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EARLY DETECTION OF CURRENCY CRISIS IN INDONESIA BASED ON STOCK PRICE INDEX USING VOLATILITY MODEL AND MARKOV SWITCHING

Berlyana Ayu Prasasti [1], Sugiyanto [2], Sri Subanti [3]
Department of Statistics, Sebelas Maret University [1]
Department of Statistics, Sebelas Maret University [2]
Department of Statistics, Sebelas Maret University [3]

berlyanaayup@student.uns.ac.id[1], sugiyanto61@staff.uns.ac.id[2], srisubanti@staff.uns.ac.id[3]

ABSTRACT:

The currency crisis occurred in Indonesia from 1997 until 1998 and 2008. These crises had a negative impact, both in terms of the economy and social life. Therefore, a system is needed to detect currency crisis to create economic and currency stability. The crisis can be detected through economic indicators, such as stock price index. This study aims to determine the appropriate model and determine the results of the prediction of the currency crisis in Indonesia from November 2022 to October 2023 based on stock price index. The research started by forming AR model, then the volatility model which is $ARCH$, and then formed a combination of volatility and markov switching model. This combined model is used to form a smoothed probability that can detect crisis. The results showed that $MS-ARCH(2,1)$ is a suitable model and from November 2022 to October 2023 it is predicted that there will be no currency crisis in Indonesia.

Keyword: *Early Detection of Currency Crisis, Stock Price Index, AR, $ARCH$, Markov Switching*

Corresponding Author:
hanapermataheldisari@gmail.com

Author Biodata:
Universitas Indonesia

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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 in January 2008 to Rp12,100 in November 2008 (Sri & Suliswanto, 2016). These crises had a negative impact, both in terms of the economy and social life. Therefore, a system is needed to detect currency crisis to create economic and currency stability, especially in Indonesia.

Kaminsky et al. (1998) proposed 15 indicators that can be used to detect currency crises in a country. These indicators are imports, exports, term of trade, international reserves, stock price index, real exchange rates, real interest rates, bank deposits, the difference between lending and deposit rate, the difference between BI rate and fed fund rate, narrow money, money multiplier, M2 to foreign reserve ratio, real output, and gross domestic product. In Indonesia itself, the 1997-1998 crisis was caused by exchange rate, interest rates, debt service ratios, and inflation, while the 2008 crisis was caused by stock price index, interest rates, and inflation (Keumala Sari *et al*., 2016). Abdushukurov (2019) stated that there is a significant relationship between currency crises and financial crises, so in financial crisis modeling, currency crisis indicators can be used. The stock price index is one of the indicators that can detect currency crises in a country. The stock price index is defined as the stock price expressed in index numbers used for analysis purposes. The stock price index indicates or reflects 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. These models do not mind the changing conditions in economic variables caused by economic crises, wars, or other causes that cause the value of the data to change significantly. Then, Hamilton and Susmel (1994) introduced the Markov Switching Model as an alternative to modeling fluctuating data.

Many crisis detection models are developed using a combination of volatility models and markov switching. Ananda (2015) conducted research on the detection of financial crises in Indonesia based on stock price index using a combination of volatility and Markov switching models with three states. The study found that the suitable model was the MS-ARCH(3,1) with AR(1) as the mean model. Dina (2015) conducted early detection of financial crises in Indonesia based on stock price index. The data contained heteroskedasticity, asymmetry, and structural changes, so it was modeled using a two-state MS-TGARCH model. Wibowo et al. (2016) researched forecasting stock returns in 2016 using the Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model. Suwardi (2017) conducted research on the early detection of financial crises in Indonesia based on import, export, and international reserve indicators using the MS-ARCH model. Pratiwi (2017) also conducted research on the early detection of financial crises in Indonesia using the MS-ARCH model based on narrow money, M2 to foreign reserve ratio, and money 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 stock price index indicator. The data used is monthly data from January 1990 to October 2022 obtained from the official website of Yahoo Finance. This study aims to determine the appropriate model and determine the results of the prediction of the currency crisis in Indonesia from November 2022 to October 2023 based on stock price index.

METHODS

1. Research method

This study uses monthly data of the Indonesian stock price index from January 1990 to October 2022 obtained from the official website of Yahoo Finance. The research begins with creating a time series plot of the data and then performing 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 then performing a Lagrange multiplier test to see the heteroscedasticity effects on the residuals. If the residuals have heteroscedasticity effects, 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. Then calculate the smoothed probability value and forecast the smoothed probability value for November 2022 to October 2023 and perform crisis detection.

2. Stock Price Index

Stock price index is the stock price expressed in index numbers that are used for analysis purposes. The stock price index is an indicator or reflection of stock price movements (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 (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).

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

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 in the t-th period, ϕ_0 is a constant, ϕ_p is parameters on autoregressive models, and a_t is the residue in the t-th period. (Tsay, 2002).

4. Autoregressive Conditional Heteroscedasticity (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).

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

with α_0 is the constant of $ARCH$ model, α_t is the parameter of $ARCH$ model, and σ_t^2 is the residual variance in the t-th period (Tsay, 2002).

5. Markov Switching-ARCH (MS-ARCH)

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

$$\sigma_{t,st}^2 = \alpha_{0,st} + \alpha_{1,st} a_{t-1}^2 + \cdots + \alpha_{m,st} a_{t-m}^2 \quad (3)$$

with K is the number of states, m is the order of $ARCH$ model, and $\sigma_{t,st}^2$ is the residual variance of a state in the t-th period.

6. Transition Probability Matrix

The markov process is called a stochastic process if the probability of any behavior (state) in the future depends only on the behavior (state) in the present and is not changed by additional knowledge of the behavior (state) in the past (Frey et al., 1994). The markov chain process can be written as in Equation (4).

$$P(X_{n+1} = j | X_0 = i_0, \dots, X_{n-1}, X_n = i) = P(X_{n+1} = j | X_n = i) = P_{ij} \quad (4)$$

With P_{ij} is the transition probability matrix in 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).

$$P = \left[P_{ij}\right] = \begin{bmatrix} P_{11} & P_{12} & \cdots \\ P_{21} & P_{22} & \cdots \\ \vdots & \vdots & \ddots \end{bmatrix} \quad (5)$$

with $P_{ij} > 0$ for $i, j = 1,2, \dots$ and $\sum_{j=1}^{\infty} P_{ij} = 1$ for $i = 1,2, \dots, n$.

7. 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).

$$(Pr(S_t = i | \psi_r)) = \sum_{j=1}^{K} \Pr\,(S_{t+1} = K | \psi_T) \Pr\,(S_t = i | S_{t+1} = K, \psi_T) \quad (6)$$

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.

$$(\Pr(S_t = i | \psi_r)) = \sum_{j=1}^{K} p_{ij} \Pr\,(S_t = j | \psi_T) \quad (7)$$

In $\Pr\,(S_t = j | \psi_T)$ is the value of smoothed probability at the t -th time for the j -th regime and p_{ij} is 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.

RESULTS AND DISCUSSION

1. Identify Data Patterns

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

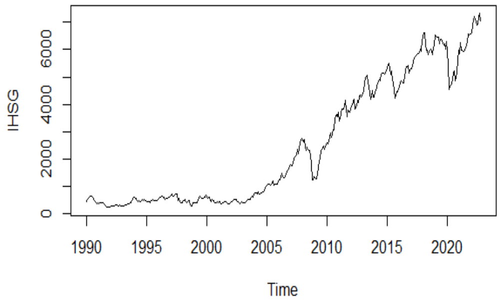

Figure 1 Time series plot of stock price index

Figure 1 shows fluctuations in the stock price index data, where the data increases over time and the variance is not constant, thus indicating that the data is not stationary. To prove this conjecture, an ADF test was carried out and the probability value is 0.978. Since this value is greater than $\alpha = 0.05$, it can be concluded that the data is not stationary. To solve this problem, a log-return transformation is performed on the data, and time series plot for the transformed data is presented in Figure 2.

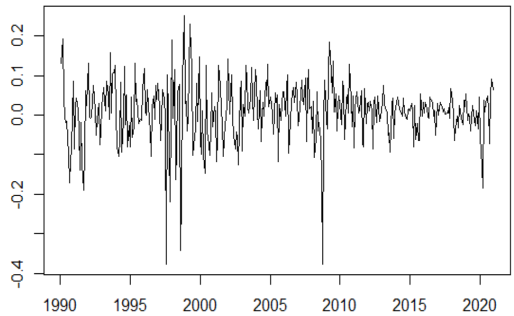

Figure 2 Time series plots of transformed data

Figure 2 shows that the transformed data is already stationary, as the data fluctuates around the average value. Based on the ADF test, the probability value is 0.01, which is smaller than $\alpha = 0.05$, so it can be concluded that the log return data is stationary. This transformation data is used for model formation.

2. Performing AR Model

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

$$r_t = 0.2158 r_{t-1} + a_t$$

Furthermore, the Lagrange multiplier test was carried out to determine whether the residue from the AR model contained the effect of heteroskedasticity or not. From the tests, a probability value of 4.19×10^{-9} was obtained. This value is smaller than $\alpha = 0.05$, so it can be concluded that the residues of the AR model contain the heteroskedasticity effect. Therefore, advanced modeling with volatility models is carried out.

3. Performing Volatility Model

The formation of the volatility model is based on the PACF plot of the squared residual of AR model. From the several possible models formed, significance tests were performed on each parameter and the model with the smallest AIC value was selected. For stock price index indicators, the best volatility model is $ARCH(1)$ with the following model.

$$\sigma_t^2 = 0.0043 + 0.2328 a_{t-1}^2$$

Furthermore, a diagnostic test was performed on the volatility model residue to determine the adequacy of the model. These diagnostic test includes a normality test, non-autocorrelation test, and heteroscedasticity test. The normality test was performed using Kolmogorov-Smirnov test and obtained a probability of 0.8811, which is greater than $\alpha = 0.05$. 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 $\alpha = 0.05$. 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 $\alpha = 0.05$. It means that the residuals of the model do not contain heteroskedasticity effects.

4. Sign Bias Test

Furthermore, a sign bias 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 $\alpha = 0.05$. This shows that the residue of the volatility model does not have an asymmetric effect (leverage effect), so there is no need for further volatility modeling.

5. Performing a Combined Model of Volatility and Markov Switching

The volatility Model that has been formed 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 the result of an unobserved random variable called a state. This state is divided into two, namely low and high volatility conditions. To describe the change in these conditions, a transition probability matrix is used. The transition probability matrix for the stock price index 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 is presented in Figure 3.

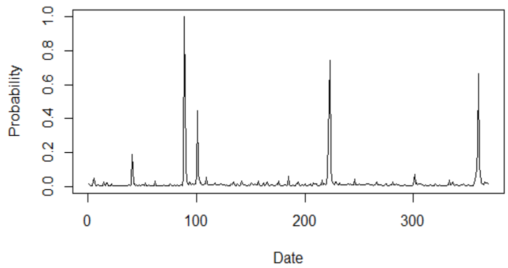

Figure 2 Smoothed probability plot

Crisis detection is carried out by looking at the minimum value of smoothed probability results when there was a currency crisis in Indonesia, which is in 1997 - 1998 and 2008. For the stock price index indicator, crisis conditions occur if the smoothed probability value is more than or equal to 0.5116. Forecasting the detection of the currency crisis in Indonesia for 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.

CONCLUSION

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 stock price index indicator is $MS - ARCH(2,1)$ model with $AR(1)$ model as the average model.
b. Based on stock price index indicators, from November 2022 to October 2023 there will be no currency crisis in Indonesia.

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