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EARLY DETECTION OF CURRENCY CRISIS IN INDONESIA BASED ON JCI INDICATOR USING A COMBINATION OF VOLATILITY AND MARKOV SWITCHING MODELS

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ABSTRACT

Currency crises have occurred in Indonesia in 1997-1998 and 2008, causing significant losses both in terms of economy and social life. Therefore, a system is needed that can detect currency crises to create economic and currency stability. Crises can be detected through economic indicators such as Indonesia Stock Exchange Composite Index (IDX Composite) or Jakarta Composite Index (JCI). This study aims to determine the appropriate model and to predict the currency crisis in Indonesia from November 2022 to October 2023 based on the JCI indicator. The study begins by forming an AR model, then a volatility model in the form of an ARCH model, and finally a combined volatility model and Markov switching two-state model. This combined model is then used to form a smoothed probability that can detect crises. The results of the study indicate that the MS-ARCH(2,1) model is the appropriate model, and from the detection results, it is found that Indonesia will not experience a currency crisis from November 2022 to October 2023.

Introduction

Currency crises have occurred in many countries around the world, including Indonesia. The Indonesian currency crisis occurred in 1997-1998, which began with the fall of the Thai baht exchange rate by 27.8%, followed by the weakening of the South Korean won, Malaysian ringgit, and the Indonesian rupiah. During this period, Indonesia's economic growth decreased by 13.13%, and the rupiah depreciated by 600%, from Rp2,350 to Rp16,650 per 1 USD (Sri & Suliswanto, 2016). In addition, Indonesia also experienced the Sub-prime Mortgage crisis in 2008, which originated from the bankruptcy of the US property business. The rupiah depreciated by 30.9% from Rp9,840 per January 2008 to Rp12,100 per November 2008 (Sri & Suliswanto, 2016). These two currency crises caused significant losses in terms of the economy and social life. Therefore, a system is needed to detect currency crises to create economic and currency stability, especially in Indonesia.

Kaminsky et al. (1998) proposed 15 indicators that can be used as a guide to detect currency crises in a country. These indicators are imports, exports, trade exchange rates, foreign exchange reserves, Composite Stock Price Index (CSPI), real exchange rates, real savings interest rates, bank deposits, loan and deposit interest rate ratios, real domestic rate differentials and FED real rate differentials, M1 (narrow money), M2 (broad money) multiplier, M2 to foreign exchange reserve ratios, real output, and domestic credit to GDP ratios. In Indonesia itself, the 1997-1998 crisis was influenced by exchange rate indicators, interest rates, debt service ratios, and inflation, while the 2008 crisis was influenced by CSPI indicators, interest rates, and inflation (Keumala Sari *et al*., 2016). stated that there is a significant relationship between currency crises and financial crises, so that in financial crisis modeling, currency crisis indicators can be used. The CSPI is one of the indicators that can detect currency crises in a country. The CSPI is defined as the stock price expressed in index numbers used for analysis purposes and to avoid the negative effects of using stock prices. The stock price index is an indicator or reflection of stock price movements (Widodo, 2017).

Since 1982, many methods have been developed to build models that can detect currency crises. Engle (1982) developed the Autoregressive Conditional Heteroscedasticity (ARCH) model to detect volatility in data that causes heteroskedasticity effects. Then, Bollerslev (1986) developed the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model as a development of the ARCH model. Both models do not take into account the changes in the economic variable conditions caused by economic crises, wars, or other causes that cause significant changes in data values. Then, Hamilton and Susmel (1994) introduced the Markov Switching Model as an alternative in modeling time series data with fluctuating data.

The crisis detection model is often developed using a combination of Markov switching and volatility models. Ananda (2015) conducted research on the detection of financial crises in Indonesia based on the IHSG indicator using a combination of volatility and Markov switching models with three states. The study found that the suitable model was the MRS-ARCH(3,1) model with AR(1) as the mean model. Dina (2015) conducted early detection of financial crises in Indonesia based on the IHSG indicator. The IHSG indicator data contained heteroskedasticity, asymmetry, and structural changes, so it was modeled using a two-state MS-TGARCH model. Conducted research on forecasting stock returns in 2016 using the Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model. Suwardi (2017) conducted research on early detection of financial crises in Indonesia based on import, export, and foreign exchange reserve indicators using the MS-ARCH model. Pratiwi (2017) also conducted research on early detection of financial crises in Indonesia using the MS-ARCH model based on the M1 indicator, the M2-to-foreign exchange reserve ratio, and the M2 multiplier. Sugiyanto and Hidayah (2019) conducted early detection of financial crises in Indonesia using the MS-GARCH model with the smallest smoothed probability value during the financial crisis in Indonesia in 1997-1998.

In this research, a combination of volatility and Markov switching models with two states will be used to detect currency crises in Indonesia based on the IHSG indicator. The data used is monthly data from January 1990 to October 2022 obtained from the official Yahoo Finance website. The aim of this research is to determine the suitable model and to predict the results of currency crises in Indonesia from November 2022 to October 2023.

Research Method

1. **Research method**

This study uses monthly data of the Indonesian Composite Index (IHSG) from January 1990 to October 2022 obtained from the official Yahoo Finance website. The study begins with creating a time series plot of the IHSG data and then conducting an Augmented Dickey-Fuller (ADF) test to determine the stationarity of the data. If the data is not stationary, a log return transformation is performed. The transformed data is then used to form an AR model, and a Lagrange multiplier test is conducted to test for heteroscedasticity effects on the residuals. If there are heteroscedasticity effects on the residuals, a volatility model is formed, and diagnostic tests are conducted on the residuals. These diagnostic tests include tests for normality, non-autocorrelation, and heteroscedasticity effects. From the formed volatility model, a sign bias test is then conducted to examine whether there is an asymmetric effect on the volatility model or not. If there is no asymmetric effect, there is no need for further volatility modeling, and the modeling can continue by forming a combined volatility and Markov switching model with two states. The study then calculates the smoothed probability value and forecasts the smoothed probability value for the period from November 2022 to October 2023, and performs crisis detection.

2. **Indonesia Stock Exchange Composite Index (IDX Composite) or Jakarta Composite Index (JCI)**

Indonesia Stock Exchange Composite Index is the stock price expressed in index numbers that are used for analysis purposes and to avoid the negative impacts of using stock prices. The stock price index is an indicator or reflection of the movement of stock prices (Widodo, 2017). A high stock index value indicates a busy market condition, while a low stock index value indicates a sluggish market condition. The tendency of increasing stock prices in the long term indicates rapid economic growth, while in the short term, stock prices tend to fluctuate (Widoatmodjo, 2009).

3. **Autoregressive Model (AR)**

The autoregressive process is the process of modeling predictions r_t as a function of the value in the previous period. The AR(p) model can be written as in Equation (1).

$$r_t = \phi_0 + \phi_1 r_{t-1} + \phi_2 r_{t-2} + \cdots + \phi_p r_{t-p} + a_t$$

with r_t is the log return value of the data in the t-th period formulated as $r_t = ln\frac{P_t}{P_{t-1}}$, with P_t is the data of each indicator in the t-th period, ϕ_0 is a constant, ϕ_p parameters on autoregressive models, and a_t is the residue in the t-th period (Tsay, 2002).
Autoregressive Conditional Heteroscedasticity Model (ARCH)

The Autoregressive Conditional Heteroscedasticity (ARCH) model is a type of volatility model that can overcome the heteroskedasticity effect on the average model. The ARCH(m) model can be written as in Equation (2).

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_t a_{t-i}^2$$

with α_0 is constant model of ARCH, α_t is parameter model ARCH, and σ_t^2 is the residual variance in the t-th period.

4. **Model Markov Switching-ARCH (MS-ARCH)**

The Markov Switching-ARCH (MS-ARCH) model is a combination of the ARCH and Markov Switching volatility models. According to Hamilton and Susmel (1994), the MS-ARCH(K,m) model can be formulated as in Equation (3).

$$\sigma_{t,st}^2 = \alpha_{0,st} + \alpha_{1,st} a_{t-1}^2 + \cdots + \alpha_{m,st} a_{t-m}^2$$

with K is the number of states, m adalah orde pada model ARCH, and σ_(t,st)^2 is the residual variance of a state in the t-th period.

5. **Transition Probability Matrix**

The markov process is called the stochastic process if the probability of any future behavior (state) depends only on the behavior (state) in the present and is not changed by additional knowledge of the behavior (state) in the past. The markov chain process can be written as in Equation (4).

$$P(X_{n+1} = j | X_0 = i_0, \dots, X_{n-1}, X_n = i) = P(X_{n+1} = j | X_n = i) = P_{ij}$$

With P_ij adalah matriks probabilitas transisi berada pada state i at the time n will go to j at time n+1. The one-step transition probability matrix for an infinite state can be written as in Equation (5).

$$P = [P_{ij}] = \begin{bmatrix} P_{11} & P_{12} & \cdots \\ P_{21} & P_{22} & \cdots \\ \vdots & \vdots & \ddots \end{bmatrix}$$

dengan $P_{ij} > 0$ untuk $i, j = 1,2, \dots$ dan $\sum_{j=1}^{\infty} P_{ij} = 1$ untuk $i = 1,2, \dots, n$.

6. **Smoothed Probability**

Smoothed probability is the probability value in a state based on information up to T. According to Fruhwirth-Schnatter, et al., (2000) the smoothed probability value can be written as in Equation (6).

$$(Pr(S_t = i|\psi_r)) = \sum_{j=1}^{K} \Pr(S_{t+1} = K|\psi_T) \Pr(S_t = i|S_{t+1} = K, \psi_T)$$

With ψ_T is a collection of all information up to the T -th. Crisis detection in the following year can be detected using smoothed probability forecasting at selected states in that data period.

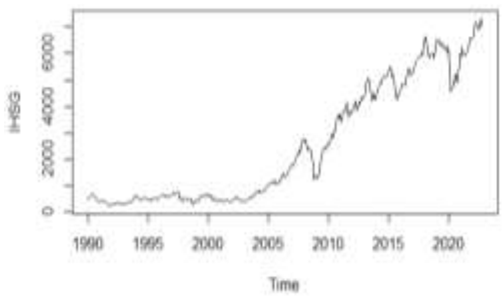
$$(\Pr(S_t = i|\psi_r)) = \sum_{j=1}^{K} p_{ij} \Pr(S_t = j|\psi_T)$$

In Pr(S_t=j|ψ_T) is the value of smoothed probability at the t -th time for the j -th regime and p_ij the probability of transition in the regime. If the smoothed probability value is high, there is a possibility of a crisis and vice versa, if the smoothed probability value is low, there is a possibility that there will be no crisis. According to Hermosillo and Hesse (2009) smoothed probability values of 0 – 0.39 indicate indicators of a financial crisis in a stable state, 0.4 – 0.59 indicates a vulnerable condition, and 0.6 – 1 indicates a crisis state.

Result And Discussion

1. Identify Data Patterns

To determine the pattern in JCI data, an analysis was carried out on the time series plot as presented in Figure 1.



Gambar 1 Plot time series IHSG

Figure 1 shows fluctuations in the JCI data, where the data increases over time and it can be seen that the variance is not constant, thus indicating that the data is not stationary. To prove this conjecture, an ADF test was carried out and a probability value of 0.978 was obtained. Since this value is greater than α=0,05, it can be concluded that the data is not stationary. To solve this problem, a log-return transformation was carried out on the data and a time series plot was obtained for the transformation result data as presented in Figure 2.

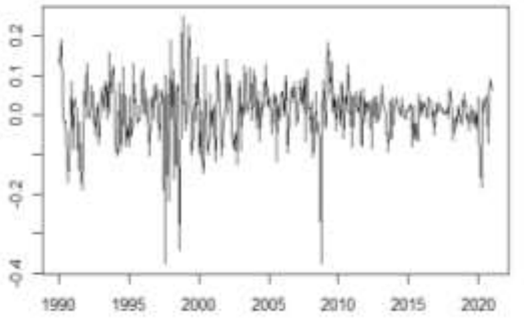


Figure 2 Time series plots of transformed data

Figure 2 shows that the transformed data is already stationary, as the data fluctuates around the average value. Based on the ADF test, a probability value of 0.01 was obtained, which is smaller than α=0,05, so it can be concluded that the log return data is stationary. It is this transformation result data that is used for the formation of the model.

2. Formation of the AR Model

The Autoregressive model identification process is based on the PACF behavior of the transformed data. From several possible models formed, significance tests were carried out on each parameter and the model with the smallest AIC value was selected. For JCI indicators, the best model is AR(1) with the following model.

$$r_t = 0{,}2158 r_{t-1} + a_t$$

Furthermore, testing was carried out using the Lagrange multiplier test to determine whether the residue from the ARMA model contained the effect of heteroskedasticity or not. From the tests that have been carried out, a probability value of 4,19× 〖10〗 ^(-9) was obtained. This value is smaller than α=0,05, so it can be concluded that the residues of the AR model contain the effect of heteroskedasticity. Therefore, advanced modeling with volatility models is carried out.

3. Formation of a Volatility Model

The formation of the volatility model is based on the ACF plot of the squared residual AR model that has been formed. From several possible models formed, significance tests were carried out on each of the parameters and the model with the smallest AIC value was selected. For the JCI indicator, the best volatility model is obtained, namely ARCH(1) with the following model.

$$\sigma_t^2 = 0{,}0043 + 0{,}2328 a_{t-1}^2$$

Next, diagnostic tests were conducted on the residuals of the volatility model to determine the adequacy of the model. These diagnostic tests included tests for normality, non-autocorrelation, and heteroskedasticity. The normality test was conducted using the Kolmogorov-Smirnov test and obtained a probability of 0.8811, which is greater than α=0,05. This indicates that the residuals of the volatility model are normally distributed. The non-autocorrelation test was performed using the Ljung-Box test and obtained a probability value of 0.8457, which is greater than α=0,05. Therefore, it can be concluded that there is no autocorrelation in the residual. The heteroskedasticity test was performed to determine the presence of heteroskedasticity effects on the residual. This test used the Lagrange multiplier test and obtained a probability value of 0.9897, which is greater than α=0,05. This means that the residuals generated by the model do not contain heteroskedasticity effects.

4. Sign Bias Test

Furthermore, a sign refractive test is carried out to check whether there is an asymmetric effect on the volatility model or not. This test was carried out with a sign bias test and obtained a probability value of 0.5479 which is greater than α=0,05. This shows that the residue generated in the volatility model does not have an asymmetric effect (leverage effect), so there is no need for further volatility modeling.

5. Formation of a Combined Model of Volatility and Markov Switching

The already formed volatility model is then combined with a two-state switching markov model to detect stable and crisis conditions. Changes in conditions that occur in the model are considered as the result of an unobserved random variable called a state. This state is divided into two, namely low and high volatility conditions. To describe such changes in conditions, a transition probability matrix is used. The transition probability matrix for the JCI indicator is as follows.

$$P_2 = \begin{pmatrix} 0{,}9822 & 0{,}0178 \\ 0{,}7530 & 0{,}2470 \end{pmatrix}$$

Based on the matrix, it can be seen that the probability value of staying in a low volatility state is 0.9822, the probability of changing state from low to high volatility is 0.0178, the probability of changing state from high to low volatility is 0.7530, and the probability of staying in a high volatility state is 0.2470.

6. Smoothed Probability Value and Smoothed Probability Forecasting Value

From the MS-ARCH(2,1) model, the smoothed probability value presented in Figure 3 is obtained.

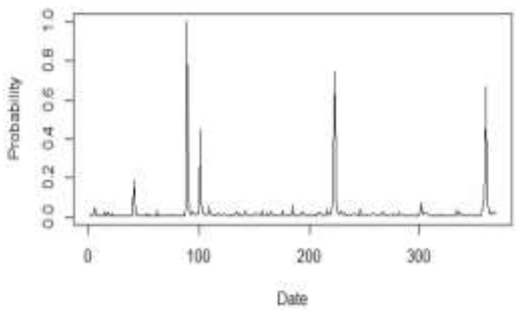


Figure 3 Plot smoothed probability

Crisis detection is carried out by looking at the minimum value of smoothed probability results when there was a currency crisis in Indonesia, namely in 1997 - 1998 and 2008. For the JCI indicator, crisis conditions occur if the smoothed probability value is more than or equal to 0.5116. Forecasting the detection of currency crisis in Indonesia for the period of one year ahead is presented in Table 1.

Table 1 Currency crisis detection prediction

Period	***Smoothed Probability Value***	**Condition**
Nov-22	0,140698	Stable
Dec-22	0,050036	Stable
Jan-23	0,029253	Stable
Feb-23	0,02449	Stable
Mar-23	0,023397	Stable
Apr-23	0,023147	Stable
May-23	0,02309	Stable
Jun-23	0,023077	Stable
Jul-23	0,023074	Stable
Aug-23	0,023073	Stable
Sep-23	0,023073	Stable
Oct-23	0,023073	Stable

Table 1 shows that all smoothed probability values are smaller than the threshold value, so it can be concluded that in the period from November 2022 to October 2023 there was no currency crisis in Indonesia.

Conclussion

Based on the research that has been done, it can be concluded as follows.

a. The combination of volatility and markov switching models that are suitable for early detection of currency crises in Indonesia based on the JCI indicator is the MS-ARCH(2,1) model with the AR(1) model as the average model
b. Based on JCI indicators, Indonesia will not experience a currency crisis from November 2022 to October 2023.

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