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

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ABSTRACT:

The currency crisis that occurred in Indonesia in 1997/1998 and 2008 had a significant impact on the Indonesian economy. An early detection system for crises is necessary to minimize the impact of such crises. One model that can detect currency crises is a combination of volatility and Markov switching models. There are several indicators that can be used to detect currency crises in a country, and one of them is exports. Research results indicate that the best combination of volatility and Markov switching models for the export indicator is MS-ARCH (2,2) with an assumption of two states. The crises of 1997/1998 and 2008 can be detected using the smoothed probability values with certain limits. Predictions for the period of July 2022-June 2023 based on the export indicator show no signs of a crisis in Indonesia.

Keyword: *Detection, Crisis, MS-ARCH, Export.*

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INTRODUCTION

The stronger the economic relationships between countries, the more vulnerable a country's economy is to external shocks. This makes it easy for crises to spread from one country to another. Financial crises are one of the causes of damage to the pillars of an economy in a country. Mishkin (1992) defines a financial crisis as a disturbance in the financial market that results in inefficient allocation of funds to economic agents. Indonesia has experienced two major crises, namely the Asian financial crisis in 1997 and the global financial crisis in 2008.

The Asian financial crisis was caused by the devaluation of the Thai currency, the Bath (Harapap, 2013). The 2008 crisis was caused by the subprime mortgage program or mortgage-backed securities given to low-credit-quality borrowers in the United States (Santoso, 2018). Financial crises have a significant impact on the Indonesian economy, so an early detection system for crises is needed to minimize the impact of future crises.

Exports are one of the indicators that can be used to detect financial crises in a country (Kaminsky, Lizondo, & Reinhart, 1998). High exports and low imports can be an indication of a crisis in that country (Dwi, Sugiyanto, & Susanti, 2017). The presence of fluctuations causes crises to recur (Rusydiana, Nurfalah, & Laila, 2021). Changes in fluctuations can be explained using volatility models and changes in conditions can be explained using Markov switching models (Adebun, Sugiyanto, & Slamet, 2019).

Detection of financial crises in Indonesia has been developed by Sugiyanto, Zukhronah, & Sari (2018) using banking indicators. Similar research has also been conducted by Sugiyanto, Zukhronah, & Pratiwi (2017) using M2/foreign exchange reserves, M1, and M2 multiplier indicators. Sugiyanto, Zukhronah, & Setianingrum (2018) also conducted research using real output indicators, domestic credit/GDP, and ICI indicators. Nafisah, Sugiyanto, & Pratiwi (2020) conducted research on the detection of crises in Indonesia using real exchange rates and M2/foreign exchange reserves. In this study, a suitable model was developed using the export indicator. The resulting model can be used for early detection of financial crises in Indonesia in the future.

RESEARCH METHOD

Time-series analysis is a useful analysis to know or predict future circumstances (Soejoeti, 1987). Stationary time-series data can be modeled with an Autoregressive Moving Average (ARMA) model. The general form of the ARMA model (p, q) can be expressed in the following equation

$$r_t = \phi_0 + \phi_1 r_{t-1} + \cdots + \phi_p r_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q} \quad (1)$$

where $r_t = \ln\frac{Z_t}{Z_{t-1}}$ is log *return* data in the time at-*t*, a_t is residue in time at-*t*, $\phi_1, \dots, \phi_p$ is model parameter *AR(p)*, and $\theta_1, \dots, \theta_q$ is model parameter *MA(q)* (Tsay, 2005).

ARMA models that experience symptoms of heteroskedasity can be modeled using a volatility model where a_t expressed as

$$a_t = \sigma_t e_t \text{ untuk } e_t \sim N(0,1) \text{ dan } a_t | F_{t-1} \sim N(0, \sigma_t^2)$$

where e_t is standard residue model *ARMA* and F_{t-1} is *set of all information at time to- t-1.*

The ARCH (m) model can be written as

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

Which α_0 is model constants, α_i is a parameter of the ARCH model, m is the order of the ARCH model and σ_t^2 *is the residual variance at the t-th time* (Tsay, 2005).

GARCH models are used if the order on the ARCH model is too high. The GARCH model (m, s) is written as

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2 \quad (3)$$

Where β *is a GARCH model parameter* (Tsay, 2005).

The MS-ARCH model is a combined model between the ARCH and Markov Switching models. The MS-ARCH model (st, m) formulated by Hamilton & Sumsel, (1994) can be written as

$$r_t = \mu_{st} + a_t \quad (4)$$

$$a_t = \sigma_t e_t$$

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

Where μ_{st} is a conditional average on a state, σ_{t,s_t}^2 is a model of residual variance at the t-th time of a state.

According to Kuan, (2002), *smoothed probability* can be written as

$$P(S_t = i|F_r) = \sum_{j=1}^{3} P(S_{t+1} = j|F_T)P(S_t = i|S_{t+1} = j, F_T) \quad (5)$$

Crisis detection in the next period can be detected using smoothed probability forecasting. According to Sopipan, Sattayatham, & Premanode, (2012) smoothed probability forecasting can be written as

$$P_r(S_{t+1} = i|F_r) = p1iP_r(S_t = 1|F_T) + p2iP_r(S_t = 2|F_T) \quad (6)$$

with $P_r(S_t = 1|F_T), P_r(S_t = 2|F_T)$ is the smoothed probability value for states 1, 2, and 3 in the previous data.

The type of data used in this research is monthly time series data with an observation period of January 1990 to June 2022. The data used is obtained from the International Financial Statistics (IFS) published by the International Monetary Fund (IMF). The method of data analysis in this research is by using a combination of volatility and Markov switching models. The steps used to achieve the research objective are as follows:

1) Create a data plot and perform an Augmented-Dickey Fuller (ADF) test to test the stationarity of the data. If the data is not stationary, perform a log return transformation.
2) Determine the ARMA (p, q) model by examining the ACF and PACF plots. If a model is obtained, test for heteroskedasticity effects, normality, and autocorrelation on the ARMA (p, q) model residuals.
3) Form and test for heteroskedasticity effects, normality, and autocorrelation on the best volatility model.
4) Test for leverage effects to see the symmetry of the residuals.
5) Form a combination of volatility and Markov switching models using the assumption of two states.
6) Calculate the smoothed probability value and the smoothed probability forecast value to detect crises.

RESULT AND DISCUSSION

The export data used in this study were taken from January 1990 to October 2022 as many as 394 observations. Figure 1 shows the plot for the export data.

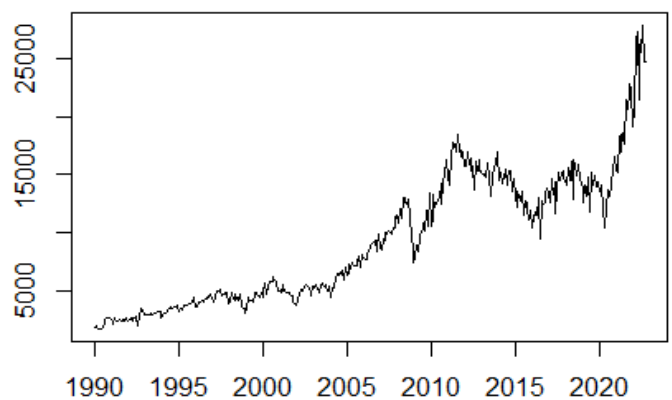

Figure 1. Plot Export Data

Figure 1 shows that the export data has increased and decreased over time so it can be indicated that the data is not stationary. The ADF test produces a probability value of 0.3314 where the probability value is greater than the significance level used, which is 0.05 so that it can be concluded that the data is not stationary. The return log transformation is used to address impostigations in the export data. The transformed data plot is shown in Figure 2.

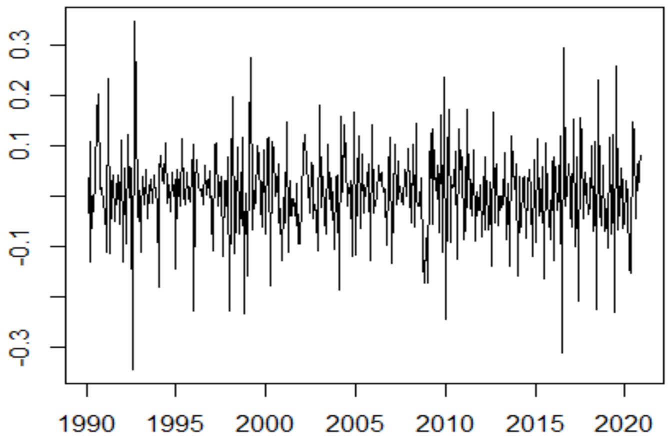

Figure 2. Plot Data Log Return Export

Figure 2 indicates that the log return data plot is already stationary against the average but has non-constant variance. The ADF test strengthens the indication because the resulting probability value of 0.01 is smaller than the significance level so it can be concluded that the log return data is stationary. Estimation of ARMA model parameters (p,q) is identified using PACF and ACF plots. The ACF and PACF plots can be seen in Figure 3 and Figure 4.

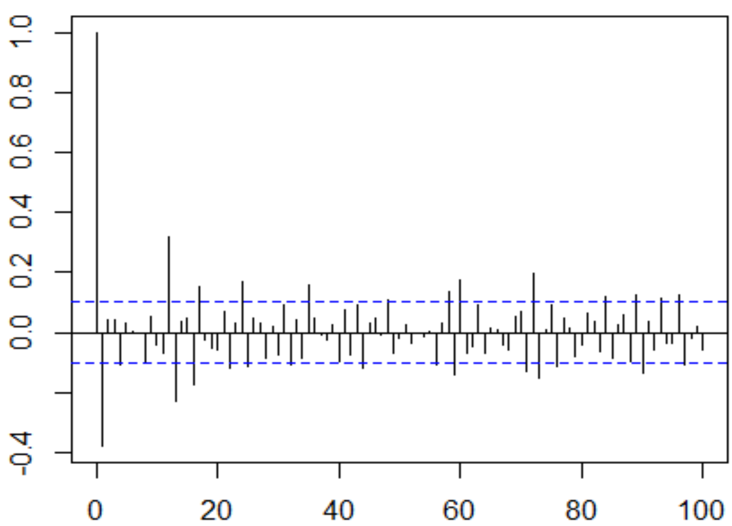

Figure 3. Plot *ACF* Data Log *Return* Export

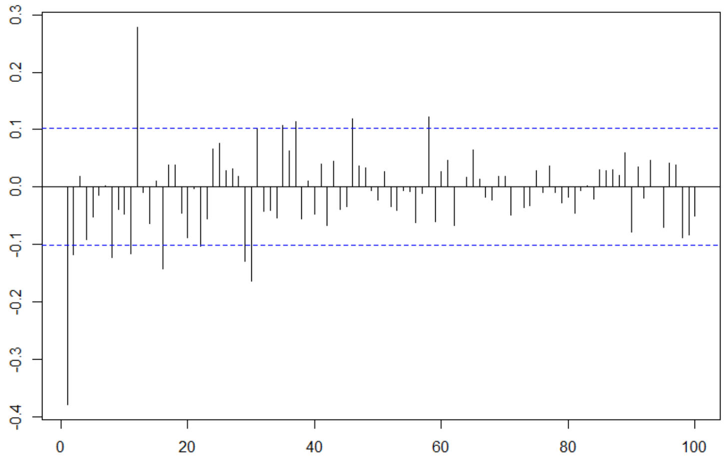

Figure 4. Plot *PACF* Data Log *Return* Export

Figure 3 shows that the ACF plot is disconnected at the 1st lag. Figure 4 shows the PACF plot disconnected on the 2nd lag so that showing the corresponding models for export log returns are AR (1), AR (2), ARMA (1,1), and ARMA (2,1). The parameters of the model that can be used are estimated using the least squares method as in Table 1.

Table 1. Estimated Average Model Parameters for Export Return Log

Model	Parameter	Probability	AIC
AR (1)	ϕ_1	9,064$\times 10^{-15}$	-754,83
AR (2)	ϕ_1	1.083$\times 10^{-15}$	-757.25
	ϕ_2	0.03501	
ARMA (1,1)	ϕ_1	0.28460	-756.87
	θ_1	0.04435	
ARMA (2,1)	ϕ_1	0.002363	-756.36
	ϕ_2	0.005000	
	θ_1	0.097368	

Table 1 shows that the parameters of the MA model have a probability of more than 0.05 which means that the corresponding models are AR (1) and AR (2) because all the parameters are significant. The selected average model is the model with the smallest AIC value which is AR (2). The average model for export return logs can be written as

$$r_t = -0{,}4141 r_{t-1} - 0{,}1090 r_{t-2} + a_t$$

After obtaining the best average model, a residual diagnostic test is then carried out. Residual diagnostic test results are shown in Table 2.

Table 2. Residue Diagnostic Test

Uji Normalitas	Uji Autokorelasi	Uji Heteroskedastisitas

0.8763	0.8764	0.022

Table 2 shows the AR model (2) meets the normality test and the autocorrelation test, but not the heteroskedasticity test. Since there is a heteroskedasticity effect on AR model residues, it is necessary to form a volatility model for export return logs. The AR model used to model the export return log data, has the effect of heteroskedasticity. The volatility model parameters that can be used for export return log data can be seen in Table 3.

Table 3. Volatility Model Parameter Estimation Results for Export return log data

Model	Parameter	Probabilitas	AIC
ARCH (1)	α_0	<2×10^{-16}	-776.8361
	α_1	0.00167	
ARCH (2)	α_0	<2×10^{-16}	-777.0353
	α_1	0.00276	
	α_2	0.04869	

Table 3 shows that the parameters of the ARCH (1) and ARCH (2) models are significant, since they have a probability of less than 0.05. The selected volatility model is the model with the smallest AIC value which is ARCH (2). The volatility model for export return logs can be written as follows

$$\sigma_t^2 = 0.0049\alpha_0 + 0.2731\alpha_1 + 0.0918\alpha_2$$

Estimasi parameter model volatilitas menunjukkan bahwa model volatilitas yang digunakan adalah ARCH (2). Dilakukan uji diagnostik residu meliputi uji normalitas, uji autokorelasi, dan uji heterokedastisitas seperti dalam Tabel 4.

Table 4. Volatility Model Residue Diagnostic Test

Uji Normalitas	Uji Autokorelasi	Uji Heteroskedastisitas
0.8757	0.4107	0.08043

Table 4 shows that the ARCH (2) model has met the assumption test for residuals because all tests have probabilities greater than 0.05, indicating that the ARCH (2) model is proven to be good for modeling export data.

The sign bias test is used to detect the presence of leverage effects on residuals. The probability for the sign bias test produces a value of 0.6724 which is greater than 0.05, so it can be concluded that there is no leverage effect or that the residuals are symmetric.

The conditional mean and conditional volatility models for export log return data are the AR (2) and ARCH (2) models. A combination of the volatility model and the Markov Switching model was formed into an MS-ARCH model. Using the elbow and silhouette methods, it is known that the clustering of residuals produces 2 clusters. This means that the volatility model that has been obtained is combined with a 2-state Markov switching model to overcome the low and high volatility in the data. The transition probability matrix for export data is as follows.:

$$P_1 = \begin{bmatrix} 0.1812 & 0.8188 \\ 0.2658 & 0.7342 \end{bmatrix}$$

The transition probability matrix P_1 interprets that the probability values of persisting at low states and high states are 0.1812 and 0.7342. Meanwhile, the probability of moving from high to low and low states to highs is 0.2658 and 0.7342. The MS-ARCH model (2,2) can generate a smoothed probability value for each export data period. The smoothed probability value is used to determine conditions not crises and crises. The smoothed probability plot for export data can be seen in Figure 5.

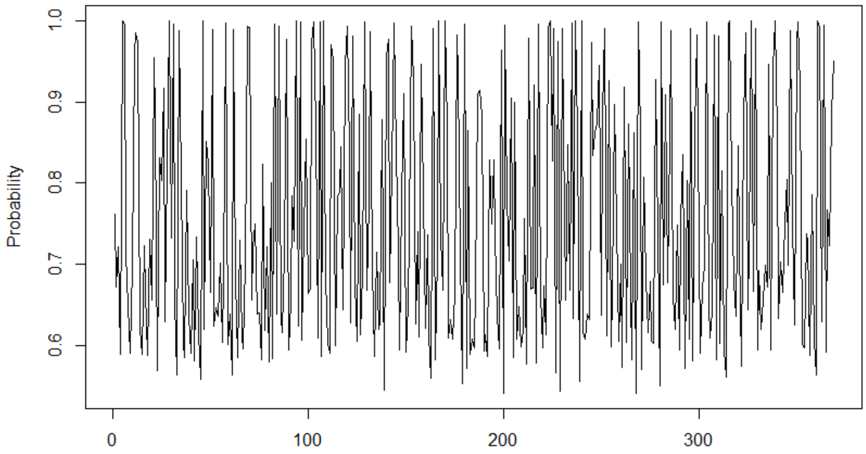

Figure 5. Plot *Smoothed Probability* Export

The crisis limit calculation resulted in a smoothed probability value for the export data of 0.94362. A smoothed probability value that is greater than the crisis limit will enter into a condition of high volatility or commonly referred to as a crisis state. Financial crisis detection for export indicators can be seen in Table 5.

Table 5. Export Data Crisis Detection

Crisist Period
Januari 1991-Maret 1991
Juli 1992-September 1992
Agustus 1998-Oktober 1998
September 2008-Desmber 2008
Mei 2016-Juli 2016
April 2019-Juni 2019

Comparison of forecasting values and actual smoothed probability for export indicators and interest rate differences on deposits and loans is presented in Table 6.

Table 6. Forecasting Value and Actual Smoothed Probability

Periode	Ekspor	
	Peramalan	Aktual
Jan-21	0.76872	0.62009
Feb-21	0.76630	0.62009

Mar-21	0.76601	0.62009
Apr-21	0.76598	0.62009
May-21	0.76597	0.62008
Jun-21	0.76597	0.62008
Jul-21	0.76597	0.62009
Aug-21	0.76597	0.62008
Sep-21	0.76597	0.62008
Oct-21	0.76597	0.62009
Nov-21	0.76597	0.62009
Dec-21	0.76597	0.62009
Jan-22	0.76597	0.62010
Feb-22	0.76597	0.62010
Mar-22	0.76597	0.62009
Apr-22	0.76597	0.62009
May-22	0.76597	0.62011
Jun-22	0.76597	0.62012

Table 6 shows that there is no significant difference between the forecasting value of smoothed probability and its actual value. Furthermore, the results of smoothed probability forecasting for the next one-year period will be shown as in Table 7.

Table 7. Smoothed Probability Export Forecasting Value

Periode	***Smoothed Probability*** **Ekspor**
Jul-22	0.748912735
Aug-22	0.763978169
Sep-22	0.765740429
Oct-22	0.765946568
Nov-22	0.765970681

Dec-22	0.765973501
Jan-23	0.765973831
Feb-23	0.76597387
Mar-23	0.765973874
Apr-23	0.765973875
May-23	0.765973875
Jun-23	0.765973875

Table 7 shows that for export data, there is no smoothed probability value greater than 0.94362 so it can be seen that in the period July 2022-June 2023 Indonesia is not indicated to have a financial crisis.

CONCLUSSION

Based on the results and discussion, it can be concluded that the appropriate model for export indicators is MS-ARCH (2,2). The prediction results show that in the period July 2022-June 2023 Indonesia is not indicated to experience a financial crisis.

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