\frac{Z_t}{Z_{t-1}}) \end{aligned}$$

With q_t is the return value at the time ke-t, Z_t is the data value at t time, and Z_{t-1} is data at $(t-1)$.

Then, time series modeling was carried out on data that was already stationary. According to Cryer (1986) the $ARMA$ model can be used for stationary data. The general form of the $ARMA(p,q)$ model can be written as follows :

$$r_t = \phi_0 + \phi_1 r_{t-1} + \cdots + \phi_p r_{t-p} + \alpha_t - \theta_1 \alpha_{t-1} - \cdots - \theta_q \alpha_{t-q}$$

with r_t is log *return* at t, α_t is residue model $ARMA(p,q)$ at t, and p is order from AR and q is order from MA.

In general, modeling time series data must satisfy the residual assumption that has constant variance. Engle (1986) introduced the $ARCH$ model as residual variance modeling. According to Tsay (2002), the $ARCH$ model can be written as follows:

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

with m is order from model $ARCH$, α_0 is constant, α_i is parameter model $ARCH$, and σ_t^2 is variant residue period at-t.

Furthermore, a combination of Markov Switching (MS) and $ARCH$ models was used. According to Hamilton and Susmel (1994), the $MS - ARCH$ model can be written as follows :

$$\sigma_{t,s_t}^2 = \alpha_{0,s_t} + \sum_{i=1}^{m} \alpha_{i,s_t} \alpha_{t-i}^2$$

where m is the $ARCH$ model order and σ_{t,s_t}^2 is the residual variance in a t period state. Then a smoothed probability value is generated which is the probability value of a state at the t time to identify a change in conditions in the fluctuating data. According to Kim and Nelson (1999) the smoothed probability value can be written as follows :

$$\left(P_r(S_t = i|\psi_r)\right) = \sum_{s=1}^{3} P_r(S_{t+1} = s|\psi_T) P_r(S_t = i|S_{t+1} = s, \psi_t$$

with ψ_t is a collection of information on observational data up to the T time. The magnitude of the smoothed probability prediction value indicates the occurrence of a crisis

RESULT AND DISCUSSION

1. Model Identification

The initial stage performed in model identification is to plot the data to see the stability of the data using the Augmented Dickey-Fuller (ADF) test. Here is a plot image of the real deposit rate indicator.

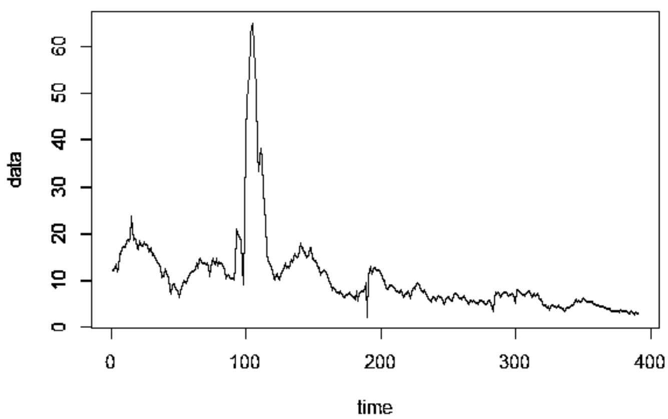

Figure 1 Real Deposit Rate Indicator Data Plot

Figure 1 shows that the data decreases over time or has a downward tendency so that it can be indicated that the data is not stationary. Based on the results of the Augmented Dicky-Fuller (ADF) test, the probability value of the real deposit rate indicator is 0.0951, which means that the probability value is more than the significance level, so the data is not stationary. Furthermore, a transformation is carried out on the real deposit rate indicator using a log return transformation. Here is a plot image of the transformed real deposit rate indicator.

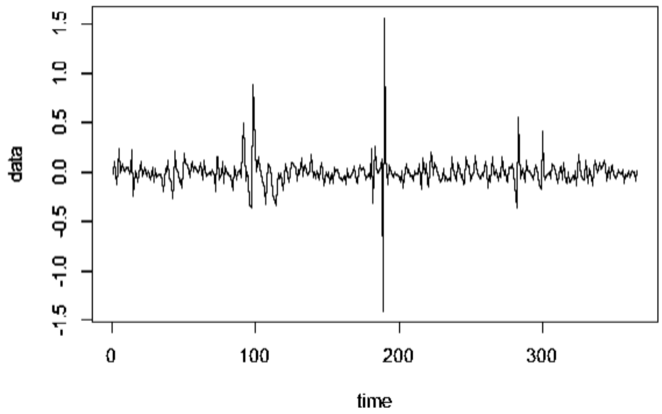

Figure 2 Plot of Real Deposit Rate Indicator Transformation Data

Figure 2 shows that the data that has been transformed is stationary. Based on the Augmented Dickey-Fuller (ADF) test, the probability value of the transformed real deposit rate indicator is 0.01, which means that the data is stationary.

2. **2. Model Formation $ARMA(p, q)$**

Model $ARMA(p, q)$ can be determined based on the ACF and PACF plots of the transformation data of each indicator. Here is the ACF and PACF plots of the real deposit rate indicators.

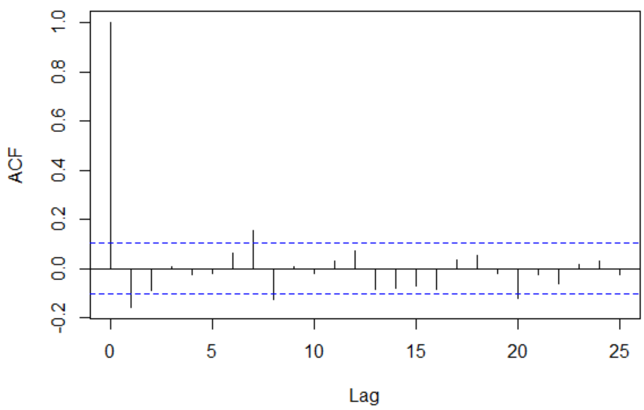

Figure 3 ACF Plot of Real Deposit Rate indicator

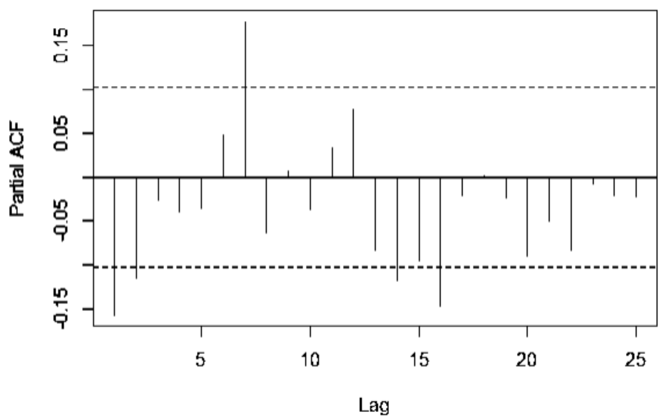

Figure 4 PACF plot of Real Deposit Rate indicator

Gambar 3 dan 4 menunjukkan bahwa plot *ACF* dan *PACF* terpotong setelah lag ke-2 sehingga model yang dapat digunakan adalah model $AR(1)$, $AR(2)$, $ARMA(0,1)$, dan $ARMA(0,2)$. Namun untuk lebih meyakinkan maka dilakukan perbandingan antara model $AR(1)$, $AR(2)$, $ARMA(0,1)$, dan $ARMA(0,2)$. berdasarkan signifikansi parameter dan nilai *Akaike Information Criterion (AIC)* terkecil. Nilai probabilitas dan nilai *AIC* dari ketiga model disajikan pada Tabel berikut.

Table 1 Probability and AIC values of $AR(1)$ and $AR(2)$ models

Model	Parameter	Estimation value	Probability Value	*AIC Score*
$AR(1)$	ϕ_1	-0.15559	0.00258	-302.28
$AR(2)$	ϕ_1	-0.17321	0.000845	-304.61
	ϕ_2	-0.11440	0.027552	
$ARMA(0,1)$	θ_1	-0.19548	0.00055	-304.62
$ARMA(0,2)$	θ_1	-0.17571	0.000746	-305.07
	θ_2	-0.09166	0.075313	

Table 1 shows that parameter ϕ_1 in the $AR(1)$ model, parameters ϕ_1 and ϕ_2 in the $AR(2)$ model, and parameter $\theta_1$in both the $ARMA(0,1)$ and $ARMA(0,2)$ models are significant as their probability values are less than the significance level. However, the smallest AIC value is found in the $ARMA(0,2)$ model. Since the parameter θ_2 in the $ARMA(0,2)$ model is not significant, the $ARMA(0,1)$ model is chosen as the best model as it has significant parameter values with an AIC value of -304.62. The equation of the $ARMA(0,1)$ model can be written as $r_t = -0.195548\theta_{t-1} + e_t$.

Next, diagnostic tests are performed on the residuals of the $ARMA(0,1)$ model using tests for normality, autocorrelation, and heteroskedasticity. The probability values resulting from the normality test using Shapiro-Wilk and the autocorrelation test using Ljung-Box are 0.9126 dan 0.7429, respectively, indicating that the model satisfies the assumptions of normality and autocorrelation. However, the probability value from the heteroskedasticity test using Lagrange Multiplier is 2.2^{-16}, indicating that the model has heteroskedasticity effects. Therefore, modeling using a volatility model is required.

3. Formation of Volatility Models

The best volatility model for the real deposit interest rate indicator is the ARCH(1) model with an AIC value of -569.5623 and can be written as $\sigma_t^2 = 0.0051456 + 1.1832861\alpha_{t-1}^2$. Next, a sign bias (sign test) is conducted to examine whether there is an asymmetric effect in the volatility model. The probability value resulting from the sign bias test is 0.9516767, indicating that the model does not have an asymmetric effect (leverage effect). Therefore, the model does not require further advanced volatility modeling analysis.

Next, the formed volatility model is subjected to residual diagnostic tests. The probability values resulting from the normality test using Shapiro-Wilk and the autocorrelation test using Ljung-Box are 0.9096 and 0.08784, respectively, indicating that the model satisfies the assumptions of normality and autocorrelation. Furthermore, the probability value from the heteroskedasticity test using Lagrange Multiplier is 0.9999, indicating that the formed volatility model is suitable for use in modeling.

4. Formation of Combined Volatility and Markov Switching Models

Changes in conditions in markov switching models are considered as an unobserved random variable commonly referred to as a state. The conditions referred to in this study are low and high volatility conditions. In modeling these changes, the probability of transition is formed. Obtained transition probability matrix for real deposit rate indicator as follows.

$$P_1 = \begin{pmatrix} 0.93 & 6.14^{-2} \\ 0.99 & 6.20^{-5} \end{pmatrix}$$

Based on the probability transition matrix P_1 obtained that the probability of persisting at the state of low to high volatility is 0.93 and 6.20^{-5}. While the probability shift from high to low is 0.99 dan 6.14^{-2}.

5. Formation of Smoothed Probability

Crisis detection can be done using the minimum value of the smoothed probability results when the currency crisis occurred in Indonesia in 1997 and 2008. The result of the smoothed probability in the real deposit rate indicator indicates that a currency crisis occurs when the smoothed probability value is greater than 0.97. The following is a smoothed probability plot of the real deposit rate indicator.

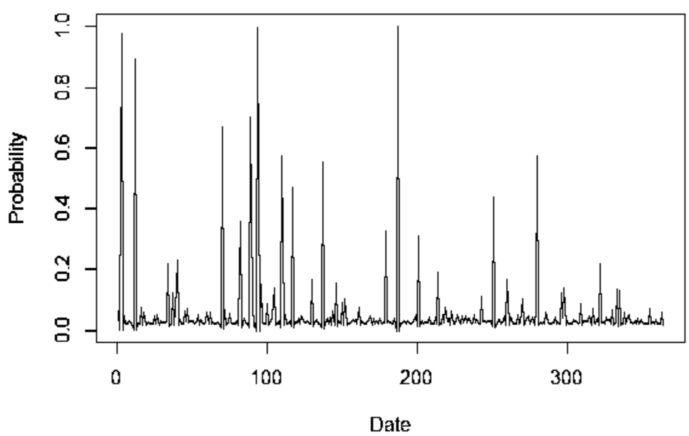

Figure 5 Smoothed Probability of Real Deposit Rates

Currency crisis detection for real deposit rate indicators can be seen in the following table.

Table 2 Currency Crisis Detection Real Deposit Interest Rate Indicator 1990 - 2020

Year	Months
1997	January, February, March, April, Mei, June, July, September, October, November
2008	January, February, April, June, August, September, October, November, December

After obtaining the smoothed probability value, the predicted smoothed probability value from August 2020 to August 2021 is determined on the real deposit rate indicator.

Table 3 Comparison of Predicted Values with Actual Real Deposit Rate Indicators

Period	Predict	Crises Condition	Actual	Crises Condition
Aug-20	0.0576669113	stable	0.362829	stable
Sep-20	0.0578231818	stable	0.362829	stable
Oct-20	0.0578136046	stable	0.362832	stable
Nov-20	0.0578141932	stable	0.362831	stable
Dec-20	0.0578141587	stable	0.362824	stable
Jan-21	0.0578141624	stable	0.36282	stable
Feb-21	0.0578141637	stable	0.362817	stable
Mar-21	0.0578141652	stable	0.362817	stable
Apr-21	0.0578141667	stable	0.362819	stable
May-21	0.0578141681	stable	0.362822	stable
Jun-21	0.0578141696	stable	0.362821	stable
Jul-21	0.0578141711	stable	0.362823	stable
Aug-21	0.0578141726	stable	0.362826	stable
Sep-21	0.0578141740	stable	0.362826	stable
Oct-21	0.0578141755	stable	0.362828	stable
Nov-21	0.0578141770	stable	0.362834	stable
Dec-21	0.0578141784	stable	0.36284	stable
Jan-22	0.0578141799	stable	0.36285	stable
Feb-22	0.0578141814	stable	0.362849	stable
Mar-22	0.0578141829	stable	0.36285	stable
Apr-22	0.0578141843	stable	0.362841	stable
May-22	0.0578141858	stable	0.362834	stable
Jun-22	0.0578141873	stable	0.36283	stable
Jul-22	0.0578141888	stable	0.36283	stable

In Table 3 the predicted value of smoothed probability with the actual for the real deposit rate indicator is below the threshold which means the indicator is in a stable condition. Crisis detection in Indonesia for the next period is shown in Table 4.

Table 4 Prediction of Currency Crisis in Indonesia Based on Real Deposit Interest Rate Indicator

Period	Predict	Crises Condition
Aug-22	0.3628300661	stable
Sep-22	0.3628300323	stable
Oct-22	0.3628300077	stable
Nov-22	0.3628299902	stable
Dec-22	0.3628299783	stable
Jan-23	0.3628299709	stable
Feb-23	0.3628299668	stable
Mar-23	0.3628299655	stable
Apr-23	0.3628299663	stable
May-23	0.3628299688	stable
Jun-23	0.3628299726	stable
Jul-23	0.3628299775	stable

Table 4 shows that the predicted smoothed probability values from August 2022 to July 2023 are less than the threshold. This shows that Indonesia is predicted not to experience a currency crisis or be stable in the period from August 2022 to July 2023.

CONCLUSION

The best model for currency crisis modeling on the real deposit rate indicator is $MS - ARCH(1)$ because it can detect currency crises that occurred in 1997 and 2008. Based on the prediction results, it can be concluded that from August 2022 to July 2023, it is estimated that the Indonesian state will not experience a currency crisis or the country's economy will be stable

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