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Research Article

The accuracy of financial distress prediction models in various Indonesian industrial companies

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ABSTRACT

Market participants use the forecast of the financial crisis as an indication and early warning system. This study aims to examine the efficacy of eight models for predicting bankruptcy in Indonesian industrial enterprises. Secondary data from various industrial sector companies listed on the IDX for the 2016–2020 timeframe was utilized in this study. The approach employed in this study, which is not based on the Z-Score from 1968, the Revised Z-Score from 1984, the Z-Score Modified from 1995, Springate from 1978, Ohlson from 1980, Zmijewski from 1983, Fulmer from 1984, or Grover from 2001, is a quantitative descriptive study method. Fulmer's model was proven to be foreseeable by the study's findings, and Grover and Almant improved it to make it more accurate than competing prediction models.

Keywords: financial distress; accuracy; various industry; Indonesia

1. INTRODUCTION

In general, the financial distress-FD prediction is a projection of the company's situation in times of financial distress. According to Platt and Platt (2006), although a company's financial difficulty and bankruptcy cannot be compared, the bankruptcy model can be used to predict impending financial distress by representing bankruptcy as the resolution of the company's suffering. FD is a financial issue that a company encounters, according to Sun, et al. (2014). The projection of financial distress (PFD), then, is a forecast of financial distress circumstances before being declared bankrupt, according to the definition provided above. The state of being bankrupt is when a firm is unable to fulfill its financial obligations. Gitman (2012) defines bankruptcy as a situation where a company's debt exceeds the value of its assets. According to Hilda (2013), FD is associated with persistent firm liquidity issues.

According to Karas and Srbová (2019), both conventional and non-traditional models can be used to predict bankruptcy. The discriminant models mentioned by Wieprow and Gawlik (2021) of Poland include using the Almant Z-Score indicator as a reliable prediction model for forecasting bankruptcy. Using a neural network application with short-term memory, claim Vochozka, et al. (2020), is one method of bankruptcy prediction. In contrast, Alam et al. (2020) found that a machine learning-based bankruptcy prediction model is still more accurate at predicting bankruptcy than discriminant approaches like the Almant Z-Score. Discriminant models, among other PFD models, are used in various references to analyze corporate bankruptcy, including the Z-Score (1968), the Revised Z-Score (1984), the Z-Score Modified (1995), the Altman (1978), the Ohlson (1980), the Zmijewski (1983), the Fulmer (1984), and the Grover (2001) models. However, each of these models produces a different set of results when applied. According to Adnan Aziz and Dar (2006), each of these predictive models has its flaws and lacks any unique characteristics. For investors, PFD models take on a significant indication role. According to Agrawal and Maheshwari (2019), predicting a company's bankruptcy is extremely sensitive and has a big impact on the return on investment. Insolvency prediction is a significant aspect in an unpredictable time, as stated by Idress and Qayyum (2018) and Bateni and Asghari (2020). According to ElBannan (2021), implementing certain tactics for boosting capital and corporate ownership as well as keeping steady investments will improve risk mitigation and lessen financial suffering.

There has been numerous research done in different nations, and the findings from Indonesia reveal mixed outcomes. According to research on the American Stock Exchange by Andreou, Andreou, and Lambertides (2021), there is a sizable amount of encouraging information regarding the relationship between changes in bankruptcy risk and future stock prices in the short term. Altman, Conan, and Holder, Tafler, Springate, and Zmijewski models were used by Bărbuţă-Mişu and Madaleno (2020) in their analysis of 5 bankruptcy prediction models for the years 2006–2015. In various European countries, they discovered that traditional prediction models had a significant impact on the success of businesses that take on too much risk. Prusak (2018) conducted tests in several Eastern European nations, including Poland, Lithuania, Latvia, Estonia, Ukraine, Hungary, Russia, Slovakia, the Czech Republic, Romania, Bulgaria, and Belarus. The study discovered that the Czech Republic, Poland, Slovakia, Estonia, Russia, and Hungary adopted a bankruptcy prediction model in addition to their conventional methods, except for Lithuania, Ukraine, Romania, Belarus, Bulgaria, and Latvia. Indriyanti (2019), who looked at the top 25 tech-producing nations worldwide found that the Grover model offered the highest accuracy when compared to other prediction models out of the seven bankruptcy prediction models used for the 2015–2016 period.

Using data from companies listed in the Visegrad Country group for the years 2015–2016, Kliestik, et al. (2018) discovered a model for predicting bankruptcy that combined financial ratios to have a higher level of accuracy. The ratios of current assets to current liabilities, net income to total assets, current liabilities and non-current liabilities to total assets, cash, and cash equivalents to total assets, and return on equity are examples of these ratios. The study's findings suggest that predicting bankruptcy can be a useful tool for creditors, suppliers, and business partners to determine the viability of their partner companies. Additionally, research in developing nations also yields undifferentiated results. The profitability and solvency ratios were discovered to be ratios that were influenced by financial distress by Sareen and Sharma (2022), who tested the bankruptcy prediction of automotive businesses in India. The bankruptcy prediction model, according to Ullah, et al. (2021), is still valid for Pakistani financial companies. Idress and Qayyum (2018) claimed that business stock returns on the Pakistan Exchange were not significantly impacted by the financial distress ratio. Examining data from both bankrupt and non-bankrupt Iranian enterprises, Bateni and Asghari (2020) discovered that the logit model and genetic algorithm are highly reliable predictors of bankruptcy.

Boni, et al. (2020) discovered at the start of the bankruptcy process the Alman Z-Score prediction model to be a better bankruptcy prediction model in Serbia. Before bankruptcy, the Zmijewski model was superior to the Almat Z-Score model. In Colombia, Arroyave (2018) found discriminant models like the Almant Z-Score and others. In Vietnam, Accounting and market indicators continue to be the primary elements in bankruptcy prediction, in addition to macroeconomics, according to Pham, et al. (2018). In predicting bankruptcy using a variety of financial performance and corporate governance metrics, Chen, et al. (2020) highlighted the importance of CEO duality and debt ratios in Taiwan. The usage of financial measures, such as the Almant-Z score model, is still sensible in predicting financial distress, according to a study by Vietnamese researchers Thinh, et al. (2021). According to Matenda, et al. (2021), non-SOE bankruptcy prediction studies still need to be performed because of diverse business characteristics. Inconsistent results were also obtained from recent Indonesian research that examined the impact of stock returns on bankruptcy prediction models. The Almant Z-Score methodology affects the stock prices of Indonesia's national private banks, according to Sarumpaet (2021). For restaurants and hotels, Kesuma, et al. (2021) found that the Grover model was more accurate than the Springate model; Nugroho, et al. (2021) revealed that financial distress contributed to stock returns in Indonesia. According to Tristanti and Hendrawan (2020), the Almant Z-Score model was more accurate in predicting state-owned company bankruptcy.

According to Susilowati and Simangunsong (2019), the Almant Z-Score model affects the stock prices of companies that manufacture consumer goods. Junaeni (2018) discovered the Almant prediction model had a nearly 96% influence on Indonesian banking stock prices. Prasetiyani and Sofyan (2020) claimed that the Almant-Z Score and the Springate model are superior models for predicting bankruptcy in retail trading companies. According to Syamni, et al. (2018) research on mining businesses, the modified Ohlson and Almant model has a more significant impact on mining stock prices than the Grover, Springate, and Zmijewski models. The explanation that has been given above demonstrates that there is still disagreement regarding the optimum model for examining this financial distress prediction model. These variations include the diversity and traits of various businesses. The purpose of this study is to evaluate the efficacy of the financial distress prediction models Z-Score-1968, Revised Z-Score-1984, Z-Score Modified-1995, Springate-1978, Ohlson-1980, Zmijewski-1983, Fulmer-1984, and Grover-2001 in a variety of Indonesian industrial companies.

Companies in diverse industries were chosen because they come extremely near to satisfying the demands of the community. Additionally, businesses in various industries are divided into several groups with a variety of activities. For instance, heavy machinery, automobiles, auto parts, clothing, footwear, cables, and electronics. Because of this variability, various results are anticipated from this study. The research is organized into four parts: part 1 provides an introduction, a discussion of the data and research models in Part 2, results and discussion in Part 3, and Part 4 as a conclusion.

2. RESEARCH METHOD

This study was carried out in Indonesia on a number of industrial sectors that issued securities on the Indonesian Stock Exchange between 2016 and 2020. A sample of 40 companies was obtained by employing a purposive sampling strategy to choose each of these samples from 51 populations. the data has been tabulated and assembled in a data format that follows the bankruptcy prediction model. Companies are assessed to have the potential to be healthy, bankrupt, or not, according to the calculation results. Knowing the bankruptcy prognostication values for each of the financial hardship prognostication models—Z-Score (1968), Revised Z-Score (1984), Z-Score Modified (1995), Springate (1978), Ohlson (1980), Zmijewski (1983), Fulmer (1984), and Grover (2001)—is the first step in predicting bankruptcy.

Table 1. Formulas of Model Financial Distress

Altman Z Score -1968	Z = 1,2 X1 + 1,4 X2 + 3,3 X3 + 0,6 X4 + 0,999 X5	Z = Altman Z score X_1 = Working capital/Total asset X_2 = Retained Earnings/Total Asset X_3 = Earnings Before Interest and Taxes/Total Asset X_4 = Book value of (Equity/total debt) X_5 = Sales/total assets	Z > 2,99 = healthy Z < 1,8 = bankrupt Z 1,81-2,99 = grey area
Altman Z- Score Revised -1984	Z' = 0,717X1 + 0,847X2 + 3,107X3 + 0,420X4 + 0,998X5	Z = Altman Z score revision X_1 = Working capital/Total asset X_2 = Retained Earnings/Total Asset X_3 = Earnings Before Interest and Taxes/Total Asset X_4 = Book value of (Equity/total debt) X_5 = Sales/total assets	Z > 1,23 = healthy Z < 2,9 = bankrupt Z 1,23-2,9 = grey area
Modified Altman-Z-Score -1995	$ZM = 6{,}56X_1 + 3{,}26X_2 + 6{,}72X_3 + 1{,}05X_4$	ZM = Modified Altman-Z-Score X_1 = Working Capital/Total Asset X_2 = Retained Earnings/Total Asset X_3 = Earnings Before Interest and Taxes/Total Asset X_4 = Book value of (Equity/total debt)	ZM < 1,10 = bankrupt ZM = 1,10-2,60= grey ZM > 2,60 = health
Springate-1978	$SS = 1{,}03X_1 + 3{,}07X_2 + 0{,}66X_3 + 0{,}4X_4$	SS = Springate Score X_1 = Working capital/Total asset X_2 = Net profit before interest taxes/total asset X_3 = Net profit before Taxes/Current liabilities X_4 = Sales/Total asset	SS > 0,862 = healthy SS < 0,862= bankrupt
Ohlson-1980	$OS = -1{,}32 - 0{,}407X_1 + 6{,}03X_2 - 1{,}43X_3 + 0{,}0757X_4 - 2{,}37X_5 - 1{,}83X_6 + 0{,}285X_7 - 1{,}72X_8 - 0{,}521X_9$	OS = Ohlson Score X_1 = Log (total assets/GNP index) X_2 = Total liabilities/total assets X_3 = Working capital/total assets X_4 = Current liabilities/current assets X_5 =1 if total liabilities>total assets; 0 if otherwise X_6 = Net income/total assets X_7 = Cash flow from operations/total liabilities X_8 = 1 if Net income negative; 0 if otherwise X_9 = (NIt – NIt-1) / (NIt + NIt-1)	OS > 0,38 = bankrupt OS < 0,38 = healthy
Zmijewski-1983	$Z = -4{,}3 - 4{,}5X_1 + 5{,}7X_2 - 0{,}004X_3$	ZS = Zmijewski Score X_1=ROA (Net income/ total assets) X_2= Leverage (Total liabilities/total assets) X_3 = Liquidity (Current assets/current liabilities)	ZS > 0 = bankrupt ZS < 0= health
Fulmer-1984	$H\text{-Score} = 5{,}52X_1 + 0{,}212X_2 + 0{,}073X_3 + 1{,}27X_4 - 0{,}12X_5 + 2{,}335X_6 + 0{,}575X_7 + 1{,}082X_8 + 0{,}894X_9 - 6{,}075$	FS = Fulmer Score X1 = Retained Earning/Total Asset X2 = Revenue/Total Asset X3 = EBIT/Total Equity X4 = Cash Flow from Operation/Total Liabilities X5 = Total Liabilities/Total Equity X6 = Current Liabilities/Total Asset X7 = Log (Fixed Asset) X8 = Working Capital/Total Liabilities X9 = Log (EBIT)/ Interest Expense	H-score< 0 = bankrupt H-score> 0 = health
Grover-2001	$GS = 1.650X_1 + 3.404X_2 - 0.016ROA + 0.057$	GS = Grover Score X1 = Working capital/Total assets X2 = Earnings before interest and taxes/Total assets ROA = net income/total assets	GS ≤-0,02 = bankrupt GS ≥ 0,01 = health

Accordingly, the predicted value of each of the three categories—healthy, bankrupt, and between bankrupt and healthy—is calculated using the prediction model in Table 1 above. After comparing the model with the highest predictive value to the number of samples, a model with a higher accuracy value is drawn.

3. RESULTS AND DISCUSSION

The findings of this study agree with Table 2, which is based on the bankruptcy prediction models that were chosen for analysis. The outcomes of anticipating financial distress for businesses in several industrial sectors between 2016 and 2020 are detailed in Table 2 below. The Z-model Score-1968, Revised Z-Score-1984, Z-Score Modified-1995, Springate-1978, Ohlson-1980, Zmijewski-1983, Fulmer-1984, and Grover-2001 are used as the starting points for the explanation. Almant's three financial distress prediction models, including the Almant model made up of the original Z-score model, the revised S-score model, and the modified Z-score, are described in Table 2. The three Almant models—bankrupt, healthy, and gray—include these three criteria in their analysis of financial distress. Other financial distress prediction models exclude gray criteria and merely employ bankrupt and healthy criteria.

The original Z-Score-1968 model's average predictive value for healthy companies is 31%, for bankruptcy, it is 43%, and for gray enterprises, it is 25% during the five years of the study period. The bankrupt value is below normal in 2018 and 2019, whereas it is above average in prior years. Aside from other years above the average healthy value, 2020 and 2017 are the years with predictions of healthy companies above 31%, 35%, and 33%, respectively. While the average value of companies with gray performance falls below the average value of 18% in the years 2017 and 2020, respectively. For the five-year research period, the Z-Score-Revised 1984 model produced an average predictive value of 35% for healthy companies, 25% for bankrupt, and 41% for gray companies. The bankruptcy rate is below average in 2017 and 2019, while it is greater in certain other years. Additionally, healthy company predictions for 2016 and 2017 are below 25%, 23%, and 20%, respectively, while other years are above the average healthy value and equal to the average value. While 2017 is a year with an average value of companies performing better than the average gray performance of 41, i.e. 50%, the other years are all lower than 41%.

After detailing the outcomes of data analysis using the original and modified Almant prediction models, the modified Almant prediction model's (Z-Score-M) outcomes are then discussed. According to the modified Almant prediction results, the average value of a healthy company is 66%, a bankrupt company is 27%, and a gray company is 8%. In other words, more businesses are expected to be in good health than those that may face bankruptcy or have questionable business practices. In 2017 and 2019 and 2020 (28%%, 28%, and 30%), as well as other years below the average value, groups of companies forecasting bankruptcy have been identified to be higher than the average value.

Table 2. Prediction Results of Potential Bankruptcy

Year	*PFD-Z-Score-0-1968*			Year	*PFD-Z-Score-Revised-1984*		
	Bankrupt	**Healthy**	**Grey**		**Bankrupt**	**Healthy**	**Grey**
2016	48%	25%	30%	2016	38%	23%	40%
2017	45%	35%	18%	2017	30%	20%	50%
2018	38%	30%	33%	2018	35%	25%	40%
2019	35%	30%	28%	2019	33%	30%	38%
2020	50%	33%	18%	2020	38%	25%	38%
Average	43%	31%	25%	Average	35%	25%	41%
Year	*PFD-Z-Score-Modified-1995*			Year	*PFD-Springate-1978*		
	Bankrupt	**Healthy**	**Grey**		**Bankrupt**	**Healthy**	**Grey**
2016	25%	65%	10%	2016	60%	43%	-
2017	28%	65%	8%	2017	60%	40%	-
2018	25%	65%	10%	2018	65%	35%	-
2019	28%	65%	8%	2019	58%	43%	-
2020	30%	68%	3%	2020	75%	23%	-
Average	27%	66%	8%	Average	64%	37%	-
Year	*PFD-Zmijewski*			Year	*PFD-Ohlson*		
	Bankrupt	**Healthy**	**Grey**		**Bankrupt**	**Healthy**	**Grey**
2016	78%	23%	-	2016	75%	25%	-
2017	78%	23%	-	2017	60%	40%	-
2018	80%	20%	-	2018	53%	48%	-
2019	72%	28%	-	2019	58%	43%	-
2020	78%	23%	-	2020	48%	53%	-
Average	77%	23%	-	Average	58%	42%	-
Year	*PFD-Fulmer*			Year	*PFD-Grover*		
	Bankrupt	**Healthy**	**Grey**		**Bankrupt**	**Healthy**	**Grey**
2016	20%	80%	-	2016	23%	80%	-
2017	25%	75%	-	2017	25%	75%	-
2018	20%	80%	-	2018	25%	70%	-
2019	20%	80%	-	2019	25%	78%	-
2020	23%	78%	-	2020	33%	68%	-
Average	22%	79%	-	Average	26%	74%	-

According to the Springate model, 63% of businesses are expected to fail, while 37% remain stable. 2018 and 2020 have bankruptcy probabilities of 65% and 75%, respectively, while 2015, 2017, and 2019 have probabilities that are lower than the average value of a bankrupt company. Companies that are expected to be healthy in 2016, 2017, and 2019 presented more optimistic estimates for their health than the typical year, at 43%, 40%, and 43%, respectively. The percentage of accurate predictions in 2018 and 2020—35% and 23%, respectively—is below average. According to the Zmijewski model, the likelihood of an average business failing is predicted to be 77% with a healthy 23%. The number of bankruptcies predicted for 2018 is higher than the average, which is 80%; the scores for 2016, 2017, and 2020 are all 78%, except 2019, which has a value of 72%. A total of 20% of 2018's healthy enterprises exhibit values slightly below average. Except for 2019, where the score is 28% higher than the healthy norm, 2016, 2017, and 2020 all match the average.

The worth of 58% of insolvent companies and 42% of healthy enterprises is predicted using Ohlson's prediction model. With above-average bankruptcy rates of 75% and 60% in 2016 and 2017, below-average bankruptcy predictions in 2018 and 2020, and the same average bankruptcy prediction of 58% in 2019, respectively. The projected percentage for healthy enterprises is 53% for 2020, followed by 48% and 43% for 2018 and 2019; the lowest predictions are 25% for 2016 and 40% for 2017. According to data analysis and Fulmer's Prediction Model, the value of the company is expected to go bankrupt by 21% and 79%, respectively. A healthy prediction value of 80% is observed in the years 2016, 2018, and 2019, while 75% and 78% occur in the years 2017 and 2020. Companies expected to file for bankruptcy in 2016 are somewhat less likely to do so than the average (20%) company, while those expected to file in 2018 and 2019 are slightly more likely to do so than the average (25% and 23%, respectively). According to Grover's prediction model, a healthy company has an average value of 74% while a bankruptcy-prone one is worth 26% less. The year with the highest percentage of predicted bankruptcies is 2020 (33%), followed by 23% in 2016 and a range of 25% from 2017 to 2019. A strong company in 2016 earns the greatest rate, 80%, and is considerably above the national average. In contrast, it remains above average from 2017 to 2019 except for 2020, which fell below it at 68%.

After a thorough explanation of every model employed, it is possible to draw a general conclusion from the research findings that the three Almant models used the modified Almant Model as a prediction model with greater accuracy. This is because the modified Almant model, with a prediction value of 66%, has a higher accuracy in predicting corporate insolvency under healthy conditions. If the number of gray criteria is added to the healthy criteria, the healthy prediction rate is much higher. As stated by Jayanti and Rustiana (2015), claimed that combining firms with gray criteria into a healthy group because the potential of gray companies often results in healthy criteria. While the healthy predictive value of the other two Almant models is below 50%. Furthermore, according to Fulmer and Grover's prediction model, 79% and 74% of the financial projections have the highest healthy criteria, respectively, according to the average value of the model. The bankruptcy rate for the Springate, Zmijewski, and Ohlson models is higher than that of the healthy models. It may be concluded from the above prediction findings that the modified Fulmer Grover and Almant criterion models are more accurate at predicting healthy companies than bankrupt ones. Therefore, it can be said that the three modified Almant and Fulmer Grover prediction models are more accurate than the other models. The findings of this investigation are consistent with previous research.

4. CONCLUSION

According to the study's findings, the Fulmer, Grover, and modified Almant prediction model provides accuracy levels above 50%. This suggests that the prediction model is more accurate than other prediction models in forecasting the company's accuracy. Future research will focus on other firm sectors that have the potential to yield diverse research findings. This study restricted itself to companies from a variety of industrial sectors. Thus, based on the findings of the data analysis, it is possible to conclude that the 8 models implemented in this study have different values. According to the findings, the Fulmer model, which presented 79% of healthy companies, was the most accurate, followed by the Grover prediction model, which presented 74% of healthy companies, and the Modified Almant model, which ranked third in terms of bankruptcy prediction. While the healthy company value for the other four prediction models is less than 60%.

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AUTHOR'S CONTRIBUTIONS

The authors discussed the results and contributed to from the start to final manuscript.

CONFLICT OF INTEREST

The authors declare that he has no competing interests.

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