Markov-switching and noise-to-signal ratio approach for early detection of currency crises

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ABSTRACT

Economic instability can easily lead to a currency crisis. Therefore, observing a number of crisis indicators is crucial for building an early warning system (EWS). However, selecting the indicators most responsive to the crisis is the best choice. For this purpose, the noise-to-signal ratio (NSR) method was used. Monthly data from 1990-1925 were used in the autoregressive moving average (ARMA), generalized autoregressive moving average with generalized autoregressive conditional heteroscedasticity (GARMACH), and Markov-switching (MS)-GARMACH hybrid models to explain the crisis. Model interpretation indicates that there will be no crisis from May 2025-April 2026.

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1. INTRODUCTION

From the 1970s to the mid-1990s, Indonesia recorded solid economic growth, controlled inflation, and a healthy external balance. Because of this strong performance, the World Bank once called Indonesia an economic miracle [1]. However, this situation changed drastically when the Asian Financial Crisis struck in 1997. The Indonesian economy again faced turbulence during the 2007-2008 Global Financial Crisis [2], and more recently, the COVID-19 pandemic in 2020 triggered a global recession that also affected Indonesia's financial stability [3]–[7].

Past financial stability does not always guarantee protection against future disruptions [8]–[12]. These conditions have prompted policymakers to design an early warning system (EWS) using macroeconomic indicators to anticipate potential crises. Previous research has identified around fifteen key indicators—such as export and import performance, foreign exchange reserve adequacy, interest rate differentials, and monetary aggregates—that tend to move ahead of financial stress [13], [14]. Among various selection techniques, the noise-to-signal ratio (NSR) approach has been widely adopted because lower NSR values imply stronger predictive power for detecting crises [13]–[15].

Economic and financial data often display volatility clustering, making it necessary to use models that account for time-varying variance. The autoregressive conditional heteroskedasticity (ARCH) and generalized autoregressive conditional heteroskedasticity (GARCH) models introduced by Engle [16] and Bollerslev [17] are well suited for this purpose [18]. Yet, these models alone are unable to capture structural changes or regime shifts that frequently accompany crises. The Markov-switching (MS) model proposed by Hamilton [19] provides an alternative by allowing the system to switch probabilistically between stable and crisis states [20], [21]. Hybrid versions such as Markov-switching-generalized autoregressive conditional heteroskedasticity (MS-GARCH) and Markov-switching dynamic conditional correlation generalized autoregressive conditional heteroskedasticity (MS-DCC-GARCH) extend this flexibility, offering better tools for analyzing nonlinear financial dynamics [22], [23].

In recent years, several studies have employed such hybrid models to examine financial vulnerability in Indonesia and other Asian economies [24]–[29]. Nonetheless, only a few combines NSR-based indicator selection with regime-switching volatility frameworks. Addressing this gap, the present study integrates both approaches to construct an early-warning system for detecting potential currency and financial crises in Indonesia. The objective is to offer a more adaptive, data-driven framework that can support macroprudential policy design and enhance the country's financial stability monitoring [30]–[33].

2. RESEARCH METHOD

This study selects 15 macroeconomic indicators as potential crisis signals based on their lowest NSR values. Monthly data from January 1990-April 202 covering trade, reserves, interest rates, exchange rates, money supply, stock prices, output, and domestic credit per gross domestic product (GDP) were obtained from International Financial Statistics (IFS) and Bank Indonesia (BI). Indicator selection was based on each variable's ability to detect crises using the exchange market pressure (EMP) index, as shown in (1), calculated as the weighted average of exchange rate and reserve changes [13], [34]–[36].

$$EMP_t = \left(\frac{u_t - u_{t-1}}{u_{t-1}}\right) - \left(\frac{\sigma_u}{\sigma_c}\right)\left(\frac{c_t - c_{t-1}}{c_{t-1}}\right) \quad (1)$$

Where u_t is the rupiah exchange rate against the US dollar in month t, c_t is the foreign exchange reserve in month t, σ_u is the standard deviation of the rupiah exchange rate against the US dollar, dan σ_c is the standard deviation of foreign exchange reserves. The threshold value representing crisis conditions is calculated using (2).

$$b = \bar{x} + \delta\,\sigma \quad (2)$$

Where δ is set at 1.5; 2; 2.5; or 3. Based on this threshold, crisis periods are identified through (3).

$$KC = \begin{cases} 1, & if\ EMP > b \\ 0, & if\ EMP \le b \end{cases} \quad (3)$$

Where 1 denotes a crisis, and 0 denotes no crisis [13], [36], [37].

Macroeconomic indicators were transformed to improve their sensitivity to crises. Seasonal variables were converted into annual growth rates, while non-seasonal variables were differenced. Additionally, the lending-to-deposit rate ratio was log-transformed, and the real exchange rate was split into trend and cycle components using the Hodrick–Prescott filter as (4) [15], [18], [38]–[40].

$$H = \sum_{t=1}^{t}(z_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1}[(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \quad (4)$$

Where z_t is the time series observation at t, τ_t is the trend component at t, λ is the penalty term, set to 129,600 for monthly data.

Signal effectiveness was evaluated using a 24-month signal horizon. If a crisis signal occurs and a crisis follows within 24 months, it is classified as a correct signal (A); if no crisis follows, as a false signal (B); if there is no signal and no crisis, as (D); and if there is no signal but a crisis occurs, as (C). The signal matrix is presented in Table 1, and the NSR value is calculated as (5) [15].

$$NSR = \frac{B/(B+D)}{A/(A+C)} \quad (5)$$

Table 1. Signal indicator matrix

	Crises occurred	No crises occurred
Signal	A	B
No signal	C	D

The three indicators with the lowest NSR values were selected for further modelling. The data were divided into in-sample (January 1990-April 2024) and out-of-sample (May 2024-April 2025) periods. Stationarity testing was performed using the augmented Dickey-Fuller (ADF) test, and if non-stationarity was detected, a log-return transformation was applied in (6) [18], [38], [41].

$$r_t = ln\, z_t - ln\, z_{t-1} \quad (6)$$

Granger causality testing was conducted to examine relationships among the indicators [18], [42], [43]. The optimal lag length was determined using Schwarz's Criterion (SC) as in (7).

$$SC = -2\ln(L) + k\, ln(T) \quad (7)$$

Where T is the number of observations, k is the number of parameters estimated in the model, and L is the maximum likelihood value of the model. The Granger causality test statistic is formulated as in (8) [18], [43], [44].

$$F_G = \frac{(JKR_R - JKR_{UR})/l}{JKR_{UR}/(T-k)} \quad (8)$$

Where $JKR_R = JKR_{UR} = \sum_{i=1}^{T}(Y_t - \widehat{Y}_t)^2$, JKR_{UR} is the residual sum of squares from the unrestricted regression, and JKR_R is from the restricted regression.

If no causal relationship was found, univariate autoregressive moving average (ARMA) (p, q) modelling was performed. The orders p and q were determined from the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, and the best model was selected based on the Akaike Information Criterion (AIC) as in (9) [18].

$$AIC = -2\ln L + 2k \quad (9)$$

Where k denotes the number of variables, and L denotes the maximum likelihood value of the model.

The ARMA model was validated using three diagnostic tests. Autocorrelation with the Ljung-Box test [41], heteroskedasticity with the Lagrange multiplier test [16]–[18], and normality with the Kolmogorov-Smirnov test [28]. If heteroskedasticity was detected, ARCH(m) and GARCH (m, s) models were applied in (10) and (11) [16]–[18].

$$\sigma_t{}^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i\, a_{t-i}^2 \quad (10)$$

$$\sigma_t{}^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i\, a_{t-i_1}^2 + \sum_{j=1}^{s} \beta_j\, \sigma_{t-j}^2 \quad (11)$$

To capture economic regime changes, the MS model was applied. Combining MS with GARCH produced the MS-GARCH model, which was estimated using maximum likelihood estimation (MLE) as in (12) [17]. This approach allows volatility to shift between regimes, providing a clearer identification of periods that may signal the onset of a currency crisis.

$$\sigma_{t,s_t}^2 = \alpha_{0,s_t} + \sum_{i=1}^{m} \alpha_{i,s_t}\, a_{t-i}^2 + \sum_{j=1}^{s} \beta_{j,s_t}\, \sigma_{t-j}^2 \quad (12)$$

The probability of a crisis at time t was calculated using smoothed probability as in (13) [24].

$$P(s_t = v|\Psi_T) = \sum_{w=1}^{K} Pr(s_{t+1} = w|\Psi_T) \times Pr(s_t = v|s_{t+1} = w, \Psi_t) \quad (13)$$

Forecasting of crisis probability for the period May 2025-April 2026 was performed using (14) [45]–[49].

$$Pr(s_{t+1} = w|\psi_T) = \sum_{v=1}^{K} p_{vw} Pr(s_t = v|\psi_T) \quad (14)$$

The model is considered accurate if the forecast status and the actual smoothed probability in the out-of-sample period show consistent results. The crisis threshold was set as the lowest smoothed probability value observed during past crisis periods, representing the probability of transitioning into a crisis regime.

3. RESULTS AND DISCUSSION

3.1. Selection of crisis signal indicators

Financial crisis periods in Indonesia were identified using the EMP threshold with a sigma coefficient of 1.5, revealing crises in August 1997-June 1998, October 2008, and March 2020 corresponding to the Asian, Global, and COVID-19 crises. Macroeconomic indicators were transformed through annual growth rates for seasonal variables, differencing for non-seasonal ones, logarithmic conversion for the lending to deposit ratio, and Hodrick-Prescott filtering for the real exchange rate. Using these transformations, a signal matrix was constructed, and NSR values for 15 indicators were computed, as shown in Table 2. The three indicators with the lowest NSR values, real deposit interest rate, M2 per foreign exchange reserves, and real exchange rate, were identified as the most crisis-sensitive. Their transformation and threshold comparisons used in NSR calculation are illustrated in Figure 1, where the real deposit interest rate as shown in Figure 1(a), M2 per foreign exchange reserves as shown in Figure 1(b), and the real exchange rate as shown in Figure 1(c).

Table 2. NSR values

Variables	NSR	Ranking
Imports	1.35489	13
Exports	1.71226	15
Foreign exchange reserves	1.20042	9
Stock price	1.14040	7
The ratio of lending to deposit interest rates	1.23317	11
Real deposit interest rate	0.96257	1
Gap between real BI rate and real Fed rate	1.02563	5
Bank deposits	1.15657	8
Real exchange rate	0.99558	3
Trade exchange rates	1.21056	10
M1	1.03744	6
M2 per foreign exchange reserves	0.99348	2
M2 multiplier	1.01198	4
Real output	1.39156	14
Domestic credit per GDP	1.24414	12

The three indicators selected in this study reflect patterns of monetary instability in Indonesia during the period 1990-2024. During the 1997-1998 Asian currency crisis, all three exhibited significant fluctuations. This fluctuation reflects the dramatic changes in currency conditions. After 2000, market conditions gradually stabilized. However, in 2020, a new wave of volatility emerged following the COVID-19 pandemic. The wave resurfaced in early 2024, likely due to a series of geopolitical disruptions. These episodes highlight the time-varying nature of volatility and underscore the importance of dynamic modeling frameworks such as ARMA, generalized autoregressive moving average with generalized autoregressive conditional heteroscedasticity (GARMACH), and MS-GARMACH for explaining and predicting currency stability.

3.2. Data pattern identification and stationarity

Figure 2 displays the movement of the real deposit interest rate, the M2 to foreign exchange reserves ratio, and the real exchange rate over time from January 1990-April 2024. Figure 2 shows that the three indicators fluctuate considerably over time, indicating that their original series are likely non-stationary. Once the log-return transformation was applied, the ADF test produced p-values of 0.01. These results confirm that the real deposit interest rate, as shown in Figure 2(a), and the M2-to-reserves ratio, as shown in Figure 2(b), and the real exchange rate became stationary after transformation as shown in Figure 2(c).

3.3. Granger causality test

The causal relationships between the indicators were examined using the Granger causality test. The results are summarized in Table 3. Since all p-values exceed $\alpha = 0.01$, no significant causal relationships were found; thus, each indicator was modeled univariately using ARMA.

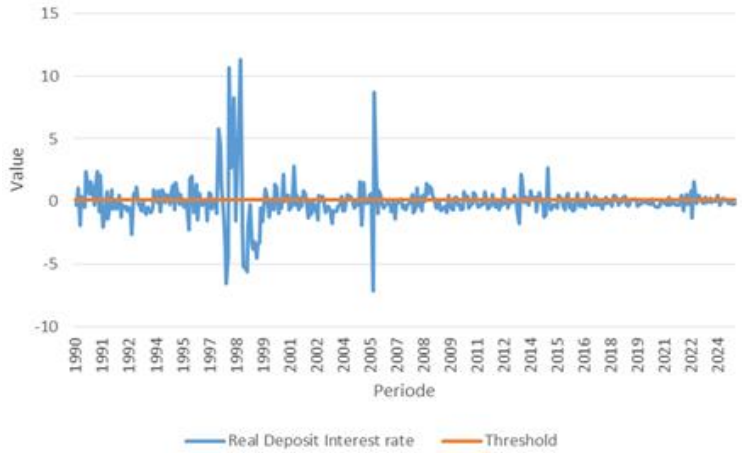
3.4. ARMA models

The best model for the real deposit interest rate indicator, with significant parameters and the lowest AIC value, is ARMA (1,2), as expressed in (15). Subsequently, for the M2 per foreign exchange reserves indicator, the best ARMA model is ARMA (2,1), as presented in (16). Finally, for the real exchange rate indicator, the best ARMA model selected is ARMA (2,2), as shown in (17). Residuals from each best model were tested for normality (Kolmogorov–Smirnov), autocorrelation (Ljung–Box), and heteroskedasticity (Lagrange multiplier). The first two tests showed p-values >0.01, indicating normality and no autocorrelation. However, the Lagrange multiplier test produced p-values <0.01 for all indicators, confirming heteroskedasticity and justifying the use of volatility modeling.

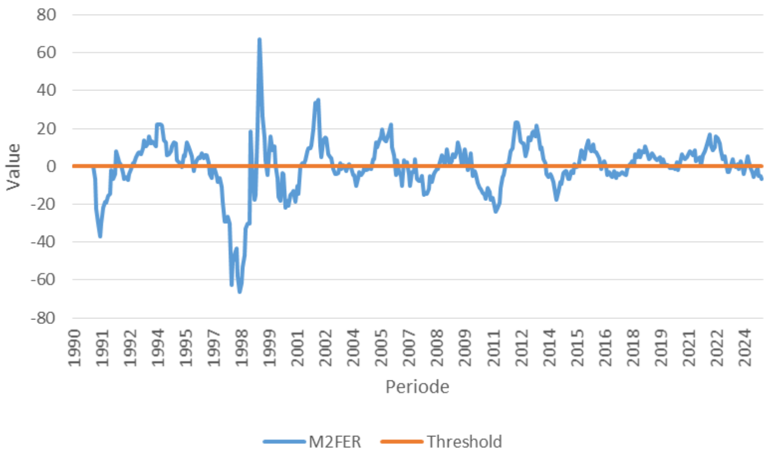
$$r_t = -0.0046 - 0.9830\, r_{t-1} + 0.5613\, a_{t-1} - 0.4387\, a_{t-2} + a_t \quad (15)$$

$$r_t = -0.0007 + 0.3545\, r_{t-1} - 0.1444\, r_{t-2} - 0.3930\, a_{t-1} + a_t \quad (16)$$

$$r_t = 0.0097 - 0.3367\, r_{t-1} - 0.7791\, r_{t-2} + 0.5436\, a_{t-1} + 0.8638\, a_{t-2} + a_t \quad (17)$$



(a)



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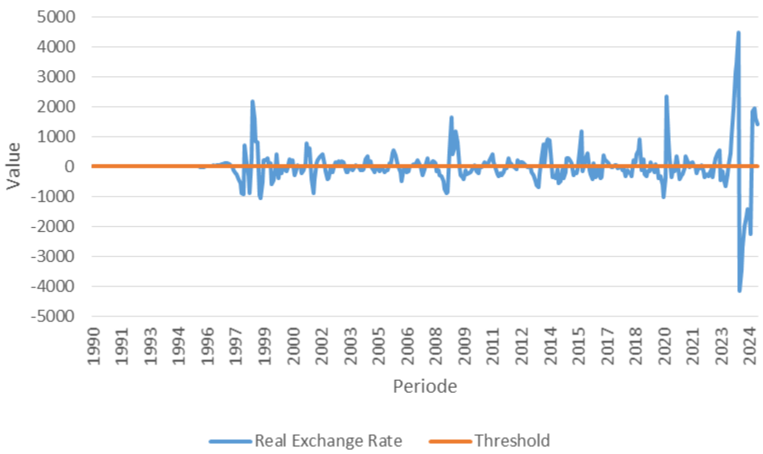
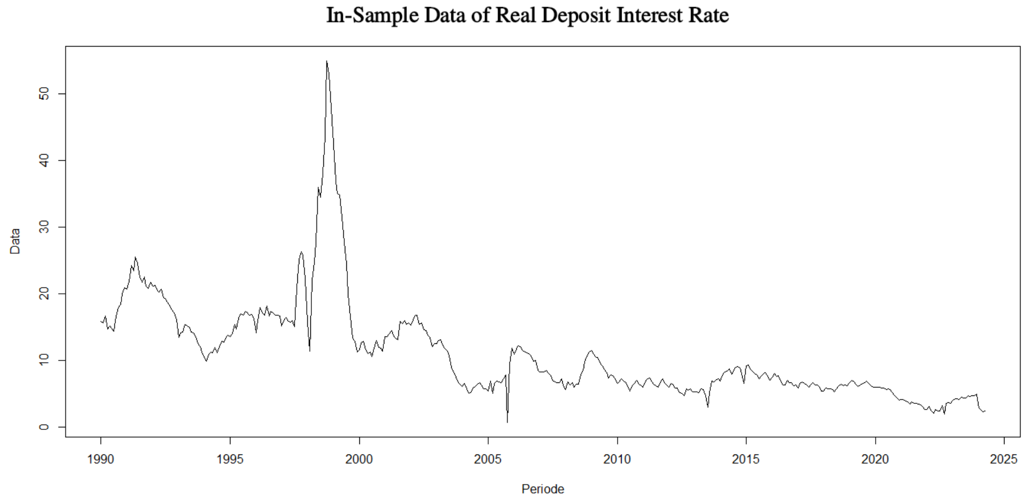


(c)

Figure 1. Transformation values and threshold plots of (a) real deposit interest rate, (b) M2 per foreign exchange reserves, and (c) real exchange rate



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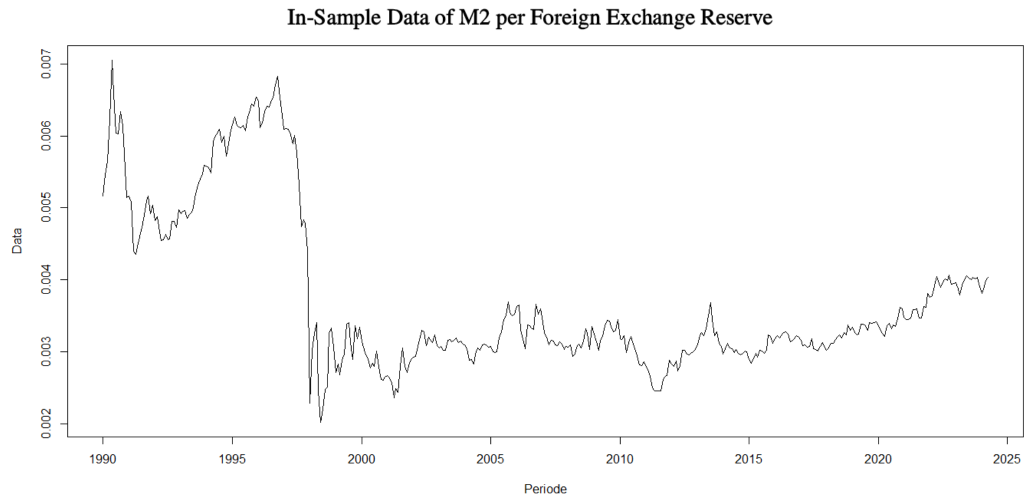

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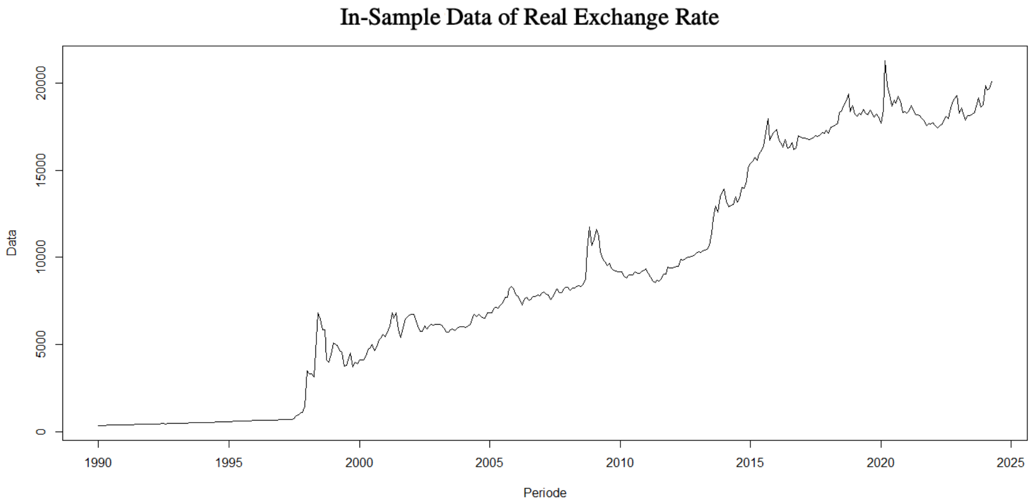


(c)

Figure 2. Time series plots of (a) real deposit interest rate, (b) M2 per foreign exchange reserves, and (c) real exchange rate

Table 3. Granger causality test results

Indicator relationship	P-value
Real deposit interest rate~M2 per foreign exchange reserves	0.6079
M2 per foreign exchange reserves~real deposit interest rate	0.7698
Real deposit interest rate~real exchange rate	0.5499
Real exchange rate~real deposit interest rate	0.8343
M2 per foreign exchange reserves~real exchange rate	0.6289
Real exchange rate~M2 per foreign exchange reserves	0.0942

3.5. ARMACH and GARMACH models

Since the models are based on ARMA, the corresponding volatility models are ARMA-GARCH or ARMA-ARCH. For the real deposit interest rate, the best model addressing heteroskedasticity is ARMA-ARCH (1), with its variance equation shown in (18). For the M2 per foreign exchange reserves indicator, the best model addressing heteroskedasticity in the ARMA (2,1) structure is GARCH (1,1), with its variance equation shown in (19). For the real exchange rate indicator, the best model addressing heteroskedasticity in the ARMA (2,2) structure is GARCH (1,1), with its variance equation shown in (20). Diagnostic tests on the best volatility models for all three indicators showed p-values >0.01 in the Kolmogorov–Smirnov, Ljung–Box, and Lagrange multiplier tests, confirming that the residuals are normal, uncorrelated, and free from heteroskedasticity, thus validating the models.

$$\sigma_t{}^2 = 0.0043 + 2.504\, a_{t-1}{}^2 \tag{18}$$

$$\sigma_t{}^2 = 0.00009526 + 0.4084\, a_{t-1}{}^2 + 0.6537\, \sigma_{t-1}{}^2 \tag{19}$$

$$\sigma_t{}^2 = 0.00008174 + 0.7261\, a_{t-1}{}^2 + 0.4648\, \sigma_{t-1}{}^2 \tag{20}$$

3.6. MS-ARMACH and MS-GARMACH models

The silhouette test indicated two optimal clusters for each indicator. Thus, the appropriate models are MS-ARMA-ARCH (2,1) for the real deposit interest rate and MS-GARCH (2,1,1) for both M2 per reserves and real exchange rate, with their variance equations shown in (21)-(23).

$$\sigma^2_{1,S_{t_t}} = \begin{cases} 0.4953 + 0.0000\, a^2_{t-1}, state\ 1 \\ 24.1379 + 0.0001\, a^2_{t-1}, state\ 2 \end{cases} \tag{21}$$

$$\sigma^2_{2,S_{t_t}} = \begin{cases} 0.2654 + 0.0000\, a^2_{t-1} + 0.5106\, \sigma^2_{t-1}, state\ 1 \\ 0.4381 + 0.0001\, a^2_{t-1} + 0.8886\, \sigma^2_{t-1}, state\ 2 \end{cases} \tag{22}$$

$$\sigma^2_{3,S_t} = \begin{cases} 0.0013 + 0.0053\, a^2_{t-1} + 0.9883\, \sigma^2_{t-1}, state\ 1 \\ 3.6903 + 0.7299\, a^2_{t-1} + 0.0027\, \sigma^2_{t-1}, state\ 2 \end{cases} \tag{23}$$

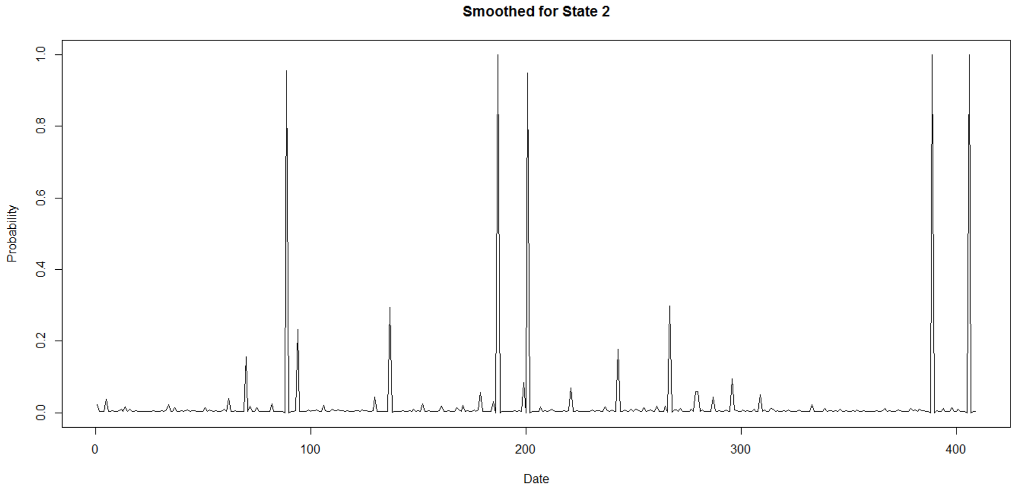
Where $\sigma^2_{1,S_{t_t}}$ represents the variance equation of the MS-ARMACH (2,1) model for the real deposit interest rate indicator, $\sigma^2_{2,S_{t_t}}$ represents the variance equation of the MS-GARMACH (2,1,1) model for the M2 per foreign exchange reserves indicator, and $\sigma^2_{3,S_{t_t}}$ represents the variance equation of the MS-GARMACH (2,1,1) model for the real exchange rate indicator.

State 1 and State 2 correspond to the low-volatility and high-volatility states, respectively. The transition probability matrices for the real deposit interest rate, the M2 per foreign exchange reserves, and the real exchange rate indicators are presented in matrices P_1, P_2, and P_3, respectively. The transition matrix results indicate that all three indicators predominantly remain in low-volatility (no-crisis) regimes. For P_1, stability persists with a 0.9781 probability, while shifts to high volatility are rare (0.0219). In P_2, the stability probability is 0.8441 with a 0.1559 chance of rising volatility, and in P_3, calm conditions persist with 0.8660, while volatility increases occur with 0.1340. Overall, transitions tend to revert quickly to stable regimes.

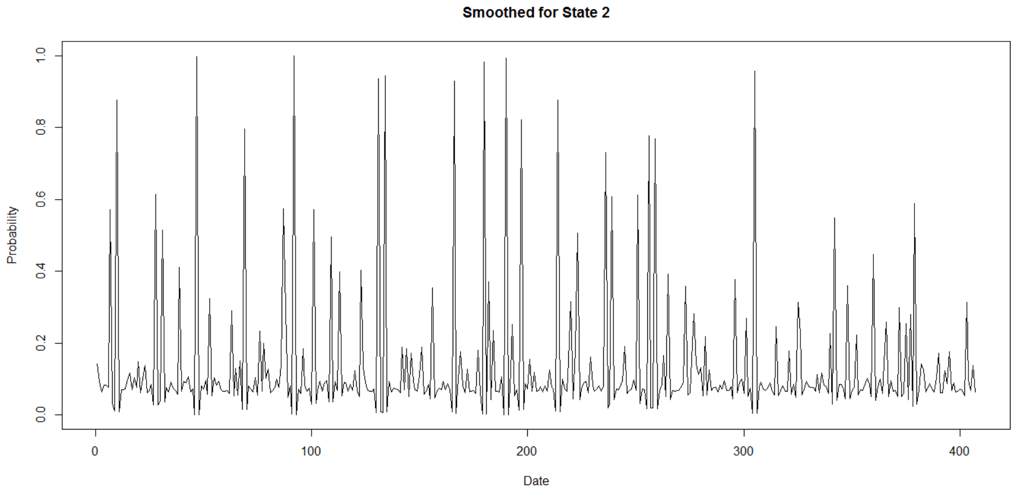
$$P_1 = \begin{pmatrix} 0.9873 & 0.0127 \\ 0.1772 & 0.8228 \end{pmatrix}, P_2 = \begin{pmatrix} 0.8441 & 0.1559 \\ 0.9994 & 0.0006 \end{pmatrix}, P_3 = \begin{pmatrix} 0.8660 & 0.1340 \\ 0.8650 & 0.1350 \end{pmatrix}$$

3.7. Determining crisis boundaries

Using the combined volatility and MS model, smoothed probability values were generated to determine crisis thresholds. Crisis periods were identified from fluctuations in these probabilities, as shown in Figure 3. The lowest smoothed probability values in Figure 3, which show instability during the financial crisis period in Indonesia, obtained from the EMP calculation, are summarized in Table 4. Table 4 presents the smoothed probability thresholds for each indicator, where values below the threshold indicate a crisis, and those above indicate a no-crisis state.



(a)



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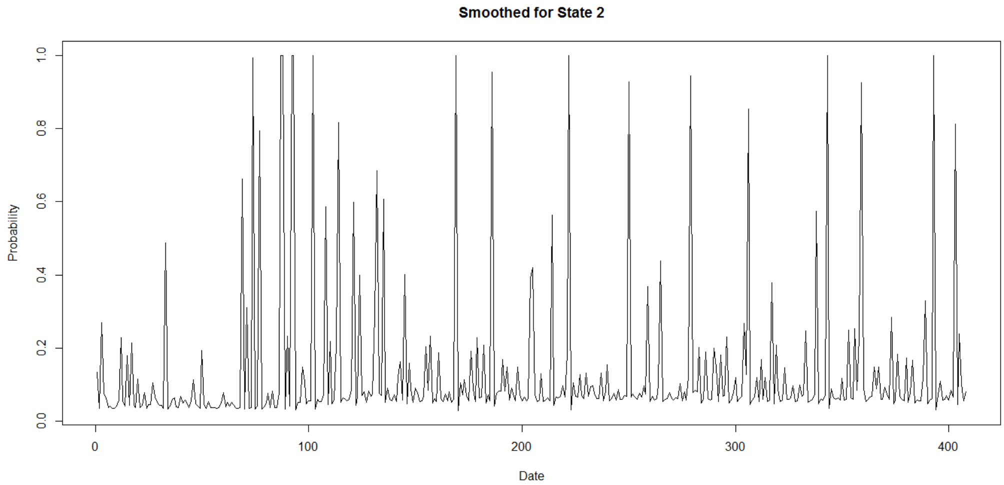

(c)

Figure 3. Smoothed probability plots for (a) real deposit interest rate, (b) M2 per foreign exchange reserves, and (c) real exchange rate

Table 4. Lowest smoothed probability values during crisis periods in Indonesia

Indicator	Period	Smoothed probability
Real deposit interest rate	July 1997	0.954871
M2 per foreign exchange reserves	February 2008	0.878202
Real exchange rate	February 2020	0.925644

3.8. Accuracy of the combined volatility and Markov-switching model

A forecast from May 2024-April 2025 was conducted to evaluate model accuracy by comparing forecasted and actual smoothed probabilities for the three indicators, as shown in Tables 5-7. As shown in Tables 5-7, the predicted and actual conditions are fully consistent, showing that the model can successfully identify crisis periods through the three key indicators. The full alignment from May 2024-April 2025 highlights the robustness of the MS-ARMA-GARCH framework in separating calm phases from turbulent ones.

Table 5. Forecasted and actual smoothed probability values for the real deposit interest rate

Period	Forecast	Forecast status	Actual	Actual status
May 2024	0.021422211	No-crisis	0.280771942	No-crisis
June 2024	0.021430854	No-crisis	0.280771937	No-crisis
July 2024	0.021430665	No-crisis	0.280771934	No-crisis
August 2024	0.021430669	No-crisis	0.280771937	No-crisis
September 2024	0.021430669	No-crisis	0.280771938	No-crisis
October 2024	0.021430669	No-crisis	0.280771945	No-crisis
November 2024	0.021430669	No-crisis	0.280771955	No-crisis
December 2024	0.021430669	No-crisis	0.28077197	No-crisis
January 2025	0.021430669	No-crisis	0.280771972	No-crisis
February 2025	0.021430669	No-crisis	0.280771981	No-crisis
March 2025	0.021430669	No-crisis	0.28077198	No-crisis
April 2025	0.021430669	No-crisis	0.280771975	No-crisis

Table 6. Forecasted and actual smoothed probability values for the M2 per foreign exchange reserves

Period	Forecast	Forecast status	Actual	Actual status
May 2024	0.133209624	No-crisis	0.462182411	No-crisis
June 2024	0.135212545	No-crisis	0.462182502	No-crisis
July 2024	0.134901492	No-crisis	0.462182459	No-crisis
August 2024	0.134949798	No-crisis	0.462182515	No-crisis
September 2024	0.134942296	No-crisis	0.462182247	No-crisis
October 2024	0.134943461	No-crisis	0.462182135	No-crisis
November 2024	0.13494328	No-crisis	0.462181996	No-crisis
December 2024	0.134943309	No-crisis	0.462181775	No-crisis
January 2025	0.134943304	No-crisis	0.4621816	No-crisis
February 2025	0.134943305	No-crisis	0.462181567	No-crisis
March 2025	0.134943305	No-crisis	0.462181645	No-crisis
April 2025	0.134943305	No-crisis	0.462181729	No-crisis

Table 7. Forecasted and actual smoothed probability values for the real exchange rate

Period	Forecast	Forecast status	Actual	Actual status
May 2024	0.134134128	No-crisis	0.774858313	No-crisis
June 2024	0.134134134	No-crisis	0.774853408	No-crisis
July 2024	0.134134134	No-crisis	0.774866636	No-crisis
August 2024	0.134134134	No-crisis	0.774853548	No-crisis
September 2024	0.134134134	No-crisis	0.774857838	No-crisis
October 2024	0.134134134	No-crisis	0.77485627	No-crisis
November 2024	0.134134134	No-crisis	0.774857409	No-crisis
December 2024	0.134134134	No-crisis	0.774856311	No-crisis
January 2025	0.134134134	No-crisis	0.774856928	No-crisis
February 2025	0.134134134	No-crisis	0.774856141	No-crisis
March 2025	0.134134134	No-crisis	0.774856612	No-crisis
April 2025	0.134134134	No-crisis	0.774857382	No-crisis

3.9. Early detection of financial crisis in Indonesia

The three indicators were used to forecast smoothed probabilities for May 2025-April 2026 as an early warning of potential financial crises, with results shown in Table 8. Based on these three indicators, the smoothed probability values are lower than their respective thresholds, indicating no crisis in the period from May 2025-April 2026.

Table 8. Forecasted smoothed probability values for the real deposit interest rate, M2 per foreign exchange reserves, and real exchange rate (May 2025-April 2026)

Period	Forecast (real deposit interest rate)	Forecast (M2 per foreign exchange reserves)	Forecast (real exchange rate)	Status
May 2025	0.020677546	0.148981744	0.152822477	No-crisis
June 2025	0.020676269	0.151308374	0.152912674	No-crisis
July 2025	0.020676283	0.15089597	0.15290977	No-crisis
August 2025	0.020676282	0.150969065	0.152909863	No-crisis
September 2025	0.020676282	0.150956104	0.15290986	No-crisis
October 2025	0.020676282	0.150958397	0.15290986	No-crisis
November 2025	0.020676282	0.150957986	0.15290986	No-crisis
December 2025	0.020676282	0.150958054	0.15290986	No-crisis
January 2026	0.020676282	0.150958038	0.15290986	No-crisis
February 2026	0.020676282	0.150958036	0.15290986	No-crisis
March 2026	0.020676282	0.150958032	0.15290986	No-crisis
April 2026	0.020676282	0.150958028	0.15290986	No-crisis

4. DISCUSSION

The central bank monitors the movement of a number of selected indicators in real time for application in the MS-ARMA-GARCH hybrid model. A crisis warning is issued whenever the smoothed probability exceeds a certain threshold for several consecutive months. The most significant events, when detected within a month, prompt stakeholders to promptly identify their causes to avoid a crisis. This study also corroborates the findings of Sugiyanto *et al*. [24] and Du *et al.* [25] and complements them by applying indicator selection through the NRS to the MS-ARMA-GARCH hybrid model. Future research could use the Currency Crisis Index (CCI) or Market Pressure Index (MPI) to determine crisis periods. The results of this study provide a practical framework and focus on Indonesia, so this methodology can be extended to other developing countries facing similar volatility patterns.

5. CONCLUSION

The stages in this research are always based on data characteristics and the selection of models that match these characteristics, resulting in a very good EWS. For example, the determination of past crisis periods is carried out using the EMP, and the determination of future crises using smoothed probabilities. Data fluctuations and regime shifts are analyzed using a hybrid MS-GARMACH. The smoothed probabilities indicate no signs of crisis risk during the period from May 2025-April 2026. Although this research framework focuses on Indonesia, the methodology can be extended to other developing countries facing similar volatility patterns.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

INFORMED CONSENT

Not applicable. This study does not involve human participants.

ETHICAL APPROVAL

The research did not involve human or animal subjects; therefore, ethical approval was not required.

DATA AVAILABILITY

All data used in this study are publicly available from the IMF at https://data.imf.org. No new data were generated.

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