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Predicting Financial Distress in ASEAN Banking: A Logistic Regression Approach

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ABSTRACT. Banking sector stability is crucial to a country's economy, but the global financial crisis and macroeconomic pressures such as the COVID-19 pandemic have heightened the risk of financial distress. This study aims to develop a prediction model for banking financial distress in ASEAN countries by combining CAMEL indicators and macroeconomic variables. Using panel data from 435 banks during the period 2017–2021 and logistic regression analysis, this study shows that the capital adequacy ratio (CAR) and return on assets (ROA) have a negative effect on the likelihood of distress, while the non-performing loan ratio (NPL) and exchange rate have a positive effect. The model that combines macroeconomic variables shows higher prediction accuracy than the model that only uses internal financial indicators. Model 1, excluding macroeconomic variables, correctly predicted 67.14% of the sample banks, while Model 2, including macroeconomic variables, increased the prediction to 72.01%. This study expands the literature on early warning systems using empirical evidence from ASEAN countries and contributes to the applied analytics domain by proposing logistic models relevant for policy-making and banking regulation.

1. Introduction

The banking sector is a central industry in a country's economy, where the health and stability of the banking sector can reflect the country's economic situation. Financial strength depends on the effectiveness and capacity of the financial framework, which is based on sound and solvent banking [1]. The banking industry is uniquely positioned in the economy and serves critical functions that promote economic stability [2]. The industry plays a fundamental role in supplying capital for funding economic activities. Banks mobilize funds from the public in terms of savings and deposits and extend the funds to individuals, businesses, and the government to

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carry out investment, consumption, and other activities. The volume of money and the interest rates credit institutions provide can dictate the economy's investment, production, and consumption levels. The banking system is a significant conduit for the spread of instability to other financial and non-financial sectors. It affects the real economy because it provides the economy with money and credit flows [3].

One of the indicators that describes the role of banking in economic growth is the Asset Ratio to Gross Domestic Product (Asset to GDP Ratio). In 2023, the amount of banking sector assets in Indonesia was 59 percent of GDP. This figure is much lower compared to the ratio of banking sector assets to GDP in Malaysia at 192 percent, Singapore at 608 percent, Thailand at 130 percent, the Philippines at 94 percent, China at 336 percent, and Vietnam at 217 percent [4]. It shows that the banking sector's contribution, so bank health is crucial to the economy. Output losses, higher unemployment, fiscal expenditures related to bank assistance measures, and the growth in public debt are some of the expenses caused by the banking crisis [3].

Financial distress prediction models play a vital function in helping management provide more concrete signals that action is required in advance, thus improving decision-making activities, especially in cases where banks are exposed to higher risks instead of depending on government action. Financial distress prediction models can also be helpful for regulators to identify and warn about potential distress among banks [2]. Models that correctly forecast bank failures can help regulatory bodies avert the same [5]. Financial ratios have been applied in empirical research of financial distress for over four decades, which Beaver in 1966 and Altman in 1968 initially formulated. Nonetheless, this subject has garnered more attention since the global financial crisis of 2008 [6] because projections can play an important role in the profitability and decisions of many stakeholders [7]. Its development uses macroeconomic variables as predictors under its construction to predict financial distress because economic conditions significantly affect a company's financial troubles. Macroeconomic factors help explain the heterogeneity of financial distress across countries [8]. Further, incorporating macroeconomic variables into the predictive model enhances the accuracy of the predictive model [9], [10], [11], [12].

Literature of research on bank failure is associated primarily with the Uniform Financial Rating System, otherwise commonly referred to as the CAMEL rating system, championed by the United States regulatory agencies in 1979. Data collected via CAMEL (Capital Adequacy, Asset Quality, Management, Earnings, and Liquidity) is commonly utilized in forecasting financial distress in banks [13], which asserts that equity is a significant element in the process of bank failure. [14] propose that the CAMEL method can enhance early warning systems for bank insolvencies. Similarly, [5] research founded on samples of banks that failed or did not fail throughout the 2008/2009 subprime mortgage crisis; demonstrates that management efficiency measurement and the other CAMEL factors play a significant role in bank failure prediction. [15]

has constructed an Indonesian bank bankruptcy model using accounting data. The model results based on CAMEL can successfully predict bank failure in Indonesia. Other researchers [12], [16], [17] also preferred CAMEL to predict bank financial distress.

Meanwhile, [18] using macroeconomic and financial variables such as capital adequacy, credit risk, liquidity, profitability, efficiency, and total assets has proven to be accurate in predicting bank failure. By including several macroeconomic factors, CAMEL is also utilized to create a financial distress prediction model in banks [1], [19]. A study at ASEAN Bank that used CAMEL and several macroeconomic variables produced a similar finding, demonstrating a positive correlation between banking failure and the debt-to-equity ratio, inflation rate, and cost inefficiency [20].

This paper aims to enhance the predictive ability of the financial distress model by determining significant variables that can predict and mitigate financial distress in the ASEAN countries' banking sector. To the best of our knowledge, bank distress indicators as early warnings have not been well addressed in the literature on the banking sector of ASEAN countries during the pre- and onset phase of COVID-19.

Financial distress has long been the object of study in corporate finance literature. Following the seminal work undertaken by Altman in 1968, henceforth commonly referred to as Altman's z-score, several researchers have attempted to enhance and replicate the findings of this study. They are [2], [9], [12], [13], [14], [16], [21], [22], [23], [24], [25], [26], who have studied financial distress in the banking industry of different nations. On the other hand, several studies have investigated financial distress in some capital markets globally [11], [27], [28], [29], [30], [31], [32], [33]. Financial distress study has been a vital area in corporate finance for researchers and practitioners, as it is a valuable early warning indicator for creditors, investors, corporate regulators, and other parties.

2. Materials and Methods

This study uses panel data of 435 bank observations in ASEAN countries from 2017 to 2021, as presented in Table 1. The five years were chosen to discover the banking phenomenon two years before COVID-19 and three years after COVID-19. Of the 435 observation data that could be continued for analysis, 425 observation data were used, where 361 banks were categorized as healthy banks, while the remaining 64 were experiencing financial difficulties.

Table 1. Bank observation data

No	Country	Amount
1.	Indonesia	100
2.	Malaysia	83
3.	Singapore	30
4.	Thailand	75
5.	Philippines	52
6.	Vietnamese	95
	TOTAL	**435**

Source: The author's calculations

Table 2 presents the definition of the variables in this study. The dependent variable is the financial distress dummy variable, where category 1 is a bank experiencing financial distress, and category 0 is the opposite. The categories of bank financial distress are as follows: (1. negative equity, (2. experiencing losses, (3. CAR <8%, (4. NPL> 5%). The independent variables include the CAMEL ratio, size, Z-score, and macroeconomics, including exchange rates, inflation, and GDP.

Table 2. Variable Description

FD	Dummy for FD =1, 0 = Non FD
CAR	Capital/ Risk weighted assets
NPL	Non-performance Loan/Total loan
CIR	Cost/Total Income
ROA	Return/Total Asset
LDR	Loan/Total Deposit
SIZE	Ln Total assets
Z-score	(Working capital/total assets) + (Retained earnings/total assets) + (Earnings before interest and taxes/total assets) + (Market value of equity/book value of total liabilities) + (sales/total assets)
Exchange rate	Currency exchange rate compared to the US dollar
Inflation	(Consumer Price Index n – Consumer Price Index n-1)/Consumer Price Index n-1
GDP	Economic growth

Source: Compiled by the authors

Logistic regression analysis is used in this study because it is less constrained by various assumptions compared to other techniques, such as discriminant analysis, so its application is more flexible. The advantage of the logistic regression method is its higher flexibility [34] and it does not require the assumption of normality for the independent variables in the model. In other words, the explanatory variables do not have to have a normal distribution or the same variance in each group. The dominant variables influencing bank financial distress can be identified with the prediction model formed from logistic regression analysis.

3. Results and Discussion

Table 3 displays the study's descriptive statistics for the variables. The failure rate of 14.7% represents the number of samples categorized as financial distress banks. For capital adequacy, the average CAR value of 15,055 indicates that the bank is relatively healthy in terms of capital adequacy because it exceeds the required CAR value of at least 8%. For asset quality, we use NPL. The higher this ratio, the greater the proportion of problematic loans and the potential for increased credit risk. The highest NPL in 2017 in Philippine banks showed problematic loans by 27.21% of the total bank loans.

CIR is an indicator of bank operational efficiency. The lower the CIR, the more efficiently the bank manages its operational costs. The average CIR is 0.5258, meaning that for every $1 of the operational income generated, the bank uses $0.5258 to cover its operational costs. An average ROA of 1,024 means that from every $1 asset, the average bank generates a net profit of $1,024. For liquidity, we use LDR. The higher ratio indicates that banks have provided many loans compared to deposits held, which can increase liquidity risk. The highest LDR in 2018 in Indonesian banks was 279.4, which indicates that the bank has provided loans in an amount that far exceeds the funds collected from depositors, which can increase liquidity risk

The size of a bank's assets indicates its ability to benefit from economies of scale. The average bank asset is 10.00466, and the standard deviation is 1.073759. The distribution is perfect because the mean exceeds the standard deviation. The average Z-score is 11.85; a low Z-score value in a bank indicates a high risk of financial difficulties.

Table 3. Descriptive statistics of variables

Variable	Obs	Mean	Std. Dev	Min	Max
FD	435	.1471264	.3546398	0	1
CAR	435	15.05533	6.038281	4.056	70
NPL	432	2.660046	2.40647	.05	27.21
CIR	428	.5257585	.4366877	.1737194	6.666667
ROA	435	1.024368	.722358	-2.2	4.9
LDR	434	87.89608	21.77658	9.9	279.4
SIZE	435	10.00466	1.073759	8.230044	13.10566
Zscore	435	11.85121	4.623025	1.92112	42.36576
Exchange rate	435	8301.643	9663.99	1.344	23230
Inflation	435	2.658726	3.027465	-1.139	14.609
GDP	435	3.380881	4.00739	-9.518	9.691

Source: data processed in 2024

Table 4 displays the results of a correlation analysis we performed between the variables utilized in this study. The correlation value is less than 0.9, indicating no multicollinearity between the independent variables. In general, the relationships among the study variables are aligned with theoretical predictions. Financial distress has a positive correlation with CIR.

Because the bank will be less effective at controlling its operating expenses, any increase in CIR will raise the likelihood of financial difficulty. According to CAR, there is a negative association between capital and financial distress. Increasing the capital adequacy ratio will cause a more negligible probability of financial distress.

Table 4. Correlation between variables

Variabel	FD	CAR	NPL	CIR	ROA	LDR	Size	Z-score	Exrate	Inf	GDP
FD	1.0000										
CAR	-0.2224	1.0000									
NPL	0.4842	0.0489	1.0000								
CIR	0.2043	-0.0558	0.1745	1.0000							
ROA	-0.2375	0.2549	0.0253	-0.1551	1.0000						
LDR	-0.0990	0.2554	-0.1699	-0.0801	0.1008	1.0000					
Size	-0.0333	-0.0532	-0.0516	-0.1503	-0.1222	-0.0927	1.0000				
Z-score	-0.2374	0.7508	0.0852	0.0169	0.4645	0.2480	-0.1505	1.0000			
Exrate	0.1283	-0.158	-0.0838	0.0513	0.1959	0.1331	-0.3261	-0.1134	1.0000		
Inf	0.0309	0.0804	0.0062	0.0369	0.1489	0.0818	-0.1454	0.0662	0.2760	1.0000	
GDP	0.0610	-0.0956	-0.0398	0.0006	0.0307	-0.0765	-0.0574	-0.1742	0.2375	0.3533	1.0000

Source: data processed in 2024

NPL is positively correlated with financial distress. An increase in NPL will follow every increase in credit risk, thereby increasing the possibility of financial distress. On the other hand, size is negatively correlated, indicating that every increase in assets causes a decrease in the likelihood of financial distress. It indicates that banks benefit from economies of scale. With effective asset management, banks can increase their net income, reducing the likelihood of financial distress. ROA indicates that it is negatively correlated with financial distress.

The Z-score is inversely related to financial distress, suggesting that higher values for the Z-score are related to lower probabilities of a bank encountering financial distress. It contrasts with macroeconomic determinants such as exchange rates and inflation, which are positively related to financial distress. In other words, it shows that an increase in either exchange rates or inflation results in a higher probability of a bank encountering financial distress.

The predictive model is built with logistic regression supported by Stata Software. Two models are employed in this study. Model 1 utilizes only bank financial indicators to identify whether the financial institution is in the financial distress category. Model 2, however, includes bank financial indicators and macroeconomic variables. The logistic regression results in Table 5 show Model 1, which does not incorporate macroeconomic variables, correctly predicts 67.14% of the banks in the sample, while Model 2, with macroeconomic variables, enhances the prediction accuracy to 72.01%.

In Model 1 and 2, CAR has an adverse effect on financial distress. Capital adequacy is important, especially during an unstable economic situation such as COVID-19. Banks with high CAR tend to be more able to survive because they have sufficient capital reserves. It supports the idea that higher equity levels contribute to financial resilience [35] in line with [22], which states that increasing capital standards for large banks in Europe is important in reducing bank fragility. Capital is the most significant leading indicator; banks with better capital are less likely to experience difficulties in the coming year [17]. Also, the equity-based risk-weighted capital ratio offers Islamic banks a stronger regulatory and supervisory framework [19]. The result of this study is consistent with [26], whereas [16] stated that CAR did not affect financial difficulties.

Table 5. Logistic regression output

Dependent variabel FD	Model 1	Model 2
CAR	-1.035181*	-1.150797*
NPL	2.058485*	2.449335 *
CIR	-.2937455	-1.000117
ROA	-2.340945*	-3.936427 *
LDR	.0053968	-.0124464
SIZE	.509889	.5757233
Zscore	.2098931	.495828*
Exchange rate		.0001423*
Inflation		-.2033587
GDP		.0567992
Constanta	-1.826887	-3.480727
LR chi2	219.85	235.80
Prob > chi2	0.0000	0.0000
Log likelihood	-53.811293	-45.836031
Pseudo R2	0.6714	0.7201

Source: data processed in 2024

Note: * denotes the level of significance at 5%

Non-performing loans impact financial distress. A high NPL suggests that more loans default, which might put banks in financial jeopardy. The impact of financial difficulties encountered by bank bailouts in Germany is that the NPL ratio raises the probability of obtaining capital injections [36]. When credit quality deteriorates, the risk of bank failure increases [23]. A portfolio of bank loans with a greater NPL ratio is of inferior quality. Accordingly, rising non-performing loans will raise the risk of bank failure and financial difficulties [22]. Significantly larger loan loss provisions and a higher percentage of non-performing loans are signs that banks' loan portfolios are riskier, which is why they have financial issues [17]. However, the study's results differed [13], [26], which states that NPL does not affect financial distress.

In this study, CIR does not affect financial distress. CIR measures efficiency from the operational side. Sometimes, a high CIR is due to investment in developing or introducing new products. However, this investment increases long-term competitiveness without directly affecting financial health. This insignificant CIR value indicates that this variable is not a suitable predictor for financial distress. This result aligns with [22], [36], who stated that CIR does not affect financial difficulties. While [16], [19], [20], [37], CIR has a positive effect on financial difficulties, conversely, [12], [13] stated to have an adverse effect.

In every model, the results indicate a significant negative coefficient of ROA. Banks are less likely to experience financial difficulties when their ROA is higher. The more effectively the bank uses its assets to produce profits relative to the total assets owned, the greater the ROA. According to [5], raising ROA lowers the likelihood of bank failure in the US between 2008 and 2009. The profitability coefficient in the CAMEL model and CAMEL plus macroeconomics is significant, which shows that banks with high profitability tend not to go bankrupt easily [20]. ROA has an adverse effect and is an important predictor of bank failure during the financial crisis [38]. However, according to [16], [39], [40] has a positive effect. While [17], [22], [26], [41], [42] does not affect financial difficulties.

LDR in Models 1 and 2 are insignificant, meaning that LDR does not affect financial distress. High LDR indicates banks have provided many loans compared to their deposits. Liquidity risk can be avoided if the bank has sufficient capital. Adequate capital is essential for banks to proactively manage risk and protect themselves from bankruptcy [43]. Based on the average CAR of banks in ASEAN countries, 15% exceeds the requirement of 8%. The results of this study are supported by [16], [41], [44] stated that LDR did not affect financial difficulties, while [5], [12], [13], [36] LDR has a positive effect on financial distress.

Size does not affect financial distress. Both models show no difference between large banks and small banks in terms of financial distress. Asset size is related to economic scale. However, large companies often have access to more resources, and if their financial management and financial structure are not managed efficiently, they are still vulnerable to financial distress. The results of this study by [20], [22] state that total assets do not affect bank failure. While [21], [44] said total assets have a positive effect on financial difficulties; on the other hand, according to [8], [17], [23], [40], [41], [45], [46] have a negative impact.

In Model 1, the Z-score does not affect financial distress. This finding is supported by [47], but in Model 2, the Z-score significantly affects financial distress. Low Z-score in banks is often caused by low liquidity, low profitability, and the company’s inefficiency in managing its assets. A low Z-score indicates a high risk of financial distress. By adding macroeconomic variables to Model 2, the Z-score affects financial distress.

Only the exchange rate significantly positively influences financial distress out of the three macroeconomic variables. While inflation and GDP do not affect the company’s financial distress. The exchange rate has a more significant effect on bank financial distress because its volatility can affect loans in foreign currency, asset stability, and cash flow from customers exposed to exchange rate risk. The results of this study contradict [8], [37], exchange rates do not affect financial difficulties.

Meanwhile, inflation and economic growth may not always have a significant direct impact because banks can adjust interest rates and have portfolios more resilient to inflationary pressures or economic slowdowns. Banks also often receive support from monetary policy that helps mitigate the negative impact of low inflation or economic growth, making these two variables less influential on the risk of bank financial distress. According to [8], [16], [22], [23], [37], [46] inflation has a positive effect on financial difficulties, conversely [17], [20] stated that it had an adverse effect. Even the findings from [12], [26] show that inflation does not affect financial difficulties. Research results [12], [26] economic growth has a positive effect on financial difficulties; conversely [17], [19], [23], [37], [38] stated that it had an adverse effect. While [8], [16], [20], [22], [44], [46] stated that economic growth did not affect financial difficulties.

This study contributes to the expanding literature by combining macro and financial data into a framework tailored to ASEAN economies. It reaffirms the role of capital buffers and operational efficiency in fostering banking stability. Prioritizing credit risk management in their internal risk assessment systems can also help bank managers. The findings also provide early warning indicators for regional financial regulators and policymakers, emphasizing the exchange rate as a crucial component of banking oversight.

4. Conclusion

This article aims to form a prediction model by determining the factors influencing financial distress in ASEAN banking. Of the 435 observation data that can be continued to be analyzed, 425 observation data were used, where 361 banks were categorized as healthy banks, while the remaining 64 were experiencing financial difficulties. Model 1 without macroeconomic variables correctly predicted 67.14% of sample banks, while Model 2 with macroeconomic variables increased the prediction to 72.01%. From the logistic regression results, it can be concluded that financial distress in ASEAN countries is positively related to CAR; banks with high CAR tend to be more able to survive because they have sufficient capital reserves, thus reducing the possibility of banks experiencing financial difficulties. High NPL indicates that more loans default, which has the potential for banks to experience financial difficulties. A higher increase in ROA will reduce the risk of financial distress for the bank. Of the three macroeconomic variables, only the exchange rate significantly positively affects financial distress. The exchange rate has a more significant effect on bank financial difficulties because its volatility can affect loans in foreign currency, asset stability, and cash flow from customers exposed to exchange rate risk.

Some limitations of this study include using logistic regression as the primary analysis tool, although appropriate for binary classification, may not fully capture nonlinear relationships or complex interactions between predictors. The dataset covering banks from six ASEAN countries has institutional, regulatory, and economic heterogeneity that may introduce bias or reduce the validity of the external model. The study time frame (2017–2021) covers a critical period surrounding the COVID-19 pandemic. While this period offers valuable insights into systemic vulnerabilities, it also reflects extraordinary circumstances that may not fully represent long-term banking dynamics.

Future research can address these limitations by adopting a hybrid model that combines statistical and machine learning approaches, allowing for the exploration of nonlinearities and higher-order interactions. Longitudinal analysis can provide deeper insights into the timing and development of financial distress. In addition, cross-regional comparisons, including developed and developing countries, can help evaluate the universality of the model.

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