Comparative analysis of models (Altman, Grover, Zmijewski, Springate) in predicting company bankruptcy potential in the non-cyclical consumer sector

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ABSTRACT

This research aims to conduct a comparative analysis of models (Altman, Grover, Zmijewski, Springate) in predicting potential bankruptcy for companies in the noncyclical consumer sector listed on the IDX in 2020-2022. The main aim of this research is to test the results of the comparison of four models and test the accuracy of the prediction model in predicting bankruptcy. The data in this research is 240 data, namely 3 years of timeseries data and 80 companies using purposive sampling techniques according to certain criteria. Data analysis used the Kruskal Wallis Difference Test and Accuracy Level Test. The research results show that the Altman, Grover, and Springate models have significant differences in results in predicting bankruptcy and the accuracy level test produces the Grover model with the best level of accuracy in predicting bankruptcy in noncyclical consumer sector companies in 2020-2022.

Keywords: financial distress; Altman, Grover; Zmijewski;

Springate; consumer non-cyclical JEL Classification: G11 & G33

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1. Introduction

Maximizing profits is the key to successful management and attracting investors. If a company achieves its goal of maximum profit, it can be considered to have good performance. (Hutabarat, 2021) An investor will only invest if they believe the company will generate high profits. Therefore, high profits are the focus of the company's assessment by investors (Indrarini, 2019). However, companies face financial distress and potential bankruptcy due to various factors such as business competition, outdated methods, and unexpected events like

global issues. Ariffin et al. (2022) have demonstrated that the geopolitical issues in 2022 will have a global impact on commodity supplies. These challenges have significantly impacted economic stability and corporate performance, especially in the consumer non-cyclical sector, which provides essential goods and services. Corporate performance data from 2019-2021 shows a clear recovery trend, with some sectors experiencing significant growth. However, the consumer noncyclical sector grew more slowly and even showed a decline in stock performance by the of 2021. This sector's end

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vulnerability, combined with the government's Implementation of Restrictions on Community Activities (or PPKM) restrictions, has made it less attractive to investors, as financial distress negatively impacts investment decisions (Hidayat et al., 2023).

The primary consumer comprises companies that produce or distribute products and services typically purchased by consumers. These are known as primary goods, which are more resistant economic cycles (non-cyclical). However, the growth potential of this sector is also highly susceptible to the PPKM introduced by the government from 2020 to early 2022, which has had varying effects. Consequently, there is a growing concern that this sector will gradually become less attractive for investors. In terms to predict potential bankruptcy, models such as Altman Z-Score, Grover G-Score, Zmijewski X-Score, Springate S-Score are used. Each model uses different financial ratios and variables to assess a company's financial health. These models have shown varying degrees of accuracy in different contexts and sectors as proven by Meiliawati and Isharijadi (2017), Permana et al. (2017), Hantono (2019), Shalih and Kusumawati Chandra (2019).et al. (2021),Stankevičienė and Prazdeckaitė (2021), and Octavera and Syafel (2022).

Signaling and agency theories are understanding essential for how management communicates financial health to the market and how conflicts of interest between owners and managers can lead to financial mismanagement. It is crucial to compare these models in the consumer non-cyclical sector from 2020 to 2022 to determine the most accurate model for predicting bankruptcy amid economic uncertainties. This study will evaluate the predictive accuracy of Altman, Grover, Zmijewski, and Springate models for companies listed on the Indonesia Stock Exchange (IDX) during this period.

2. Literature review

- Signaling theory. Signaling theory explains how information is conveyed from the sender (information holder) in term to attract the investors or receiver (Spence, 1973; Ross, 1977). This theory highlights the importance of financial statements as signals for company investors to assess informed and performance make decisions. The Altman. Grover. Zmijewski, and Springate models are tools that companies can use to predict bankruptcy risk, thereby sending signals about their financial health to the market.
- Agency theory. According to Jensen and Meckling (1976), this theory involves a contract where principals (owners) delegate decision-making authority to agents (managers). This theory addresses the information asymmetry between owners and managers. Bankruptcy prediction models like Altman, Grover. Zmijewski, and Springate help reduce this asymmetry by providing tools for owners evaluate company to performance and potential bankruptcy risks independently of managers' reports.
- Financial **Financial** statements. statements provide a snapshot of a company's financial condition at a specific time. They are essential for performance decision-making, evaluation, communicating and financial information to stakeholders (Kasmir, 2021). Every aspect of the report data finance is very necessary for consideration of the decisionmaking process in the future. Hery (2021) explains that financial reports is the final product of a series of recording processes and summarizing business transaction data.
- Users of financial statements. Key users include owners, management,

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creditors, government, and investors. Each group uses financial statements to assess the company's current condition, performance, and future prospects. For instance, owners evaluate company growth, management performance, and financial stability, while creditors assess the company's creditworthiness and risk.

- Financial statement analysis. Financial statement analysis involves critically evaluating financial information to understand a company's financial condition make informed and decisions. Methods and techniques must be accurate to avoid incorrect conclusions. According to Sari and Hidayat (2022), this analysis helps in decision-making by providing insights into financial performance potential issues.
- Objectives of financial statement analysis. The main objectives are screening, forecasting, diagnosis, and evaluation. These objectives help in understanding business activities, predicting future financial conditions, identifying potential problems, and assessing management performance.
- Financial distress. Financial distress occurs before bankruptcy when a company cannot meet its obligations. Signs include heavy debt reliance and dividend cuts. According to Arifin (2018), internal management issues economic and external factors contribute to financial distress. Causes decision-making, include poor inadequate business planning, and external economic shocks.
- Causes of bankruptcy. Bankruptcy can caused by general factors social, (economic, technological, governmental), external factors (customers, suppliers), and internal (management inefficiency. factors financial mismanagement). Jauch et al. (1995) highlights the importance of

addressing these factors to prevent bankruptcy.

- Bankruptcy prediction models
 - a. **Altman Z-Score**. This score measures bankruptcy risk using financial ratios. Scores above 3.00 indicate low bankruptcy risk, while scores below 1.81 suggest high risk. The formula includes ratios like working capital, retained earnings, and total sales to total assets.

$$Z = 0.717.X1 + 0.847.X2 + 3.107.X3 + 0.420.X4 + 0.998.X5$$

X1 is working capital/total asset, X2 is retained earnings/total asset, X3 is earnings before interest and taxes/total asset, X4 is book value of equity/book value of liability, and X5 is total sales/total assets.

b. **Grover G-Score**. This score is an enhancement of Altman's, uses three financial ratios: working capital to total assets, EBIT to total assets, and return on assets. Companies with scores ≤ -0.02 are at bankruptcy risk, while scores ≥ 0.01 indicate financial stability.

$$G ext{-}Score = 1,650\ X1 + 3,404\ X2 - 0,016\ X3 + 0,057$$

X1 is working capital/total assets, X2 is net profit before interest and tax/total assets, and X3 is return on assets.

- c. **Zmijewski X-Score**. This score predicts bankruptcy within two years using return on assets, debt ratio, and current ratio. A score below 0.5 suggests higher default probability.
 - X-Score = -4,3 4,5X1 + 5,7X2 0,004X3 X1 is return on asset, X2 is debt ratio, and X3 is current ratio.
- d. **Springate S-Score**. This score is similar to Altman's, uses ratios like working capital to total assets and net profit before taxes to current liabilities. The formula evaluates

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financial health and bankruptcy risk.

S-Score = 1,03X1 + 3,07X2 +0,66X3 +0,4X4

X1 is working capital/total asset, X2 is net profit before interest and taxes/total asset, X3 is net profit before taxes/current liability, and X4 is sales/total asset.

- Hypothesis development

a. Differences in results of Altman, Grover, Zmijewski, Springate Models in predicting corporate bankruptcy. There are significant differences in the bankruptcy prediction results produced by various models due to several factors. Each model has advantages and uses different financial report variables, which can result in different outcomes (Azzahro & Soemaryono, 2020). According to signaling theory, the information provided by companies through bankruptcy prediction models serves as a strong signal regarding the company's actual financial condition, which crucial for investors, creditors, and stakeholders making other in decisions economic (Kusumawardani et al., 2021). Agency theory also explains that bankruptcy prediction models can as monitoring tools principals to evaluate managerial performance and monitor corporate bankruptcy risks (Sari Susilowati, 2021). Chandra et al. (2021), Shalih and Kusumawati Meiliawati (2019),and and Isharijadi (2017)indicate significant differences in bankruptcy prediction results across various models. Therefore, the first hypothesis proposed is: *H1*: there are significant differences in the results of the

Altman, Grover, Zmijewski, and

Springate models in predicting corporate bankruptcy.

b. The most accurate prediction model in predicting bankruptcy. Previous studies show consensus on which prediction model has the highest accuracy. Dharma (2021) finds that the Ohlson model has the highest Prasetianingtias accuracy. Kusumowati (2019) conclude that the Grover model has the best accuracy in the agricultural sector. Damayanti et al. (2023) find that the Zmijewski model is the most accurate in the logistics transportation sector, while Edi and Tania (2018)find that Springate model is the most accurate in the plantation and crop sub-industry with an accuracy of 85.33%. These findings indicate that the most accurate model can vary depending on the context and industry sector. Therefore, second hypothesis proposed is: H2: there is one prediction model with the best accuracy predicting bankruptcy of consumer non-cyclical sector companies listed on the Indonesia Stock

3. Research method

2020-2022.

This study is quantitative and based on the positivism philosophy. It aims to examine a specific population or sample and analyze quantitative or statistical data to test predefined hypotheses (Sugiyono, 2020). Furthermore, it is comparative, comparing four prediction (Altman, Grover, Zmijewski, Springate) to determine the most accurate model in predicting corporate bankruptcy. Data is collected using documentation techniques, using secondary data from financial reports of companies listed on Indonesia Stock Exchange (IDX) in the

Exchange (IDX) for the period

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consumer non-cyclical sector for 2020-2022. The population is comprised of all companies listed on the IDX in the consumer non-cyclical sector from 2020 to 2022. Using purposive sampling, 80 companies that consistently publish audited financial reports were selected, resulting in a total of 240 samples over three years. The data analysis has some procedures as follows.

- a. The financial ratio calculation. Financial ratios are calculated from the financial statements of companies in the consumer non-cyclical sector for 2020-2022, categorized into distressed and non-distressed based on net profit.
- b. Descriptive statistical analysis. Descriptive statistics summarize the including data. mean. standard deviation. variance. maximum. minimum, sum, range, kurtosis, and skewness (Ghozali, 2021). In the sense of presenting a simple summary of the data using the mean, median, mode, range and standard deviation in the four bankruptcy prediction models.
- c. Normality test (Kolmogorov-Smirnov). This test checks if residuals are normally distributed (Ghozali, 2021). If normality is not met, the Kruskal-Walli's test will be used (Sastrawan & Dewi, 2022).
- d. Kruskal-Wallis This test. nonparametric test determines if there are differences significant between independent variables on a numerical ordinal dependent variable (Priyatno, 2013). H0 is there is no significant difference between the dependent variables while H1 is there is a significant difference between the

- dependent variables. With the following decision area: If the p-value < 0.005 then the hypothetical decision is to reject H0 and accept H1 or which means there is a significant difference, in this case analyzing the differences in the comparison of the Altman, Grover, Zmijewski, and Springate models in predicting bankruptcy.
- e. Best accuracy test. The confusion matrix method evaluates prediction models' accuracy, sensitivity, precision, comparing the performance of Altman, Grover, Zmijewski, and **Springate** models against actual financial health. There are four main classifications in the confusion matrix. Namely Sensitivity, precision. according accuracy, (Cindik Armutlulu, 2021), Metrics accuracy, sensitivity, precision and specificity are all calculated through a confusion matrix and the cells in the table represent classification. In this case the focus of the test tool is only limited to accuracy testing.

4. Result and discussion

Result

Table 1 summarizes the financial distress predictions for Altman, Grover, Zmijewski, and Springate models across the years 2020, 2021, and 2022 for companies in the non-cyclical consumer sector listed on the IDX. The data highlights varying predictions of Financial Distress (FD), Gray Area (GA), and Non-Financial Distress (NFD) categories, showcasing distinct patterns and trends observed annually.

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Table 1. Financial distress condition 2020-2022

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Prediction Model —	FD	GA	NFD	- Sample
Year 2020				
Altman	28	27	25	80
Grover	17	1	62	80
Zmijewksi	13	0	67	80
Springate	38	0	42	80
Year 2021				
Altman	17	36	27	80
Grover	12	1	67	80
Zmijewksi	8	0	72	80
Springate	30	0	50	80
Year 2022				
Altman	17	38	25	80
Grover	17	0	63	80
Zmijewksi	13	0	67	80
Springate	26	0	54	80

Table 2 shows that the mean value of the Altman Z Score model shows a positive number of 2.3583, Grover's positive 0.5620, Zmijewski's negative 1.4974, and Springate's positive 1.1400 which indicates that of the four models, only the Zmijewski model shows negative results which indicates that the majority of companies with model predictions Zmijewski was at a loss during that period. The lowest or minimum value for the Altman Model is negative 0.27 with company code (JAWA, 2020), Grover negative 1.19 with code (WICO, 2022), Zmijewski negative 4.30 with code (BOBA, 2021), and Springate negative 1.13 with issuer code (BTEK, 2020). Indicates that companies with this code are experiencing financial difficulties at the lowest point compared to other companies in that sector and period. The highest value or maximum Altman Model is positive 8.58 with code (CEKA, 2022), Grover positive 3.47 code (AISA, 2020), Zmijewski positive 2.87 code (WICO, 2022), and Springate positive 6.97 code (HOKI, 2022), indicating that the company experienced significant quite profits compared to other companies in this sector research period. The standard deviation value or how big the spread of data is in the Altman Model is positive 1.47638, Grover negative .68911. Zmijewski positive 1.45375, and Springate positive 1.01891.

Table 2. Descriptive statistics

	N	Range	Min	Max	Mean	Std. Deviation
Altman	240	8.85	-0.27	8.58	2.3583	1.47638
Grover	240	4.66	-1.19	3.47	.5620	.68911
Zmijewski	240	7.17	-4.30	2.87	-1.4974	1.45375
Springate	240	8.10	-1.13	6.97	1.1400	1.01891

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Table 3 shows the results of normality test where the average prediction model is smaller than 0.05 (especially Shapiro-Wilk). Based on results, it is concluded

that data are not normally distributed so testing the first hypothesis will use the Kruskal Wallis test.

Table 3. Normality test

	Kolmogorov	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.	
Altman	0.078	240	0.001	0.955	240	0.000	
Grover	0.052	240	0.200	0.976	240	0.000	
Zmijewski	0.054	240	0.090	0.977	240	0.001	
Springate	0.058	240	0.046	0.951	240	0.000	

Table 4 shows the results of the Kruskal-Wallis test where the significance level is 0.000 or less than 0.05. Thus, it can be concluded that H1 is accepted, which means there is a significant difference in

the results of bankruptcy predictions in the four prediction models in predicting the bankruptcy of companies in the non-cyclical consumer sector listed on the IDX for the 2020-2022 period.

Table 4. Kruskal -Wallis test

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Model prediction	N		Mean Rank
Altman		240	744.25
Grover		240	440.59
Zmijewski		240	169.70
Springate		240	567.46
Chi-square			547.298
df			3
Asymp. Sig.			0.000

Table 5 shows the prediction model comparison of the scores. The results show that the Zmijewski Model is very good in calculating the level of financial health of companies, while the Altman Model is the

worst in calculating the level of financial health of companies in the non-cyclical consumer sector listed on the IDX for the 2020-2022 period.

Table 5. Prediction model comparison results

Predict	Altman	Grover	Zmijewski	Springate
Not Healthy	62	46	34	94
Gray Area	101	2	0	0
Healthy	77	192	206	146

More specific, Table 6 presents the predicting accuracy of each model during 2020 to 2022. The results show that the accuracy level of the Altman Model, Grover Model, Zmijewski Model, and

Springate Model in predicting and analyzing financial distress conditions are 85.83%, 90.41%, 82.91%, and 77.08% respectively.

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Table 6. Predicting accuracy

	•		Actual			
			NFD	FD	Accuracy	
	D 11.	NFD	158	9 (Type 2 Error)	(150, 40) / (150, 40, 25, 0)	
Altman Z-score	Predict	FD	25 (Type 1 Error)	48	(158+48) / (158+48+25+9) = 85,83%	
Grover G-score	Predict	NFD	177	16 (Type 2 Error)	(177+40) / (177+40+7+16) = 90,41%	
Glovel G-scole	Tredict	FD	7 (Type 1 Error)	40	(177+40)7 (177+40+7+10) = 30,4170	
Zmijewski X-score	Predict	NFD	174	32 (Type 2 Error)	(174+25) / (174+25+9+32) = 82.91%	
Zimjewski A-score	Tredict	FD	9 (Type 1 Error)	25	(1/4+23)/ (1/4+23+7+32) = 62,71%	
Springate S-score	Predict	NFD	137	9 (Type 2 Error)	(137+48) / (137+48+46+9) = 77.08%	
		FD	46 (Type 1 Error)	48	(13/1740)/ (13/174074077) = //,00%	

NFD is Non-Financial Distress; and FD is Financial Distress

Discussion

a. Differences in bankruptcy prediction models. The Kruskal-Wallis test results this study definitively differences significant the bankruptcy prediction outcomes of the Altman, Grover, Zmijewski, Springate models for non-cyclical consumer sector companies listed on the IDX from 2020 to 2022. The significance of 0.000 (p < 0.05) definitively confirms these differences. This finding is in line with the findings of Meiliawati and Isharijadi (2017), and Peter et al. (2021). These findings are highly relevant to signal and agency theories. Different prediction models send different signals about a company's financial health, which directly influence investor perceptions and decision-making. Azzahro and Soemaryono (2020) assert that the distinct elements used in each model's financial statements produce different affecting outcomes, investor perceptions of a company's stability. The models' varying levels of accuracy reflect an information asymmetry between management and shareholders. This makes it clear that

- multiple models are essential for comprehensive gaining financial insights. The differences in prediction outcomes make it clear that a company's financial health must be comprehensively assessed using a variety of analytical tools. Early warning systems from different models must be used to help management and preventive investors take action. Oppusunggu (2022) asserts that a robust early warning system can preemptively address potential bankruptcies, thereby boosting investor confidence company's in transparency and reliability.
- b. Most accurate prediction model. Grover's model is the most accurate, with 90.41% accuracy rate. surpassing Altman (88.84%),Zmijewski (82.80%), and Springate (77.51%). This confirms the findings of Prasetianingtias and Kusumowati (2019), and Chandra et al. (2021). Grover's model is more accurate because it selects relevant financial ratios like ROA and WCTA, which effectively reflect the stability and efficiency crucial for the consumer non-cyclical sector. Higher liquidity

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ratios indicate better capability to cover short-term debts and operational costs, making Grover's model more reliable in predicting bankruptcy. This is according to Stepani and Nugroho (2023). Signal theory states that companies use financial reports to their signal financial health investors. Grover's financial ratios like WCTA **ROA** and provide unquestionable signals of efficiency and profitability. In a sector where stability is crucial, these ratios provide unquestionable insights into company's ability to remain operational and profitable. Signal theory also helps reduce information asymmetry between management and investors by using relevant financial ratios. According to agency theory, management might conceal financial information to maintain their positions. Grover's accurate model helps identify early bankruptcy signs, enabling timely and appropriate actions. In conclusion, the study emphasizes the importance of using diverse prediction models to capture a comprehensive view of financial health, aiding better decision-making for stakeholders and enhancing the competitive advantage in the consumer non-cyclical sector.

5. Conclusion

There are significant differences in bankruptcy prediction models. Altman, Grover, Zmijewski, and Springate models for companies in the non-cyclical consumer sector listed on the IDX for the period 2020-2022 produce significantly different bankruptcy prediction outcomes. of Kruskal-Wallis results (significance is less than 0.05) confirm these differences. This variability is the result of the distinct combinations of variables and ratios used by each model, as well as their development based on different historical data and conditions.

Grover's model is the most accurate. There is no doubt that Grover's model is the most accurate for predicting bankruptcy in noncyclical consumer sector companies listed on the IDX during 2020-2022. Its accuracy rate is 90.41%. This superiority is due to its emphasis on liquidity and profitability, which are crucial for the sector, and the use of highly relevant and sensitive financial variables that directly reflect the financial conditions of these companies. Based on this study, there are several suggestions as follows.

- a. For companies: the Grover model is the best tool for monitoring financial health. It is proven to be effective, and companies should adopt it. Management and financial staff must be trained and educated on how to use and interpret this model in order to make better decisions. Companies must also implement prudent financial policies to manage assets, investments, and financing in order to maintain financial health and reduce bankruptcy risk
- b. For investors: the Grover model is the best tool for investors to use to identify companies at risk of financial distress in the non-cyclical consumer sector. By regularly evaluating companies' financial performance using this model, investors can identify early signs of potential bankruptcy and take necessary actions, such as reducing exposure or selling shares, to mitigate investment risks.
- c. Future researchers must expand the sample size to obtain more generalized and robust results. They should also apply bankruptcy prediction models to other sectors listed on the IDX to gain deeper insights into each model's effectiveness across different industries. Furthermore, incorporating such external variables macroeconomic conditions, government policies and regulatory prediction changes will enhance

accuracy. Finally, using other statistical techniques like logistic regression or probability tests will further refine the models' predictive capabilities.

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