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Research Article

Prediction and Comparison of Bankruptcy Models in Banking Sector Companies in Indonesia

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ABSTRACT

The Covid-19 pandemic, coupled with the economic recession from 2019 to 2022, has adversely impacted various industries, leading to bankruptcies. Among the affected sectors, the banking industry faced significant challenges, experiencing disruptions in credit processes and fund distribution due to diminished purchasing power. This situation poses a severe threat to the banking sector, necessitating the monitoring of financial conditions through bankruptcy analysis as an early warning system for company performance. This study investigates potential differences in the results of financial distress prediction models—Altman, Springate, Zmijewski, Grover, and Ohlson—during the abnormal conditions of the Covid-19 pandemic. Using purposive sampling of banking companies listed on the IDX from 2019 to 2022, the study divided the samples into financial distress and non-financial distress categories. Analysis involved tests for multicollinearity assumptions, logistic regression, and accuracy/error rate calculations. The findings reveal variations in the predictive abilities of the Altman, Springate, Zmijewski, Grover, and Ohlson models. The Grover model emerged as the most accurate, with a 60% accuracy rate in predicting bankruptcy, while Altman, Springate, and Zmijewski models demonstrated low predictive values (0%, 0%, and 15% accuracy, respectively). The simplicity of the Grover model's measurement indicators, incorporating capital adequacy, EBIT, and ROA, offers a comprehensive view of bankruptcy prediction ratios. Moreover, stringent internal risk analysis and external factors, such as regulatory interventions, contribute to keeping banks resilient amid global economic crises. The research suggests that banking companies can benefit from employing the Grover method for bankruptcy analysis as part of their future anticipation strategy.

Keywords: Financial distress, Pandemic, Bankruptcy model, Banking

INTRODUCTION

The rapid spread of Covid-19 has had a serious impact on the lives of the global community in the 2019-2021 period. Trautrims et al., (2020) The pandemic plunged the world economy into the worst contraction recorded since the Great Depression mainly due to activity restrictions and curfews in major cities limiting movement and travel. As with any disaster, the spread of COVID-19 has resulted in significant losses to business interruption (Nebolsina, 2021). In Indonesia, a state of emergency was declared at an early stage to prevent the spread of the disease, and then the whole lifestyle changed. The reduction of business activities with restrictions on movement, and reduction of working hours had a significant impact on the economic slowdown. This is evidenced by the domestic economy in 2020 showing a decline in real GDP to minus 2.07 (Central Bureau of Statistics, 2021). In managing economic and financial shocks, the government itself has provided stimulus from the fiscal, monetary, and macro and microfinance sides. The government responded to these conditions by loosening several regulations, providing a policy of postponing loan payments, and temporarily classifying non-performing loans (NPLs).

The declining purchasing power of the community implies that many people choose to hold their money, even with a bad economic condition causing many banking customers to delay and even default on their loans. This can directly threaten the turnover in financial ratios, even the company can collapse and go bankrupt. Business analysis strategies by predicting company bankruptcy have become a hot topic and are very important, especially in this era of global recession. For companies, bankruptcy has many negative impacts on investors, creditors, employees, customers, and other stakeholders of the affected company. Previous research shows that firms under economic stress also suffer losses (Radovanovic & Haas, 2023). As when a company goes into financial distress/bankruptcy, there are adverse consequences for a diverse group of stakeholders (Jackson & Wood, 2013). Bankruptcy in most cases is not a sudden occurrence, but rather a gradual process, signs of financial distress can be observed years before the event. Therefore, if financial distress is an indication of possible future bankruptcy and can be detected in time, companies should be able to analyze the necessary strategies to improve their financial health and minimize the negative socio-economic impact on stakeholders.

Financial distress has been a major topic in corporate finance for decades as it is portrayed as detrimental to the firm and its stakeholders (Opler & Titman, 1994). In the context of a massive economic slowdown and global economic turmoil, firms today face a more complicated economic environment than ever before, and thus face a greater risk of financial distress (Zhao et al., 2023) Therefore, predicting financial distress is crucial for today's financial researchers and practitioners. Financial distress begins when a company fails to meet payment schedules or when cash flow projections indicate that the company will not be able to fulfill them. In order to maintain the company's survival, it is important for management to pay attention to and analyze the company's financial statements using financial ratios on a regular basis. The financial statements show all information about the company's financial condition in one period and describe the company's condition in the future (Saudi et al., 2019).

There are various indicators that can cause a company to be in financial distress, generally consisting of two indicators, namely external and internal indicators. External indicators are said to be indicators that can be accessed on financial markets regarding general company information. Meanwhile, internal indicators are said to be indicators that can be taken from the company's cash flow reports, such as management strategies and company financial reports. The legal basis used in Indonesia regarding financial distress conditions is listed in Law No. 1 of 1998. The law basically states that if the debtor has two or more creditors and cannot pay at least one debt, the debtor can be declared bankrupt (Gupita et al., 2020).

Financial distress is usually associated with various costs borne by the company which are often referred to as the costs of financial distress. Financial distress can lead to bankruptcy when the company faces the risk of failure. If the company is unable to anticipate and prepare itself to face financial difficulties, then its business will further decline and lead to bankruptcy (Kusmartono & Rusmanto, 2022). The easiest condition to see from a company experiencing financial distress is a violation of debt payment commitments accompanied by the omission of dividend payments to investors and also when the company's cash flow is less than the amount of the maturing portion of long-term debt. A company is experiencing financial distress if the company has negative net income for two consecutive years (Sumolang et al., 2021). Financial distress that is not managed properly can lead to bankruptcy. Bankruptcy is a serious problem so an early warning system is needed that can detect the initial potential for bankruptcy so that management will be greatly helped (Masdiantini & Warasniasih, 2020). This requires companies to be able to predict bankruptcy, because the earlier the signs of bankruptcy are detected, the better for management to make various improvements to the company.

Various bankruptcy prediction studies have been conducted with the aim of finding the most appropriate and accurate bankruptcy prediction model to be used as a prediction tool(Sudarman et al., 2020). There are several indicators that can be used to predict bankruptcy. These indicators can be internal indicators and external indicators. Some examples of internal indicators are company cash flow, company strategy, financial statements, sales trends, and management capabilities. Meanwhile, external indicators can be taken from financial markets, and information from related parties such as suppliers, dealers, and consumers (Kusmartono & Rusmanto, 2022). Several kinds of bankruptcy analysis methods from the financial sector have been developed and used in various countries including Altman z-score, Springate, Zmijewski, Grover, and Ohlson. These analysis models use financial ratio variables to predict company bankruptcy, carried out by analyzing the financial statements of a company two to five years before the company will be predicted and in the end the company will be classified as being in a safe zone from bankruptcy or threatened with bankruptcy (Bilondatu & Dungga, 2019).

The first model, Altman z-score was developed by Altman in 1968 through Multiple Discriminant Analysis (MDA). The model is often used in financial distress prediction studies because it has more types of ratios than other models so that it can represent the company's overall financial condition (Stefhannie & Sumiati, 2019). Research conducted by Kusmartono & Rusmanto, (2022); Pangkey et al., (2018) state that the Altman z-score model has the highest level of accuracy in calculating the potential bankruptcy of a company.

The second model, the Springrate Model (S-Score) is a model developed by Springrate in 1978 using multi discriminant analysis. Springrate also collects various financial ratios that can be used in predicting bankruptcy (Stefhannie & Sumiati, 2019). Research conducted by Gupita et al., (2020) states that the Springrate Model has the highest level of accuracy compared to other prediction models. The same thing also happened in the research of Aadilah & Hadi, (2022) and Piscestalia & Priyadi, (2019). However, the drawback of the Springate method is that the ratio value can be engineered or biased through incorrect accounting principles or other financial engineering. On the other hand, the weakness of the Altman Z-Score method and the Springrate Model is that they do not use the current ratio in predicting bankruptcy. The current ratio is a measure of the company's ability to pay short-term obligations so if you add this ratio the method will be more accurate. The weaknesses of the two methods are overcome by the Zmijewski method where the Zmijewski method uses the current ratio in analyzing financial distress.

The third model, the Zmijewski Model (X-Score) is a model developed by Mark E. Zmijewski in 1984 using ratio analysis that measures the performance, leverage, and liquidity of a company for its prediction model. The proportion of the sample and population must be determined at the beginning, so as to obtain the frequency of financial distress (Stefhannie & Sumiati, 2019). Research conducted by Chairunisa, (2017) states that the Zmijewski Model (X-Score) has the highest level of accuracy in calculating the potential bankruptcy of a company. The same thing was also found in research by Munawarah et al., (2019). On the other hand, the weakness of the Zmijewski method, namely not using the ratio of net profit before taxes to current liabilities in analyzing financial distress, is overcome by the Springate method where the Springate method uses the ratio of net profit before taxes to current liabilities in analyzing financial distress.

The fourth model, the Grover Model (G-Score) is a model that was created by designing and re-examining the Altman Model (Z-Score). Jeffey S. Grover used a sample according to Z-Score in 1968 by adding 13 new financial ratios (Stefhannie & Sumiati, 2019). Research conducted by (Saudi et al., 2019) suggests that Grover's research model has the highest level of accuracy in calculating potential bankruptcy compared to other models. The same thing also appeared in research conducted by Arini, (2013); and Mahastanti & Utami, (2022) The weakness of the Grover method which does not use the ratio of sales to total assets in analyzing financial distress is overcome by the Altman and Springate methods where the Altman and Springate methods use the ratio of sales to total assets in analyzing financial distress.

The fifth model, the Ohlson Model, is a model that uses property analysis to avoid problems related to assumptions that arise in Multiple Discriminant Analysis (MDA), namely data tested with data normality requirements. Unlike most prediction models, the Ohlson model includes the company size property as a research property. This variable is used with the assumption that the larger the size of a company, the less likely the company is to experience financial difficulties (Widyastuti & Rahayu, 2018). According to the results of research from Lestari, (2022), it shows that the Ohlson research model has the highest level of accuracy compared to other models in calculating bankruptcy predictions. On the other hand, according to some researchers, the Ohlson method has the lowest level of accuracy and has several shortcomings, including (1) There is a definite need for property testing in prediction method research, causing restrictions on the scope of research, and (2) The calculation results using the discriminant analysis method have a narrow interpretation because they are based on ranking rules, so the results obtained do not reflect the condition of the company.

Existing literature reports that the predictive ability of each model varies over time, and our empirical analysis confirms this result. For example, Wu et al. the Ohlson model performed relatively well in the mid to late 1980s, while the Shumway model performed better in the 1990s. The timeframe variation in the performance of different models that use different data and employ different econometric techniques suggests that each model may capture slightly different aspects of a firm's financial health. This leads to integrated models that include accounting data, market data, and firm characteristics such as firm size and diversification.

Previous studies related to bankruptcy prediction models have raised gaps in the results of their research. This research suspects that because the bankruptcy prediction model testing was carried out partially, this study will test the accuracy level properties of the bankruptcy prediction models, namely Altman z-score, Springate, Zmijewski, Gover and Ohlson simultaneously so that the research results can be more explorative. This research is a development of the research mode conducted by Seto, (2022) which uses the Altman (z-score), Springate, Zmijweski, Grover, and Ohlson prediction models as a measure of potential bankruptcy. The research period used was 2019-2022 with period in accordance with the issues raised. The sample used is banking companies. In addition, the difference in research results from previous researchers is one of the ropers behind the importance of conducting this research. The novelty of this research is to compare 5 bankruptcy measurement tools to assess which bankruptcy measurement tool has the best accuracy and compare the assessment results for banking sector companies. In this article, we aim to assess the level of bankruptcy experienced by banking companies during the COVID-19 pandemic period and test whether there are differences in the prediction results from 2019 to 2022. The contribution of this research is first, we provide an overview of bankruptcy predictions for the banking sector in Indonesia during the pandemic using five sets of bankruptcy prediction tools. Second, we compare the accuracy of bankruptcy prediction model performance during a pandemic. Based on this explanation, the hypothesis formed is:

Hypothesis 1: *There are differences in the results of the bankruptcy prediction model between the Altman, Springate, Zmijewski, Grover, and Ohlson Models in the Banking Sector Sector Companies for the period 2019-2022.*

Hypothesis 2: *There are differences in the accuracy of bankruptcy prediction models in Banking Sector Companies.*

RESEARCH METHODOLOGY

Data

This research uses descriptive research with a quantitative approach. The data source used in this study is secondary data obtained from the annual financial statements of banking sector listed on the Indonesia Stock Exchange (IDX) in 2019-2022. Financial reports are obtained by accessing the website www.idx.co.id. Sampling was taken by meeting the criteria of banking sector companies listed consecutively during 2019-2022 and companies publishing complete and audited financial statement data obtained a total of 180 observations.

Definition of operational variables

Altman Model

Analysis using the Altman model is done by identifying several kinds of financial ratios that have important value in influencing company performance. According to Seto, (2022), there is a standard method used as the basic method for comparison studies with the following formula:

$Z = 1{,}2X1 + 1{,}4X2 + 3{,}3X3 + 0{,}6X4 + 1{,}0\,X5$ .... (1)

Description:

Z: Overall Index (z-score)

X1: Working Capital to total assets

X2: Retained earnings against total assets

X3: Earnings before interest and taxes to total assets

X4: Stock Market Value to total debt

X5: Sales to total assets

The cut-off or limit values of the Altman Z-Score model are as follows (Nirmalasari, 2018)

Table 1. Altman Model Analysis (*Z-Score*)

	Classification
Z > 2,99	healthy
1,81 < Z < 2,99	*Grey Zone*
Z < 1,81	Bankrupt

Springate Model

The Springate model is a bankruptcy prediction model using the Multiple Discriminate Analysis approach. The Springate model uses many financial ratios to predict bankruptcy, so the Springate model is formulated as follows Seto (2022):

$S = 1{,}3X1 + 3{,}07X2 + 0{,}66X3 + 0{,}4X4$ .... (2)

Description:

S: Overall Index (s-score)

X1: Working Capital to Total Assets Ratio

X2: Ratio of Earnings Before Interest and Taxes to Total Assets

X3 : Ratio of Profit Before Tax to Total Current Liabilities

X4: Sales to Total Assets Ratio

Bankruptcy analysis using the Springate Model can be seen that if the greater the calculation results of the model, the better the company's performance or the company is less likely to go bankrupt. The cutoff or limit of the Springate model is as follows (Mahastanti & Utami, 2022):

Table 2. Springate Model Analysis

	Classification
S > 0,862	Healthy
S < 0,862	Bankrupt

Zmijewski Model

The Zmijewski model includes the validity of financial ratios in its model equation to predict corporate bankruptcy. The formula used in the Zmijewski model is as follows Seto, (2022):

$X = -4{,}3 - 4{,}5X1 + 5{,}7X2 - 0{,}004X3$ .... (3)

Description:
X : Overall Index (x-score)
X1 : Net income to Total Assets
X2 : Total Debt to Total Assets
X3 : Current Assets to Current Liabilities

Bankruptcy analysis using the Zmijewski Model can be seen that if the greater the calculation results of the model, the better the company's performance or the company is less likely to go bankrupt. The cutoff or limit of the Zmijewski model is as follows Nirmalasari, (2018):

Table 3. Measurement analysis of the Zmijewski Model

X	Classification
X > 0	Bankrupt
X < 0	Healthy

Grover Model

Specifically, the model created by Jeffrey Grover in 1968 was based on a sample of the Altman model but the selection was rebuilt by adding 13 financial ratios and then evaluated to obtain the Grover model equation. The formula used in the Grover model is as follows Seto, (2022):

$G = 1{,}650X1 + 3{,}404X2 - 0{,}016X3 + 0{,}057$ .... (4)

Bankruptcy analysis using the Grover Model can be seen that if the greater the calculation results of the model, the better the company's performance or the company is less likely to go bankrupt. The cutoff or limit of the Grover model is as follows (Seto, 2022):

Table 4. Grover Model Analysis

G	Classification
G ≥ 0,01	Healthy
G ≤ -0,02	Bankrupt

Ohlson Model

This model is one of the models that incorporates conditional logit factors to forecast bankruptcy developed by James Ohlson. The advantage of adopting this dependent logit element makes it unnecessary to assume MDA restrictions, allowing unnecessary samples to be evaluated. The formula used in the Ohlson model is as follows Seto, (2022)

$O = -1{,}32 - 0{,}407X1 + 6{,}03X2 - 1{,}43X3 + 0{,}0757X4 - 2{,}37X5 - 1{,}83X6 + 0{,}285X7 + 1{,}72X8 - 0{,}521X9$ .... (5)

Description:
O : Overall Index (O-score)
X1 : Log of Total Assets to GNP Price Index
X2 : Total Assets to Total Liabilities
X3 : Difference of Current Assets and Current Liabilities to Total Assets
X4 : Current Assets to Current Liabilities
X5 : 1 if total liabilities > total assets; 0 otherwise
X6 : Net Income to Total Assets
X7 : Cash Flow from Operating Activities to Total Liabilities

X8 : 1 if net income is negative 0 if net income is positive (2 consecutive years)
X9 : Difference between net profit of the current year and the previous year to Total net profit of the current year and the previous year
The cutoff or limit of the Ohlson model is as follows Widyastuti & Rahayu, (2018):

Table 5. Ohlson Model Analysis

O	Classification
O < 0,38	Healthy
O > 0,38	Bankrupt

Data Analysis Technique

Normality Test

The more complex and complete normality assumption test also called the model fit test is intended to test whether the proposed model has a fit with the data or not.

Difference Test

In this study uses different tests, namely the One-Way Anova Test and Kruskal Wallis Test. ANOVA is used as an analytical tool to test the research hypothesis which assesses whether there is a difference in means between groups. The final result of ANOVA analysis is the F test or F value. This calculated F value will later be compared with the value in the f table. If the value of f count> f table, it can be concluded that accepting H1 and rejecting H0 means there is a significant difference in the means of all groups. The Kruskal-Wallis test is one of the non-parametric statistical tests that can be used to test whether there is a significant difference between groups of independent variables and their dependent variables. The null hypothesis of the Kruskal-Wallis test states that "k" samples come from the same population or from identical populations, while the alternative hypothesis can be written that at least some samples come from different populations. In testing the null hypothesis, it is assumed that the variable under study is continuously distributed.

Accuracy Test

The calculation of the accuracy level of each bankruptcy prediction model is intended to assess which bankruptcy prediction model is the best predictor. The accuracy test can show the prediction model that has the highest level of accuracy and shows the percentage of error types owned by comparing the prediction results with the actual situation. In addition, this calculation is carried out to determine which model is the best model in predicting the bankruptcy of the company used as a research sample. The calculation of the level of suitability/accuracy will produce categorization prediction results which will be compared with the prediction results of the bankruptcy model (Masdiantini & Warasniasih, 2020). The formula used in measuring accuracy and error is as follows (Masdiantini & Warasniasih, 2020):

Accuracy Rate: (number of correct predictions)/(number of samples) x 100% (6)
Type error rate: (number of incorrect predictions)/(number of samples) x 100% (7)

RESULT AND DISCUSSION

Descriptive Statistics

To provide a description of the data in the calculation of the lowest (minimum), highest (maximum), average (mean), and standard deviation values of the five prediction models in this study, a descriptive statistical model is used. The companies analyzed are categorized into two, namely companies in the banking sector. The data processed are financial reports or annual reports for the period 2019 - 2022 sourced from the site www.idx.co.id. The results of the descriptive statistical test for the banking sector can be seen in Table 6 below:

Table 6. Descriptive Statistical Test Results for the Banking Sector

Variables	N	Minimum	Maximum	Mean	Std. Deviation
Altman	20	0,35999	0,447372	0,063238	0,221859
Springate	20	-0,39186	0,206026	-0,05174	0,174587
Zmijwski	20	-3,37803	1,085863	0,253088	1,281594
Grover	20	0,44631	0,402235	0,019198	0,254557
Ohlson	20	49,0387	240,0107	39,3989	111,533

From the table above, the descriptive statistical test results for the banking sector show that the Altman variable has a value range from 0.35999 to 0.447372 with an average value of 0.063238 and a standard deviation of 0.221859. This value illustrates that on average, all banking companies in Indonesia in 2019-

2022 that were sampled were in the bankrupt category. The Springate variable is at a value from -0.39186 to 0.206026 with a standard deviation of around 0.174587 and an average of -0.05174 which indicates the value of this springate measurement is in the bankrupt category. The Zmijwski variable has an average value of around -0.253088, with a standard deviation of around 1.281594. This reflects that the Zmijwski variable has a large data variation with a wide range of values as well as a positive average and high standard deviation and assesses banking companies in the 2019-2922 period in the observation to have a bankrupt value. The Grover variable has an average value of around 0.019198 with a standard deviation of 0.254557. The data in this variable is concentrated in a very small range which indicates the variability in this data is very small. The mean of the Grover model measurement of 0.019198 indicates the condition of the sampling banks is Healthy. The Ohlson variable has a very narrow range of values with an average value of around 39.3989 and a very high standard deviation of 111.533 and a mean value of 39.3989. This shows that this data is very widely spread and has significant variations and predictions of bankruptcy.

Bankruptcy prediction model of banking industry

Based on the sampling criteria that have been carried out previously, we present a recapitulation in Table 7 below.

Table 7. Banking Sector Condition Based on Bankruptcy Model Analysis

CODE	YEAR	ALTMAN	SPRINGATE	ZMIJEWSKI	GROVER	OHLSON
BKSW	2019	0,398453	0,206026	0,230495626	0,381602	7,672132
	2020	0,343284	0,151758	-3,374748949	0,327353	234,1193
	2021	0,034507	-0,11154	-3,378031143	0,099729	-47,5607
	2022	0,447372	0,177156	-0,09166099	0,402235	-26,0096
BBKP	2019	-0,03088	-0,11388	0,880630005	-0,17764	7,216947
	2020	-0,22048	-0,27993	0,976225713	-0,30007	240,0107
	2021	-0,16676	-0,25833	0,669055913	-0,29129	-49,0387
	2022	-0,35999	-0,39186	0,93808316	-0,44631	-29,7187
BCIC	2019	-0,21154	-0,25476	0,832955659	-0,3743	8,016239
	2020	0,041323	-0,01506	1,023871958	0,127962	220,287
	2021	-0,13321	-0,18946	0,779266886	-0,18171	-46,9935
	2022	0,084599	-0,00193	0,752642488	0,038278	-27,7883
BEKS	2019	-0,09898	-0,13451	1,085862835	-0,11531	6,818797
	2020	0,027655	-0,14565	0,201500018	-0,0446	213,0558
	2021	0,12121	-0,02992	0,312484625	0,068417	-44,6984
	2022	0,096765	-0,09016	0,24917292	0,013556	-25,637
BVIC	2019	0,178316	0,087566	0,838761024	0,185505	7,655516
	2020	0,141047	0,053787	0,864104359	0,152092	214,4216
	2021	0,219111	0,102715	0,728284146	0,207515	-47,311
	2022	0,352979	0,203173	0,542804413	0,310949	-26,5401

Source: data processed, 2023

Normality Test

The normality test is conducted to determine whether the data is circulating normally or not. In the context of this study, the results of the normality test on banking sector data can be seen in table 8 below:

Tabel 8. One-Sample Kolmogorov-Smirnov Test

	Zscore: Financial Distress
N	100
Kolmogorov-Smirnov Z	6.221
Asymp. Sig. (2-tailed)	.000
Exact Sig. (2-tailed)	.000
Point Probability	.000

a. Test distribution is Normal.
b. Calculated from data.

The table above shows the results of the normality test using the One-Sample Kolmogorov- Smirnov Test with a significant p-value (p<0.005) and a high Z-score statistical value, so the data tested does not meet the normality test. To ensure that the analysis results are consistent and valid, non-parametric tests are used in this study.

Non-parametric Test

In this study, five financial distress evaluation models are used, namely Altman, Springate, Zmijewski, Grover, and Ohlson. This model can provide a more in-depth view of the financial stability and potential financial problems faced by the company. To measure financial distress methods in the banking sector, non-parametric tests are used. The results of the non-parametric test are presented in the table below by listing the Mean Rank values for each method.

Tabel 9. Table Ranks Bank Sector

	Metodh Financial Distress	N	Mean Rank
Financial Distress condition	Altman	20	38.00
	Springate	20	38.00
	Zmijewski	20	45.50
	Grover	20	68.00
	Ohlson	20	63.00
	Total	100	

Table 9 above shows that the Grovel model is the measurement method that has the highest mean rank value of the other four methods, namely 68.00. This result indicates that the Grovel variable is a method that tends to or is often used by banking companies in measuring financial distress compared to the other four models in this sample. Meanwhile, the lowest average value is owned by the Springate model and the Altman model with a value of 38.00. These two variables have the lowest rank from other methods which indicates that the Springate model and Altman model are less popular or rarely used to measure financial distress. The Ohlson model is ranked second after the Grovel model with a value of 63.00, while the Zmijewski model has a mean rank value of 45.50.

Hypothesis Test

Statistical tests to test two hypotheses, namely hypotheses H1 and H2. This hypothesis testing is done by processing data through Test Statistics. The Test Statistic test results which display the Exact. The sig value to determine the level of significance can be seen in the table below:

Table 10. Test Statistics[,b] Banking Sector

	Financial Condition Distress
Chi-Square	33.792
df	4
Asymp. Sig.	.000
Exact Sig.	.000
Point Probability	.000

a. Kruskal Wallis Test
b. Grouping Variable: Metode Pengukuran Financial Distress

From table 10, it can be seen that the Chi-Square test results are very significant. Exact Sig is below 0.05, so there is a difference in test results between 5 financial distress methods. This can conclude that Hypothesis H1 is accepted. In other words, there are differences in bankruptcy prediction models with the highest accuracy in Banking Sector Companies. So, the conclusion of this analysis is that there is a significant difference in the results of the bankruptcy prediction model with the highest accuracy in the 2019-2022 period.

Accuracy Test

The calculation of the accuracy level of each bankruptcy prediction model is intended to assess which bankruptcy prediction model is the best predictor. The accuracy test can show the prediction model that has the highest level of accuracy and shows the percentage of error types owned by comparing the prediction results with the actual situation. In addition, this calculation is carried out to determine which model is the best model for predicting the bankruptcy of the company used as a research sample. In this study, the results of the calculation of the accuracy level of the five models used and the error rate for banking sector companies are presented in Table 11 below:

Table 11. Calculation of Accuracy Rate and Error Rate in Banking Sector

	ALTMAN	SPRINGATE	ZMIJEWSKI	GROVER	OHLSON
Number of Observations	20	20	20	20	20
Appropriate Prediction	0	0	3	12	10
Unsuitable predictions	20	20	17	8	10
Error Rate	100%	100%	85%	40%	50%
Accuracy Level	0%	0%	15%	60%	50%

The table above shows the results of calculating the accuracy rate using the Altman, Springate, Zmijewski, Grover and Ohlson models. The Grover model has an accuracy rate of 60% and the Ohlson model makes 10 appropriate predictions out of 20 observations, so this model has an accuracy rate of 50%. Meanwhile, the Zmijewski model only makes 3 appropriate predictions out of 20 observations, so this variable has an error rate of 85% and a fairly low accuracy rate of 15%. The Altman and Springate models have 0% prediction results, meaning they are unable to predict bankruptcy in the banking sector in Indonesia.
From the results of the calculation of the Accuracy level and Error level in the Banking Sector, the results obtained from the five models can be compared to determine the rank of the most accurate model. The results of the comparison can be seen in Table 12 below:

Table 12. Comparison Table of accuracy and error rates in the Banking Sector

Model	Accuracy Level	Error Rate	Most accurate model rating
GROVER	60%	40%	1
OHLSON	50%	50%	2
ZMIJEWSKI	15%	85%	3
ALTMAN	0%	100%	4
SPRINGATE	0%	100%	4

Source: Data processed by researchers

The table above shows that the Grover model ranks first with an accuracy rate of 60%. The second place is the Ohlson model with an accuracy rate of 50%. The Zmijewski model ranks third with a value of 15%. While the Altman and Springate models have an accuracy level of 0% with an error rate of 100% or are unable to predict bankruptcy in Indonesia.

DISCUSSION

The analysis results show that there are differences in bankruptcy prediction models between the Altman, Springate, Zmijewski, Grover, and Ohlson Models in Banking Sector Companies for the 2019-2022 period. This can prove the first hypothesis in this study that there really are differences in bankruptcy prediction models. The performance of bankruptcy prediction models can be influenced by the extent to which these models are able to identify risk factors that match the actual business situation. Models that are more reliable in describing the condition of the company will provide better results. Timely predictions are very valuable for company management and investors to evaluate risk or prevent bankruptcy. In accordance with signaling theory which states that information carries signals to investors in making investment decisions. This signal can be used as an indicator or prediction of a company whether the company is classified as bankrupt or not (Connelly et al., 2011). The results of this study are in line with several previous studies that aim to find the most appropriate and accurate model as a bankruptcy prediction tool for companies (Elviani et al., 2020; Kuizinienė et al., 2022; Stankevičienė & Prazdeckaitė, 2021; Yendrawati & Adiwafi,2020). This finding is strengthened by the acceptance of the second hypothesis which states that there are differences in the accuracy of bankruptcy prediction models in Banking sector companies. the banking sector has unique characteristics such as the influence of interest rates and significant credit risk. This difference can result in bankruptcy prediction models that are more suitable for one sector but inappropriate for another sector(Kuizinienė et al., 2022).
The results of data analysis that have been carried out in the banking sector show the level of accuracy of each model to predict company bankruptcy, obtained a suitable model in predicting financial distress in banking sector companies listed on the IDX in 2019-2022, namely the Grover model. This model is successful in predicting bankruptcy conditions for all cases evaluated in the banking sector in the 2019-2022 observation sampling with the highest accuracy value of 60%. We believe that simple measurements and using the main ratios in viewing performance, namely working capital adequacy and the ability to generate profits compared to total assets, can provide an early signal of the financial performance of the industry.
The Ohlson model ranks second with an accuracy rate of 50% as an accurate model after the Grover model, the model can analyze according to the real conditions of banking companies. The results of data analysis

found that the Altman and Springate methods have a very poor prediction rate with an error rate of 100%. A high level of accuracy indicates the ability of the model to provide more useful information in business decision making and risk management. This contradicts the research of (Muñoz-Izquierdo et al., 2020; Nirmalasari, 2018; Tristanti & Hendrawan, 2020) found that the Altman Z score can predict bankruptcy with high accuracy.

To further substantiate these findings, we try to determine the resilience of the Bank by comparing the trend of capital adequacy and non-performing loan (NPL) rates.

Table 13. Comparison of capital adequacy ratio and bad debts

Company Name	YEAR	>8% CAR	<5% NPL
P1	2019	22,78%	5.63%
	2020	26,57%	4.66%
	2021	32.66%	0.08%
	2022	42.43%	0.38%
P2	2019	12,59%	5,97%
	2020	12,08%	10,13%
	2021	20,26%	11,16%
	2022	19,72%	6,72%
P3	2019	14,59%	1,49%
	2020	13,15%	2,63%
	2021	15,84%	3,90%
	2022	14,86%	1,21%
P4	2019	9,01%	5,01%
	2020	8,02%	5,69%
	2021	41,68%	14,09%
	2022	43,38%	9,45%
BVIC	2019	18.19%	6,77%
	2020	17.37%	8.29%
	2021	18,24%	7,27%
	2022	19,67%	4,12%
Average		15,62%	4,78%

Source: data processed, 2023

The Basel III Agreement is a set of financial reforms developed by the Basel Committee on Banking Supervision (BCBS), with the aim of strengthening regulation, supervision, and risk management in the banking industry. Due to the impact of the Global Financial Crisis on banking, to improve banks' ability to handle shocks due to financial stress and to strengthen transparency and information disclosure, all banks are required to have a Capital Adequacy Ratio of at least 8%. The capitalization of financial services institutions to date has also been relatively maintained at an adequate level. The Capital Adequacy Ratio (CAR) of banks was recorded at an average of over 15.62 percent, well above the regulatory threshold of 8 percent.

Our loan resilience analysis uses NPL which describes the condition where a debtor is unable to pay ongoing installments on time. Ideally, the NPL ratio should be below 5%. If it is above 5%, then it can be said that the number of bad loans is more than current loans. From the average NPL data, 4.78% is obtained or still slightly below the maximum limit of non-performing loans. Analysis of NPL trends from 2019 to 2022 in general, we see that the abnormal value occurs at the peak of the pandemic in 2020-2021 and gradually decreases in the following years. This provides an explanation that the Company has carried out risk mitigation to minimize the risk of bankruptcy. It is important to note that some banks have an NLP ratio value above 5%, this is empirical evidence that the bank is experiencing a slowdown in payments from debtors. The customer or debtor directly causes the NPL to increase because the debtor experiences unexpected events such as a decrease in purchasing power and disruption to their income during the pandemic which has a direct impact on the debtor's financial condition. The second factor is derived from the economic crisis that has occurred, which complicates the purchasing power of the public and business entities. In dealing with an extreme event scenario covid -19 The Bank conducts stress tests regularly so that it can anticipate early. In addition, the Bank continues to strive to increase risk awareness in all Bank employees as the Bank's effort to recognize the impact of macroeconomic weakening due to the COVID-19 pandemic on pandemic.

Our next investigation tries to touch on the external side of the banking company. The surviving banking conditions in Indonesia cannot be separated from the role of Bank Central Indonesia in strengthening policy coordination with the Government and other authorities in taking stabilization measures and mitigating the impact of COVID-19 risks on the domestic economy. The government provides fiscal stimulus space and provides ease of doing business in the real sector so as to support economic growth. Bank Indonesia has taken various policies to mitigate the risk of COVID-19. The policy rate, BI 7-Day Reverse Repo Rate

(BI7DRR) was reduced by 25 bps to 4.75%. The monetary operation strategy also continues to be strengthened to maintain adequate liquidity and support the transmission of an accommodative policy mix. Payment system policies also continue to be strengthened to support economic growth, among others through the expansion of QRIS (Quick Response Code Indonesian Standard) acceptance and electronification of financial transactions. Other strengthening measures include increasing the intensity of triple intervention so that the Rupiah exchange rate moves in accordance with its fundamentals and follows the market mechanism, reducing the ratio of the Foreign Currency Reserve Requirement (GWM) of Conventional Commercial Banks, from the original 8% to 4%, effective from March 16, 2020. The reduction in the Foreign Currency Reserve Requirement ratio will increase forex liquidity in banks and at the same time reduce pressure in the forex market. Encourage the momentum of economic growth, and accelerate structural reforms.

Another policy carried out by the government and banks to maintain bank liquidity is to relax credit. This credit relaxation was carried out with the aim of reducing the risk of default during the pandemic. Relaxation is carried out by relaxing the credit payment period for customers affected by the pandemic. The implementation of this relaxation aims to enable banks to reduce the risk of default by customers to maintain banking liquidity during the pandemic. The intervention of the government and the central bank of Indonesia in monitoring the development of financial markets and the economy, including the impact of COVID-19 and continuing to strengthen the policy mix is an important factor in maintaining banking stability in Indonesia.

CONCLUSION

The financial distress analysis method can be used as a benchmark to see the financial condition of a company and can be a consideration in overcoming the financial difficulties of a company. The results of the analysis can also be used by investors as a consideration in choosing a company as an investment.

In this analysis, the five financial distress prediction models that have been tested show that there are differences in the prediction results of the five models between the Altman, Springate, Zmijewski, Grover, and Ohlson Models in Banking Sector Companies for the 2019-2022 period. The findings also show that there are differences in the accuracy of bankruptcy prediction models in Banking Sector. In the Banking sector, the Grover model has accurate performance, while the Altmant and Springate methods are the least accurate in predicting bankruptcy. In further analysis, we found important factors from the external side of the company, namely regulations related to interest rates, technological innovation in digital transactions and credit relaxation provide fiscal stimulus space for the risk of bankruptcy in the banking industry.

This research makes a practical contribution, especially to managers, investors, and creditors. This finding provides an affirmation that all financial distress models are actually signaling factors for the company's financial condition, not only to see financial distress but also will make a positive contribution in assessing the policy of a financial manager in predicting operational distress or liquidation. In addition, every model created is never perfect. Therefore, these prediction results should not be considered as absolute results. The prediction results are only an indicator so that investors or creditors are more careful about companies that are predicted to experience Financial Distress and seek additional information about the company concerned. Future research can compare periods when market conditions are good and market conditions are bad, so that when the model is used to test in two market conditions whether it provides almost the same level of accuracy or not. Future researchers can also develop more specific bankruptcy prediction models according to the characteristics of each sector. External factors such as government policies, macroeconomic conditions, and regulatory changes can also be considered.

Author Contributions

Lilik Purwanti was involved in Substantial contributions to the conception, methodology, analysis, and interpretation of data for the work, and Final approval of the version to be published; Iwan Triyuwono work in investigation, reviewing critically for important intellectual content; Soelchan Arief Effendi design of the work and methodology; Melinda Ibrahim and Rino Tam Cahyadi are collecting, curation and data processing and Aryo Prakoso writing draft preparation, visualization and project administration.

All Authors Agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Availability of data and materials

This research data comes from secondary data from company financial reports available at https://www.idx.co.id/en/listed-companies/financial-statements-and-annual-report.

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