EJEM
Econ.J.Emerg.Mark.

Economic Journal of Emerging Markets
Available at https://journal.uii.ac.id/jep

Will Indonesia enter the 2023 financial crisis? Application of early warning model system

Anggito Abimanyu[1], Muhammad Handry Imansyah[2*], Muhammad Adisurya Pratama[3]

[1]Department of Economics and Business, Vocational School, Gadjah Mada University, Yogyakarta, Indonesia.
[2]Master of Development Economics Program, Faculty of Economics and Business, Lambung Mangkurat University, Banjarmasin, Indonesia.
[3]Department of Development Economics, Faculty of Economics and Business, Lambung Mangkurat University, Banjarmasin, Indonesia.
*Corresponding Author: mhimansyah@ulm.ac.id

Article Info

Article history:
Received 14 March 2023
Accepted 21 March 2023
Published 10 April 2023

JEL Classification Code:
C510, C530, E32, G17

Authors' emails:
anggito@ugm.ac.id;
mhimansyah@ulm.ac.id;
muhammad.adisuryapr@gmail.com

DOI: 10.20885/ejem.vol15.iss1.art3

Abstract

Purpose — This paper estimates the possibility of a financial crisis in Indonesia using an early warning system (EWMS) model.

Method — A quantitative EWMS model has been developed to detect a potential financial crisis in 2023 based on the econometric logistic probability model (Logit)

Findings — Based on the model estimates, Indonesia is expected to enter a financial crisis without adequate macroeconomic policies in the next 12 to 24 months. In recent years, Indonesia has implemented prudent macroeconomic policies such as increasing the Bank Indonesia policy rate and sustaining the state budget to avoid the impact of a deep financial crisis.

Implications — To avoid the potential for further financial crises, Indonesia must implement a wider range of crisis mitigation policies.

Originality/value — Although many argue that financial crises are predictable, it has been demonstrated in the literature that little is known about how to prevent them. This paper contributes to providing empirical evidence to address these issues.

Keywords — Early Warning Model System (EWMS), probability of crisis, Indonesian economy, crisis pre-emptive and mitigation policies

Introduction

Greenwood et al. (2022) argued that a financial crisis is predictable. They examined historical data on post-war financial crises around the world. Indonesia experienced many financial crises, including the 1998 Asia financial crisis, the 2008 global financial crisis, and the COVID-19 pandemic in 2019/2020. The sources and impacts of each of these financial crises varied. The source of the crisis comes from within and outside the country. The depth of the crisis depends on fundamental macroeconomic conditions. In addition to strong fundamental conditions, macroeconomic policy targets are needed to deal with the financial crisis (Chen & Svirydzenka, 2021).

Financial and banking crises in 1997 seriously affected the Indonesian economy, such as the plunge of economic growth, skyrocketing poverty, and unemployment. The fiscal cost for bailouts of national banks at that time was 45% of GDP. The source of the 1997/1998 Asia

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financial crisis is the contagion of the monetary crisis in Thailand. This crisis spread because of the weak macroeconomic fundamentals in Indonesia at that time. Indonesian economy was also affected by the 2008 global crisis, which started with the subprime mortgage crisis in America. The bankruptcy of Lehman Brothers and many global financial institutions in the US and Europe worsened the crisis. There was a selloff from the Indonesian capital market and bond investors to the US. Fortunately, Indonesia and other ASEAN countries have strong fundamentals and are better prepared after the 1998 crisis (Kian Wie, 2012).

Strong Macroeconomic fundamentals do not guarantee resilience to crises. In the case of the Covid-19 pandemic, the Indonesian economy was hit by a serious crisis. The pandemic crisis has hit external trade and reduced purchasing power. The COVID-19 pandemic and geopolitical tension between Russia and Ukraine have severely affected the global economy and Indonesia. As business and consumer sentiment wane, domestic demand is expected to weaken (ADB, 2020).

Many studies found that the pre-crisis event and impact of the economic and financial crisis in a country can be detected by economic models (Greenwood et al., 2022; Reinhart et al., 2000; Goldstein et al., 2000; Bussiere & Fratzscher, 2002). If it is unpredictable, financial crises can cause severe economic costs in the form of slowing economic growth, decreased output, corporate bankruptcies, layoffs, financial sector instability, decreased credit distribution, and others (Krugman, 1999; Chen & Svirydzenka, 2021; Hutchison & Noy, 2006; Claessens et al., 2012; Claessens & Kose, 2013a; Claessens & Kose, 2013b; IMF, 2022; Pritsker, 2013).

A single-country model provides a better estimate as it captures the uniqueness of a country rather than the global or regional model. Van den Berg et al. (2008) argued that global or other regional models frequently have lower accuracy because panel data have different quality. Several researchers have developed an early warning system using a logit model for the emerging market, including a special case for Indonesia (Koo et al., 2005; Ferdous et al., 2022). For the Indonesian case, however, these papers used data till the recovery of the Asian financial crisis. On the other hand, the Indonesian economic structure changed. Therefore, developing the EWS model using a new data set likely improves the model's accuracy and can capture the full breadth of the dynamic Indonesian economic phenomenon.

This paper aims to identify the probability of a financial crisis in Indonesia within 12 to 24 months using an experimental parametric approach. It uses macroeconomic data from 2001 to 2021. This study estimates the probability of a financial crisis or financial distress from 2022 to 2023 by applying the early warning model system (EWMS) model.

The EWMS has been developed to detect financial crises. However, the EWMS model has many questions regarding its level of accuracy. EWMS has failed to identify the 2008 global financial crisis. Padhan and Prabheesh (2019) proposed reconstructing the EWMS model to increase the accuracy of financial crisis predictions. The early warning model is a way to see the probability of a crisis based on historical financial data. From this early detection, the probability of a crisis, how big and how strong it is, when it will occur, and how to respond to it can be calculated. Early warning system uses different approaches depending on data availability and the purpose in question. Every approach has advantages and disadvantages. Therefore, policymakers may use the appropriate approach with data availability and operational practicability.

The previous EWMS models were quite successful in predicting financial crisis probabilities. Frankel and Rose (1996) used a parametric model to estimate the probability of financial crisis using 105 developing countries from 1971 to 1992. This model uses 16 indicators, including domestic credit growth, foreign exchange reserves/M2 (broad money supply), and foreign interest rates. Since the data are annual, the use is limited. Meanwhile, Kaminsky et al. (1998) were pioneers in developing early warning systems using a set of leading indicators. They focused on monitoring several indicators (15 indicators) that will provide a signal when their values break the threshold. If the indicator gives a signal 24 months before the crisis occurs and the crisis indeed occurs, the signal is considered a good signal.

There has been extensive research on financial crises using probits or logits to detect the probability of a financial crisis against several free variables (indicators). The advantage of this logit or probit approach is that the results directly reflect the probability of a crisis from the selected early indicators (independent variables) and can be carried out by standard statistical tests. Several studies of the balance of payments crisis using probit or logit, such as Eichengreen et al. (1996), used 20 industrialized countries' data; Frankel and Rose (1996) used 105 developing countries from 1971 to 1992. While Klein and Marion (1997) also used logit for Latin America, Berg and Pattillo (1999) conducted studies on various countries after the 1997 financial crisis in Asia.

Altunoz (2019) compared three financial early warning models for Turkey. The result showed that the early warning system is relatively accurate and can be used to identify financial health. In their research, Frankel and Rose (1996) used independent variables of 16 indicators, such as domestic credit growth, foreign exchange reserves/M2 ratio, and foreign interest rates. Since the data are annual, the use is limited. The following is the model's equation:

$$y_i = a + \sum_{i=1}^{16} \beta_i x_i + u_i \quad (1)$$

where, y_i = 1 when there is a crisis; 0 otherwise
x_i = 16 Indicators
u_i = error term

Meanwhile, Goldfajn and Valdés (1998) used data from 26 countries applying the logit model to predict the next month of chance of a crisis as a function of devaluation expectations and real exchange rates. Frankel and Rose's (1996) model differs from the IMF model. While the former uses annual data and 16 variables, the latter employs monthly data and 6 variables, namely the exchange rate to its trend, the inflation rate, the ratio of the balance sheet to gross domestic product, the decline in foreign exchange, the growth of exports, and the ratio of short-term debt to foreign exchange dollars.

Meanwhile, Berg and Pattillo (1999) show that the probit model outperformed the signal model, where the probit or logit model has generated some broader empirical studies, including Caramazza et al. (2000), Esquivel and Larraín (1998), Kamin et al. (2007), Milesi-Ferretti and Razin (2000), Mulder et al. (2002), and also Berg et al. (1999) including Goldfajn and Valdés (1998). Meanwhile, some researchers use specifications not only two options, i.e., crisis and not crisis but have some possibilities, e.g., not crisis, crisis, and post-crisis. Included in this group are Kaufmann et al. (2005), who use the probit sequence (order probit), while Bussiere and Fratzscher (2002) use multinomial logits. Their research generally uses panel data (time order and between countries), while Sachs, Tornell, and Velasco (1996) use interstate data to study the severity of the crisis. The studies used a number of independent variables recommended by the first and second-generation models, including political economy approaches.

In general, the results of such studies cannot predict the financial crisis that occurred in 1997. It could be because the model used is a general model that uses data panels, even though each country has different economic characteristics. In that connection, this paper tries to apply the single-country model as an experiment in developing an early warning system using the database after the Asian financial crisis.

While Koo et al. (2005), with data of ASEAN plus 3, developed a parametric model with a relatively short data range from 1981-1995 and specifically for Indonesia starting in May 1987. The results of the *fixed effect* logit and probit models are not good, meaning that they cannot predict the 1997 financial crisis in Indonesia. However, for the *random effect* logit and probit for the Indonesian case, the results are good enough to predict the 1997 financial crisis. This paper uses new data starting from January 2001 to June 2022. Thus, the early indicators will also differ because the economic structure has changed.

While EWMS largely failed to notice the 2008 global financial crisis, the current EWMS model adds to the dynamic nature of financial crises at all stages. The dynamic aspects associated with the various causes of the financial crisis, firstly, it can cross the country of origin or, secondly, spreads across its borders (Padhan & Prabheesh, 2019).

The current EWMS remains to use the logit and probit models. The main advantage of these logit and probit models is that they reflect all the information provided by the indicators to estimate the probability of a crisis. However, the downside is that they do not precisely measure the forecasting capabilities of each indicator, although each indicator can provide a degree of significance. No specific literature on EWMS detects the financial crisis of the Covid-19 period. The causes and impact of the financial crisis from Covid are still unclear, but the EWMS model is hoped to predict the probability of a financial crisis.

Methods

A qualitative dependent variable model is an econometric analysis using dependent variables as discrete/dummy variables that are valued at 1 and 0. While the independent variables are non-discrete, the dependent variables are discrete or binary (No crisis = 0 and crisis = 1), then the logit model specifications are as follows:

$$P = F(Z) = \frac{1}{1+e^{-Z}} = \frac{1}{1+e^{-(a+\beta x)}} \tag{2}$$

where P is a probability; F is a cumulative function of logistical probability valued from 0 to 1. X is the dependent and α variable and β is the parameter. The equation can change into:

$$ln\frac{P}{1-P} = Z = a + \beta x \tag{3}$$

Determining the definition of a crisis period to fill in the values of the dependent variables 1 and 0 is based on the following formulation:

$$Crisis\ Index = \frac{1}{\delta_e} \times \Delta e \tag{4}$$

δ_e = standard deviation from the change in exchange rate Rp/dollar
Δe = change in exchange rate Rp/dollar

From the formula above, the change used is the change to the previous month. Meanwhile, to determine whether the month is a crisis month period, the threshold of the Crisis Index is an average of the Crisis Index plus 2 standard deviations from the Crisis Index. If the value of the Crisis Index exceeds the threshold, then the month is considered to be the period of the crisis month, so the dependent variable's value is 1. While the month with no crisis, then it is given a value of 0.

In determining the period leading up to the crisis, for example, 24 months before the crisis, early indicators will give a signal, then the variable dependents in the previous 24 months are given a value of 1. Meanwhile, if the period of time limit for the period leading up to the crisis is 18 and 12 months, then the dependent variables on the previous 18 and 12 months are given a value of 1. Since the dependent variables are in categorical data, the estimation uses the likelihood of crisis using a logistic regression model. The baseline model can be presented as follows:

$$Window_{12,18,24} = ln\left\{\frac{\Pr\,(Y_i=1|X_i}{\Pr\,(Y_i=0|X_i}\right\} = \beta_0 + \beta_1 RGDP_t + \beta_2 BRENT_t + \beta_3 RER_t + \beta_4 IRES_t + \beta_5 FDEF_t + \beta_6 EXP_t + \beta_7 INVGDP_t + \beta_8 M2RES_t + \beta_9 CBCP_t + \beta_{10} DEFR_t + \varepsilon_t \tag{5}$$

Where $Window_{12,18,24}$ denotes our dependent variable, namely the window period before crisis based on the 12-Month, 18-Month, and 24-Month period; $\beta_{0,..,10}$ presented as the coefficient for both constant and variables' elasticity. Table 1 shows the name of the variables.

In the performance evaluation of the model, a threshold of probability values is determined to indicate the high probability of a crisis. For each month, the observed data will give results on whether the data belongs to an area that exceeds the probability threshold limit, which means giving a warning signal. This signal will be correct if 24 months later there is a crisis (or it falls into category A), or the signal is wrong if 24 months later there is no crisis (or it falls into category B), or it is called a type II error. By the same analogy, if the observed model does not give a signal, but within 24 months, a crisis occurs, and there is no signal (or falls into category C), it is called a type I error. In comparison, if there is no signal and no crisis 24 months later (or falls into category D).

Table 1. Data Description

Category	Variables	Definition	Data Source
Window Period	Window12 Window18 Window24	Categorical variables represent the window period before the crisis where 1 = period before the crisis and 0 = otherwise.	Author's Computation
Macroeconomic Conditions	INVGDP	The ratio of Foreign Direct Investment (FDI) to Nominal Gross Domestic Product	Bank Indonesia and CEIC Database; Author's computation
	RGDP	Annualized growth of Real Gross Domestic Product	CEIC Database; Author's computation
	EXP	Annualized growth of export	CEIC Database; Author's computation
International-Related Variables	RER	Real USD/IDR exchange rate. Calculated by employing the following formula: $RER = NER \times \frac{CPI_{ID}}{CPI_{US}}$ where *NER* is denoted as Nominal USD/IDR exchange rate, and CPI_{ID} and CPI_{US} represent consumer price index of Indonesia and USA, respectively.	International Monetary Fund (IMF); Author's computation
	BRENT	International oil price of BRENT	Federal Reserve Economic Data (FRED)
Central Government	FDEF	Ratio of fiscal deficit to Nominal Gross Domestic Product	Ministry of Finance; Author's computation
Monetary-Related Variables	IRES	Annualized growth of international reserves	IMF; Author's computation
	M2RES	Ratio of broad money (M2) to international reserves	CEIC Database and IMF; Author's computation
	CBCP	Ratio of central bank credit to the public to Nominal Gross Domestic Product	Bank for International Settlements; Author's computation
	DEFR	Spread between Indonesian deposit rate and effective federal funds rate	CEIC Database and FRED; Author's computation

Table 2. Summary of Crisis Probabilities

	The Crisis Occurred 24 Months Later	No Crisis 24 Months Later
Signal	A	B
No Signal	C	D

Source: Goldstein et al. (2000)

From the matrix above, a good model falls into categories A and D. What belongs to category A is the model that gives a signal warning of a crisis, and a crisis indeed occurs. Meanwhile, category D includes the model that does not provide a warning signal because no crisis will happen. On the contrary, what falls into category C is a model that does not give a signal but turns out to be a crisis. While those included in category B are models that give signals, but no crisis occurs.

Kaminsky et al. (1998) created an optimal threshold limit for abnormal regions to be minimal, which is called *the noise-to-signal ratio* (NSR). *NSR* is defined as a comparison of the probability of an indicator giving a signal during a non-crisis time to the probability of an indicator giving a signal during a crisis. The formula of the NSR is as follows:

$$NSR = \frac{\left[{}^{B}/_{(B+D)}\right]}{\left[{}^{A}/_{(A+C)}\right]} \tag{6}$$

Results and Discussion

The features of the data are in Table 3. Descriptive statistics and other statistics results are also provided.

Table 3. Descriptive Statistics

Variable	Mean	S.D.	Skewness	Kurtosis	JB-Stat	*p*-Value	Obs.
$Window_{12}$	0.100	0.307	2.583	7.672	521.610	0.000	258
$Window_{18}$	0.150	0.359	1.948	4.793	197.700	0.000	258
$Window_{24}$	0.200	0.399	1.518	3.305	100.120	0.000	258
$RGDP$	6.500	6.115	-0.108	3.165	0.800	0.672	258
$BRENT$	66.780	29.012	0.337	2.125	13.130	0.001	258
RER	11729.960	4719.400	0.318	1.487	28.940	0.000	258
$IRES$	8.680	14.881	1.223	4.660	93.980	0.000	258
$FDEF$	-20.040	13.042	-0.283	4.208	19.130	0.000	258
EXP	9.080	21.374	0.474	2.500	12.330	0.002	258
$INVGDP$	28.690	4.659	-0.678	1.970	31.200	0.000	258
$M2RES$	35.980	8.564	0.627	2.307	22.050	0.000	258
$CBCP$	85.260	8.057	0.133	2.562	2.820	0.244	258
$DEFR$	6.280	2.587	1.003	3.995	53.870	0.000	258

Note: S.D. stands for Standard Deviation; JB-Stat and *p*-value represent Jarque-Berra statistics and corresponding probability, respectively; Obs. represents the number of observations.

The estimation of the logistic probability regression model is based on a sample from January 2001 to June 2021 to evaluate the effect of certain variables in increasing (decreasing) the probability of a crisis period. In addition, the estimation uses three different dependent variable window periods. The first is the 12-month window period (Model I), the second is the 18-month window period (Model II), and the third is the 24-month window period (Model III). These 12-Month, 18-Month, and 24-Month window periods mean the number of months that provide a signal before the onset of a crisis or distress.

The results for models with January 2001-June 2021 samples are satisfactory for the three different window periods. All independent variables are significant at 10%. Even some independent variables are significant at 5% and 1%. The independent variables in Models I and II are all significant in explaining the increase (decrease) in crisis probability during the onset of a crisis.

The meaning of the sign goes against the theory. These variables are growth in gross domestic product, growth in foreign exchange reserves, the ratio of the money supply (M2) to foreign exchange reserves, and the ratio of Central Bank credit to the public to GDP. However, some of the six variables are correctly marked and provide a strong measure of crisis probability because the coefficients are large. These variables are oil prices, budget deficits, exchange rates, and export growth, investment ratios, and central bank policy rates. However, four variables have wrong signs and are not as expected in Model II.

McFadden R-Squared is 0.6616, indicating that all independent variables explain 66.16% of the variability of the pre-crisis window period. However, it is interesting to note that all model estimates have the McFadden R-Squared greater than 0.50, indicating a high fit in examining the pre-crisis window period. Furthermore, when assessing the goodness of fit for all models, it was suggested that Model II be the best model in terms of R squared.

For Model II, the price of Brent crude oil affects the possibility of a financial crisis. This increase in crude oil affects the domestic economy in two ways. First, it will have an impact on imported inflation. Second, it will affect the budget because the price of several types of fuel is subsidized. Therefore, a budget deficit will occur because of this factor, and the probability of a crisis will increase.

The real exchange rate (RER) also influences the possibility of a crisis because a too-high Rupiah exchange rate against the USD will weaken export competitiveness. Finally, exports will decrease and affect foreign exchange reserves. The budget deficit to GDP ratio also affects the probability of a crisis. The budget deficit increase will affect domestic interest rates because the increased demand for budget financing will increase interest rates. Export growth will affect the possibility of a crisis because the decline in export growth will affect foreign exchange reserves. The ratio of investment to GDP also impacts the probability of a crisis, as it is critical to fostering sustainable growth. The spread of the policy rate over the effective Federal funds rate will influence the crisis probability. The lower the spread, the higher the probability of a crisis. This condition will increase the risk of capital outflow (Park, 2008; Fratzscher, 2011).

Table 4. Logistic Regression Results

	Model I	Model II	Model III
Variables	Window $_{12}$	Window $_{18}$	Window $_{24}$
$RGDP$	0.592*** [0.005]	0.736*** [0.000]	0.272** [0.030]
$BRENT$	0.094*** [0.000]	0.072*** [0.003]	0.064*** [0.000]
RER	0.002*** [0.001]	0.0021*** [0.000]	0.001*** [0.004]
$IRES$	0.138*** [0.007]	0.072* [0.082]	0.026 [0.365]
$FDEF$	-0.124** [0.014]	-0.125*** [0.001]	-0.075*** [0.004]
EXP	-0.193*** [0.000]	-0.204*** [0.000]	-0.096*** [0.001]
$INVGDP$	-1.324*** [0.000]	-1.177*** [0.000]	-1.060*** [0.000]
$M2RES$	-0.328* [0.079]	-0.590*** [0.003]	-0.295 [0.133]
$CBCP$	-0.223*** [0.000]	-0.306*** [0.000]	-0.070 [0.312]
$DEFR$	-0.476** [0.036]	-1.441*** [0.002]	-1.408*** [0.000]
$Constant$	31.847*** [0.000]	48.203*** [0.000]	29.916*** [0.003]
McFadden R-Squared	0.588	0.678	0.576
LR-Statistics	100.130	145.850	144.690
[Probability]	[0.000]	[0.000]	[0.000]

Note: Number of observations employed are 246; The *p*-value of coefficients are presented in brackets; ***, **, and * denote the level of significance at 1%, 5%, and 10%, respectively.

All models do not substantially differ in terms of R squared, and the number of variables are with the correct sign and statistically significant. For Model III, four of the variables have wrong signs, but three of the variables are not significant. Only one variable, GDP growth, is significant. Therefore, policymakers will use a longer window period because they have time to take financial crisis prevention measures.

Forecasting outside the sample period to see crisis probabilities is carried out using the three models from July 2021 to June 2022. Based on these three models, Model III shows an increase in the probability of crises in the next 24 months. This means that in the next 24 months there will be a financial crisis. The other models (Model I and Model II) also show an increased probability of a crisis, but the probability of a crisis is only a few months leading up to June 2022.

Overall, the best model is Model II. However, there are no substantial differences among the three models based on many different evaluation tools. The next section presents detailed model performance. Model III shows that the probability of a crisis increases during July 2021-June 2022 (see Figure 3), meaning that a crisis is likely to go up using a 24-month window. Therefore, as the probability of a crisis increases, in the next 24 months, there will be a financial crisis. However, no one knows exactly when a financial crisis will occur. This early warning system model cannot be used to predict precisely when a financial crisis will occur. However, this early warning system model can indicate how likely a financial crisis is to occur if the initial indicators used show a large change in magnitude in the selected pre-crisis period (e.g. 24 months) as proposed by Kaminsky et al. (1998).

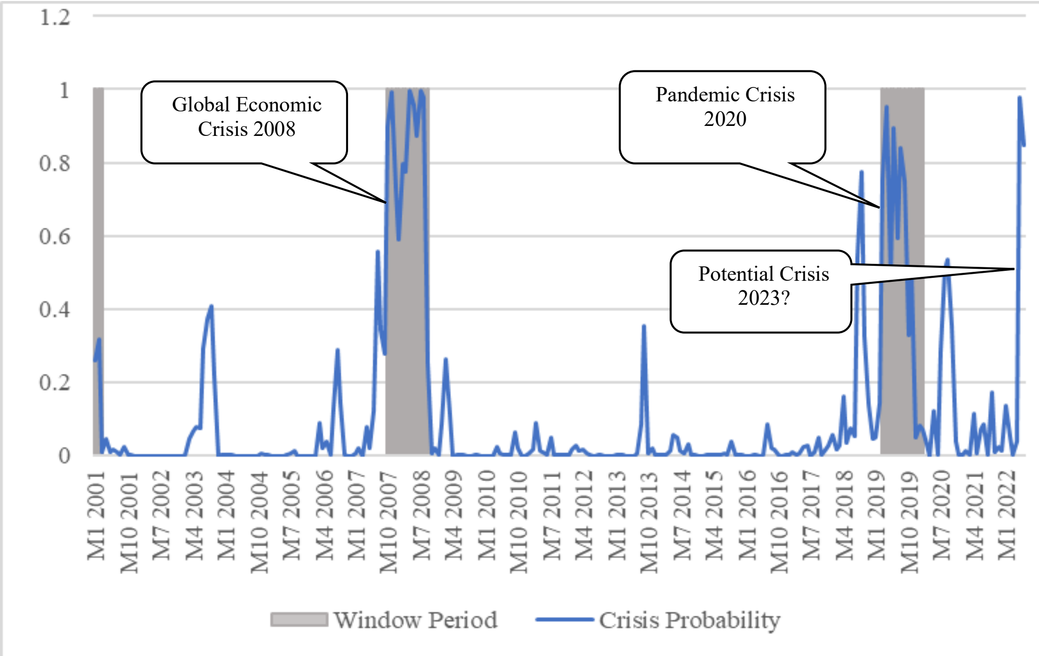

Figure 1. Logit Model Estimation Result (12-Month Window Period)

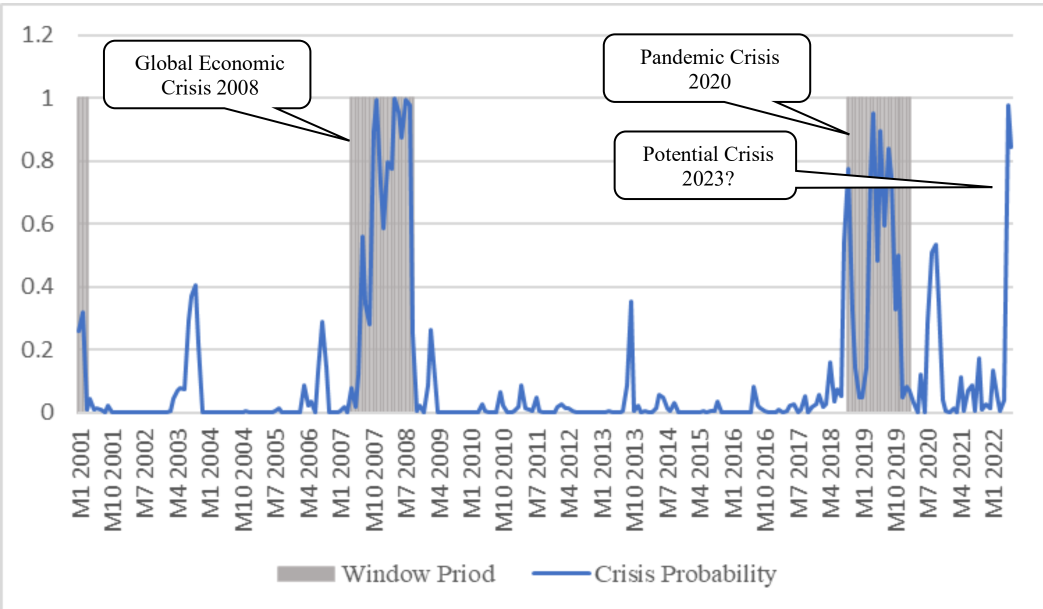

Figure 2. Logit Model Estimation Result (18-Month Window Period)

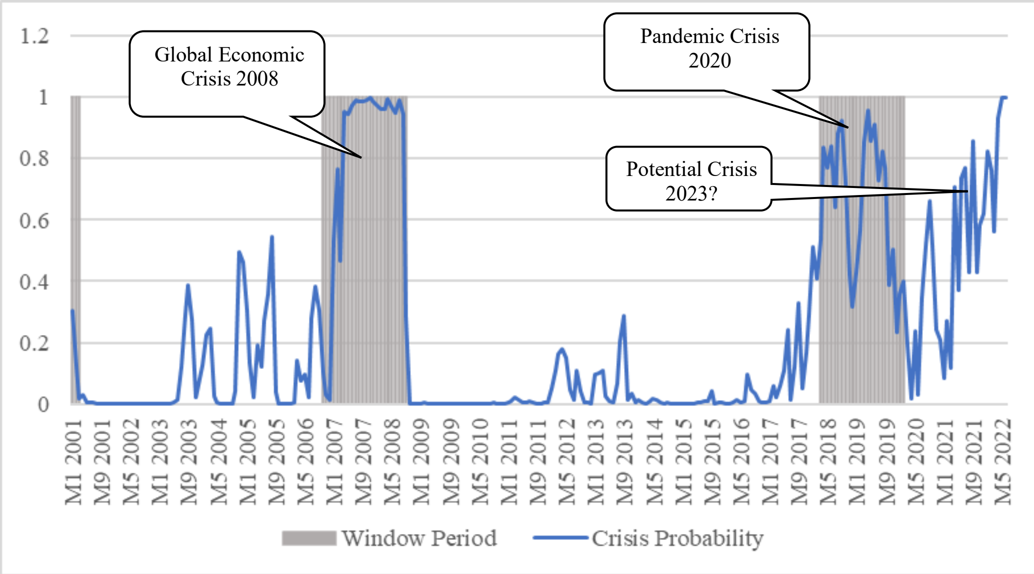

Figure 3. Logit Model Estimation Result (24-Month Window Period)

Model Evaluation

Figures 1, 2, and 3 show that the performance of the developed model is sufficient to foresee the financial distress in 2008, including the pandemic crisis of 2020. This is indicated by the ever-increasing level of probability since the pre-crisis period (with 24 months leading up to the crisis). In addition, this current model can predict the pandemic crisis in March 2020. The crisis coincided with the onset of the pandemic. Some macroeconomic indicators do not look good, and the pandemic worsens the condition.

Therefore, the pandemic provides synergistic effects on the financial crisis.

The accuracy of forecasting the probability of a financial crisis occurring is the proportion of observations that correctly predict the crisis period, and the non-crisis period will be measurable. Model performance can be measured by calculating the mean of quadratic probability score (QPS). Meanwhile, the accuracy of forecasting calibration is also measured with global squared bias (GSB).

The *quadratic probability score (QPS)* formula is as follows:

$$QPS = \frac{1}{T}\sum_{t=1}^{T} 2(P_t - R_t)^2 \quad (7)$$

Where, P= Forecasting; R= Realization; T=period

QPS ranges from 0 to 2, with a score = 0 reflecting very accurately.

Meanwhile, the calibration of probability forecasting is related to the accuracy of probability forecasting and the relative frequency observed. Calibration compares the forecasting of the average probabilities against the average realization. The formula is as follows:

$$GSB = 2(\bar{P} - \bar{R})^2 \quad (8)$$

Where,

$\bar{P} = \frac{1}{T}\sum_{t=1}^{T} P_t$ and $\bar{R} = \frac{1}{T}\sum_{t=1}^{T} R_t$

GSB values range from 0 to 2, with a score value = 0 reflecting perfect calibration.

Table 5 shows the accuracy and calibration values of probability forecasting within the sample covering January 2001 to June 2021. All measures indicate high predictive power with a probability threshold limit of 70 percent. A crisis period provides a good signal if the probability of a crisis passes or is equal to a predetermined threshold limit of 70 percent according to the number of months (12, 18, and 24 months) leading up to the impending crisis. Every option to determine the window period has advantages and disadvantages. The longer the window period used, the better for policymakers. The policymaker has a longer period to make pre-emptive policy action.

Table 5. Evaluation of the Financial Crisis Model

	Window period 12 months Cut off probability=0.7	Window period 18 months Cut off probability=0.7	Window period 24 months Cut off probability=0.7
A=Good Signal for Crisis (months)	15	25	31
B=False Signal (months)	1	1	2
C=Missed Signal (months)	12	14	20
D=No Signal Tranquil time (months)	218	206	193
Number of observation	246	246	246
% of pre-crisis period that gives signals [A/A+C]	55.56%	64.10%	60.78%
% False Signal [B/(B+D)]	0.46%	0.48%	1.03%
% No signal in Tranquil time [D/(B+D)]	99.54%	99.52%	98.97%
NSR = [B/(B+D)]/[A/(A+C)]	0.0082	0.0075	0.0168
Goodness of fit	0.9472	0.9390	0.9106
UP	0.1098	0.1585	0.2073
QPS	0.1057	0.1220	0.1789
GBS	0.0040	0.0056	0.0107

Source: Authors' Computation

Policy Implications

This model analysis provides significant results regarding Indonesia's probability of entering a financial crisis in the next 24 months. However, this financial crisis can be avoided if there are policies to mitigate financial crises. Therefore, the results can be used to develop a series of pre-emptive policies, although there is no guarantee of success (Greenwood et al, 2020).

Many studies find that even though pre-crisis events and the impact of economic and financial crises in a country can be detected, there is not much evidence that these countries provide a series of successful crisis prevention policies. Nonetheless, pre-emptive policies are still needed to avoid a severe economic downturn (Greenwood et al., 2020; Reinhart et al., 2000). The failure of the preemptive policy is also due to the need for joint policies with other countries or global cooperation (Van den Berg et al., 2008).

Recently, a pre-emptive policy was issued in Indonesia to anticipate a global financial crisis (Bank Indonesia, 2023; Kementerian Keuangan, 2023). The policies designed can be analyzed qualitatively according to the variable causes and their impact on the domestic economy.

The world crude oil price, one of the early indicators, provided a significant factor. A continued increase in the price provided stronger potential risks of increasing the probability of a financial crisis. Hence, the world crude oil price can potentially trigger a financial crisis in Indonesia (Sasmitasiwi & Cahyadin, 2008). Unfortunately, the world oil prices are external factors that are beyond the control of the government, so anticipatory policies to overcome the increase in the world oil prices on the domestic economy, of course, must be carried out following the impact of world crude oil prices on the domestic economy.

In this case, there is a potential increase in subsidy expenditure in the government budget, so there is a potential risk of swelling the state budget deficit. In addition, rising world crude oil prices will provide the potential for inflation caused by rising costs *(cost-push inflation)*. Thus, the world crude oil price indicator may serve as a policy anticipation tool if this early indicator continues to provide high potential risks.

More open export and trade policies can promote export growth variables. The government should also facilitate finding new destinations and products to enter the world export market. Other significant variables, such as the budget deficit, can be adjusted with the plan to reduce the state budget deficit in 2023 (Kementerian Keuangan, 2023).

Another important policy is to maintain the stability of the exchange rate and BI's policy interest rate, which continues to adjust to the global economy while maintaining the competitiveness of Indonesian products (Bank Indonesia, 2023).

Based on the results, the matrix in Table 6 below describes the set of policies and policy actions that need to be implemented by Indonesia in order to mitigate the crisis in the next 12-14 months.

Table 6. Pre-emptive Indonesian Policy Respond and Goals

No	Variable	Policy Respond	Goals	Notes
1	Oil Price	Automatic Domestic Energy Price Policy	Ensures world oil prices have a positive net impact on the State Budget and Balance of Payments; and not pushing up the burden of inflation.	Partially Done
2	Budget Deficit	Reducing Budget Deficit	The 2022 budget deficit is relatively low, 2,38% of GDP, and provided a budgetary absorber to the economy. The 2023 budget has a downward trend towards a deficit target of 3% of GDP (Kementerian Keuangan RI, January 2023)	Done
3	Exchange Rate	Stable Exchange Rate	The rupiah exchange rate was kept stable, floating under control, following developments in world exchange rates and the competitiveness of Indonesian products (Bank Indonesia, 2023).	Done
4	Export Growth	Trade Policy to support Export Growth	Free or open trade policies have not been fully implemented, particularly in mining and mineral products. And the need to diversify export destination and promoting non-oil products export with higher value added.	Partly done
5	BI Policy Rate	BI Seven-Day Repo Rate (7D-RR) Adjustment	Bank Indonesia increased its Policy Interest Rate to maintain the interest rate spread with the US Fed Fund Rate (FFR). — Bank Indonesia's decision to raise 7DRR is a front-loaded, pre-emptive, and forward-looking policy. It is also a measure to continue declining inflation expectations toward a long-term inflation target of 3% (Bank Indonesia, 2023)	Done

In principle, the depth of a financial crisis depends on macroeconomic fundamentals. Indonesia already has macroeconomic policies to avoid a deep financial crisis. The Indonesian economy has demonstrated strong and solid macroeconomic fundamentals in recent years (World Bank, 2022). In addition to strong fundamental conditions, flexible but prudent macroeconomic policy targets are needed to deal with the financial crisis (Chen & Svirydzenka, 2021).

The macroeconomic policy mix was essential in promoting macro stabilization and economic recovery (Budiman et al., 2022).

The policy mix includes prudent monetary and sustainable fiscal policies implemented in 2021 and 2022. Although the experience of the macroeconomic policy mix in Europe can potentially be implemented, it is not easy to implement because the formula for policy instruments is unclear (Jones, 2022).

The macroeconomic policy mix will only succeed in the long run if sectoral reforms follow it. Unfortunately, policy reforms in Indonesia's energy, investment, and trade promotion sectors have not been fully implemented (World Bank, 2022).

Conclusion

This paper aims to make an early prediction of Indonesia's financial crisis after the pandemic. Researchers have widely used the EWSM model to detect a financial crisis in a single country (Van den Berg et al., 2008). The estimated EWM model has detected that Indonesia will enter a financial crisis in the next 12-24 months. However, this can be mitigated because Indonesia has implemented most pre-emptive policies. Based on observations, the Government and Bank Indonesia have implemented adequate policy responses and anticipation of the global financial crisis (Bank Indonesia, 2023; Kementerian Keuangan, 2023).

The parametric EWMS model developed in this case has fairly good performance. Various indicators used to see the model's performance provide quite good results. In addition, the model can be used to forecast the probability of a financial crisis in Indonesia in 2008 due to the global financial crisis. However, the impact is not very strong. The pandemic crisis in March 2020 can also be predicted using the model. Indeed, this parametric model must continue to be refined by adding or replacing early indicators more representative in contributing to the probability of a financial crisis or by changing the number of months of the pre-crisis period.

This model of early warning systems can be used not only to forecast or predict the probability of financial distress but also to diagnose the health of the economy in quiet times. It is possible that in quiet times, some early indicators show an increased magnitude but overall have not reached a high probability level for the occurrence of a crisis so that policymakers can make policies to improve economic performance in specific sectors that give a bad signal. Thus, economic performance will improve, and the continuous deterioration of economic performance leading to the financial crisis may be avoided.

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