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THE BATTLE OF FINANCIAL PREDICTION METHODS: WHICH IS THE MOST PREDICTIVE?

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ABSTRACT
This essay aims to see how the pandemic affects the company and evaluate its impact on operations, financial stability, and prospects. As a result, the financial difficulty model should be constructed as a model of early warning systems. Like this attempt, the aim is to prevent the company's bankruptcy. This research aims to analyze the accuracy of the most accurate predictor model of financial difficulty among the various predictors of financial difficulties. The models are Altman, Springate, Zmijewski, and Grover. Data is collected through an Excel pool and then processed in quantitative research. The dummy variable is used to do this. The sample consisted of 145 manufacturing companies listed on the Indonesian Stock Exchange from 2016 to 2020. The analytical tool used is binary logistic regression. The results suggest that the Zmijewski, Springate, and Grover models and the Altman models can be used to predict financial difficulties. Because of its highest significance level compared to other models, the Grover model is the most appropriate model for predicting financial difficulties. In cases where primary emphasis is given to assets and ROAs as indicators of financial difficulties, the Grover model is used.

Keywords: Financial Prediction, Altman, Springate, Grover.

INTRODUCTION

In an increasingly complex and dynamic business environment, the quality of management decisions is becoming critical to a company's survival. One crucial factor that needs to be considered by management is the company's financial condition. Realizing how crucial information about financial distress in the company is, management needs to predict these conditions. Financial distress is one of the circumstances in which a company faces difficulties in fulfilling its financial obligations. Companies that experience financial distress often face problems such as decreased revenue, increased debt, decreased profitability, and inability to pay debts on time. If financial distress is not appropriately predicted, the consequences can be very detrimental to the company, including the risk of bankruptcy that can potentially destroy the company. One of the reasons it is essential to predict financial distress is to reduce risks and losses for the company. By understanding and anticipating financial distress conditions, management can take appropriate preventive steps to minimize its negative impact, for example, by setting up a financial contingency plan, reducing unnecessary debt, reevaluating investment strategies, or finding alternative sources of income. Thus, companies can avoid the loss of assets, reputation, and customer trust that may occur if financial distress is not adequately anticipated.

The COVID-19 pandemic has caused various financial difficulties in various companies, such as supply chain disruptions (Orlando et al., 2022) and the economic crisis (Brennan et al., 2022), resulting in an increased likelihood of financial disaster and bankruptcy risk (Crespí-Cladera et al., 2021). To avoid bankruptcy during the COVID-19 pandemic, the company made various adaptations and innovations to survive during a pandemic. Paying attention to employee health and safety, as well as adjusting business and operational strategies to survive challenging times. However, it is undeniable that the COVID-19 pandemic has had a profound and lasting impact on companies from various sectors around the world. The event caused disruptions, financial challenges, and changes in consumer behavior, as all companies affected by COVID-19 had to adapt and change how they worked to survive in the current conditions. The COVID-19 pandemic has exposed companies to financial instability as they struggle with declining sales conditions and cash flow challenges. Given this instability, many companies are implementing cost-reduction measures, including closures and salary cuts, to survive the economic recession caused by the COVID-19 pandemic. Because many companies know the importance of innovation, risk management, and resilience in a company. However, when companies experience post-pandemic impacts, they are less likely to adapt, innovate, and prioritize security and risk management well, and many do not survive these future challenges.

Prediction of bankruptcy of enterprises has long been a significant subject of study. This proved accurate, especially when the COVID-19 pandemic hit Indonesia in early 2020, causing many companies on the Indonesia Stock Exchange (IDX) to go bankrupt. High market costs and a declining economy led to bankruptcy. Due to the economic downturn that occurred at the time, many shareholders, companies, and financial institutions were interested in financial hardship prediction models (FDPs) to help them determine whether or not their companies were in trouble in the early stages of hardship (Wei-Yang Lin et al., 2012) (Olson et al., 2012. Financial Distress Prediction (FDP) mostly used statistical models in previous years. For example, Fitzpatrick's (1932) study compared thirteen Financial Ratios (FR) of standard and bankrupt companies. In addition, financial hardship prediction (FDP) is often used with analysis such as logit analysis (Ohlson, 1980), univariate (Beaver, 1966), and discriminant analysis (Altman, 1968). However, the financial difficulty model Altman (1968) created is still frequently used today.

A 1990 study found that machine learning methods such as artificial neural networks have a higher prediction accuracy rate than statistical techniques such as logistic analysis and discrimination analysis. Numerous studies have begun using machine learning methods to predict financial problems after the statement is made. This study has used support vector machines, k-nearest neighbors, decision trees, and neural networks. Group learning methods are a category of machine learning that combines various classification methods. The group stacking method is better than the group classifier method (Kim, 2018) (Liang et al., 2018) (Aghav et al., 2016) (Xia et al., 2018).

Companies can use various methods to predict financial distress, such as the Grover method, Altman Z-score, Springate, Zmijewski, and Ohlson. Companies must consider influencing factors, such as economic conditions, liquidity, solvency, and financial performance. By predicting financial distress, companies can take appropriate action to avoid bankruptcy and maintain business continuity.

THEORETICAL FRAMEWORK AND HYPOTHESES

a. Financial difficulties (Financial Distress)

Financial distress is a condition in which an individual or organization is unable to meet its financial obligations. This can happen due to a variety of factors, such as decreased income, excessive debt load, economic recession, or poor financial management. The financial distress method offers a structured framework for effectively addressing these issues.

The business will experience financial difficulties, usually marked by negative net operating income for two consecutive years (Ningsih & Asandimitra, 2023). It is possible that this situation is a pre-bankruptcy stage of the company because the company cannot settle the responsibilities arising from its operations. In certain situations, a company's financial problems are usually referred to as financial difficulties (Kurniadi, 2021).

b. Metode financial distress

The Financial Distress Method is a formal framework that includes a variety of strategies and approaches for managing and overcoming financial difficulties. This involves reducing costs, increasing revenue streams, debt restructuring, asset dissolution, and seeking professional help. By applying this method, individuals and organizations can strive to alleviate financial hardship and regain stability. The formal nature of these approaches ensures that they are well structured and can be adopted professionally and organized, increasing the chances of a successful recovery. The formula used is as follows:

Altman Model

The equation proposed by Altman's model is:

$$Z' = 0.717X_1 + 0.847X_2 + 3.108X_3 + 0.42X_4 + 0.988X_5$$

Information:
Z = bankruptcy index
X1 = working capital or total assets
X2 = retained earnings or total assets
X3 = earnings before interest and taxes or total assets
X4 = book value of equity or book value of total debt
X5 = sales or total assets.
Source: (Altman, 1968)

Springate Model

The model equation proposed by Springate is:

$$Z = 1.03A + 3.07B + 0.66C + 0.4D$$

Information:
A = Working Capital or Total Assets
B = Net Profit before Interest and Taxes or Total As- sets
C = Net Profit before Taxes or Current Liabilities
D = Sales or Total Assets
Source: (Bimo Aryo Seto, 2021)

Żmiyevsky Model

The model equation is:

$$X = -4.3 - 4.5 + 5.7\ X_1\ X_2 - 0.004X_3$$

Description:
X1 = after-tax earnings or/total assets
X2 = total debt or total assets
X3 = current assets or current liabilities
Source: (Zmijewski, 1984)

Grover Model

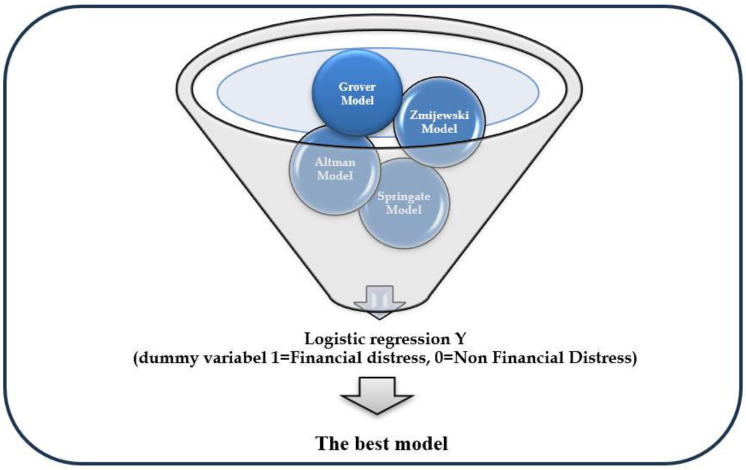
The equation in this case is as follows:

$$Score = 1.650X_1 + 3.404X_2 - 0.016ROA + 0.057$$

Information:
X1 = Working capital or Total assets
X2 = Earnings before interest and taxes or total assets
ROA = *net income or total assets*
Source: (Robiansyah et al., 2022)

Research Framework

Based on the background and description of the literature as well as some references to this study seen earlier, the research framework model can be described as in Figure 1.



Altman Model

Altman (1968) used multiple discrimination analysis. Discriminant analysis is a statistical technique that finds the financial ratios that are considered to most influence the value of an event and then creates a model to make it easier to draw conclusions about that event. The Altman model is one method for measuring bankruptcy performance. It changes over time, not fixed or stagnant. Altman's bankruptcy model has evolved to allow it to be applied to corporate bonds, manufacturing, and non-manufacturing companies, as well as public and non-public companies. Making the previous model more flexible is the goal of some of these modifications. Manufacturing companies that have gone public and companies in the private sector can both use this model. This model is used in several studies. For example, research conducted by (Bimo Aryo Seto, 2021) found that Altman's predictive model was the best for predicting the delisting conditions of companies. To predict the delisting of manufacturing companies, (Robiansyah et al., (2022) conducted additional research using the Zmijewski, Altman, and Springate models. In situations of financial crisis, Altman's model became more competitive, and previous research showed that it could be used to predict such circumstances. As a result, the study developed the following hypothesis:

H1: Altman's model predicts financial hardship better than Springate, Zmijewski and Grover

Springate Model

Gordon LV Springate (1978) created the Springate model. This model is an evolution of the Altman model of Multiple Discriminant Analysis (MDA). At first, the Springate model used 19 commonly used financial ratios. However, after testing, Springate decided to use four financial ratios to determine whether the business was healthy or potentially bankrupt. According to the Springate test, the model has an accuracy rate of 92.5%. Forty companies were used as samples of this study. Adriana (2020) examined bankruptcy predictions for food and beverage companies listed on the Indonesia Stock Exchange between 2006 and 2010. The study shows that interested parties can use the Springate method to assess business conditions and performance. In addition, Springate was found to be used to forecast future corporate bankruptcies. Springate can also be used as an early bankruptcy warning system. In this study, the relevant Springate was used to test a predictive model of the financial crisis.

H2 : Springate's model predicts financial hardship better than Altman, Zmijewski and Grover

Zhmiivki Model

Zmijewski, M.E. (1984) uses financial ratio analysis to measure the debt performance, leverage, and liquidity of a firm. In his analysis, Zmijewski used probit analysis on 800 companies that are still operating and 40 companies that went bankrupt. Later, Zmijewski created a model with ROA, leverage, and liquidity ratios. Hodgin, Robert F. and Roberto Marchesini (2020) investigated the bias of the critic sample in Zmijewski's financial distress model. The study used a sample of highly leveraged companies as an indicator of bad debts, and their findings raise doubts about the bias of the critical sample. Additional studies by Fatmawati (2021) compared delisting prediction models, including the Zmijewski, Altman, and Springate models. The analysis showed that of the three models, Zmijewski showed more accurate predictions of company delisting than the Altman and Springate models. The hypotheses proposed based on previous research are as follows:
H3: Zmijewski's model predicts financial hardship better than Altman, Springate, and Grover

Grover Model

Using Grover, Altman Z-Score, Springate, and Zmijewski's bankruptcy prediction analysis model on companies in the food and beverage industry listed on the Indonesia Stock Exchange (IDX), Evi, Ni Made et al. (2018) also conducted research using Grover's model, which was created by restoration or redesign of the Altman Z-Score model. It takes X1 and X3 from the Altman model and then adds the profitability ratio indicated by ROA. The results showed that Grover's model had the highest accuracy rate, which was 100%, while Altman's Z-Score model had an accuracy rate of 80%, Springate's model 90%, and Zmijewski's model 90%. The hypotheses proposed based on previous research are as follows:
H4: Grover's model predicts financial hardship better than Altman, Springate, and Zmijewski

METHODS

1. Types of Research

The study uses the concept of non-parametric statistics which is an independent interpretation of statistics in the population corresponding to the normal distribution. Based on the characteristics of the problem, this study can also be a historical study because it uses financial statement data from 2017 to 2020. It is also considered as a descriptive study which is the study of a particular phenomenon or population obtained by the subject researcher in the form of an individual, organizational, industrial, or other perspective. Descriptive research aims to provide an overview of the financial difficulties used by outlining several financial hardship models.

2. Population and Sample

Population is a generalized area consisting of objects or subjects with certain attributes and qualities that have been determined by the researcher to study and then arrive at conclusions (Sugiyono, 2021, p. 53). The population of this study consisted of manufacturing companies listed on the Indonesia Stock Exchange. Part of the population is the Sugiyono sample (2021, p. 53). The sampling technique using non-probability sampling with certain criteria is used. The combined technique, which combines the intersection of data with a time sequence, is used to collect samples. This is done because data aggregation may be limited. Sample criteria consist of general criteria and specific criteria. General criteria are the criteria that each sample of the types mentioned below must meet:

Table 1. Sampling Criteria

No	Research Sample Criteria	Total
1.	Manufacturing companies listed on the Indonesia Stock Exchange from 2017 to 2020	171 Company
2.	Manufacturing companies that did not provide financial statements from 2017 to 2020	17 Company
3	Manufacturing companies that do not have complete data on research variables from 2017 to 2020	09 Company
Total Companies used in the study		145 Company
Amount of data analyzed 145x4		580 Year Data

There are specific standards used to determine if a business is facing financial problems. There is no clear definition of what is meant by a company experiencing financial problems or a stage of decline. According to Almilia, Luciana Spica, and Kristijadi (2017), the identification of financial problems can be done for two years of operating net income (net operating income) and negative for more than one year of not paying dividends. Sheikhi, Maryam et al. (2021) found financial problems for businesses that have lost at least half of their capital for two consecutive years. This study aims to determine whether companies experiencing financial problems have a return on equity (ROE) lower than Information Management (BI) Fees, if the equity is positive; conversely, companies that do not experience financial problems have a higher return on equity (ROE) than BI Fees. ROE shows how well the company's management uses the capital entrusted by the shares.

Table 2. Hypothesis Testing Methods

Probability Values	Classification
P < 1% 1% > P < 5%	Strong Significant Moderate Significant
5% > P < 10%	Weak Significant
P > 10%	Not Significant

According to Sri Hermuningsih (2018), the smaller the Probability Values value shows that the company has a smaller risk of bankruptcy, related to the company's performance will be able to grow again and will make investors see this as a positive signal from the company, thereby increasing investor confidence and allowing management to attract capital in the form of shares.

a. **Data Sources**

This study used secondary data taken from the Indonesia Stock Exchange (IDX). Secondary data used in the form of notes to past financial statements contained in documents both published and unpublished. Data types include combined data categories, which are combinations of time series data (time series data). Where the research time was used for four years, from 2017 to 2020.

b. **Data Collection Techniques**

Non-participant observations were applied in this study to collect data to be used. Data obtained in the form of the company's financial statements in 2017 - 2020, obtained indirectly from related sources. Financial statements are used as data obtained from the IDX website through www.idx.co.id.

c. **Operation Variable Definition**

Dependent variables use dummy variables. The dependent variable is a qualitative variable. Financial problems have various definitions as described earlier, so Dummy variables are used to assign attributes to dependent variables. Attribute 0 is for companies that are experiencing financial difficulties and attribute 1 is for companies that are not in financial difficulties. Instead, the independent variable is the score of each company's loss-predicting model. The prediction model used is a model of the financial distress prediction model that has been developed, namely the Altman Z-Score, Springate, Zmijewski, and Grover models.

d. Data Analysis Techniques

All hypotheses were tested to determine the most accurate financial distress model using logistic regression analysis. Regression logistics is used when a dependent variable is in the form of a dummy variable, to see if there is an independent variable effect on the dependent variable in the form of a dichotomous variable or a binary variable. This analysis uses program statistics from Microsoft Excel.

DATA ANALYSIS AND DISCUSSION

a. Descriptive Statistics

Table 3. Descriptive Statistics Results

Financial Distress Model	Altman	Springate	Zmijewski	Grover
Minimum	-94,27	-27,63	-159,90	-50,98
Maximum	250,81	1.744,29	1.597,14	272,18
Mean	4,66	8,11	3,15	2,30
Std. Deviation	15,00	96,46	72,11	17,82
N	580	580	580	580

In this study, 580 samples were collected from 145 manufacturers listed on the Indonesia Stock Exchange from 2017 to 2020. With different minimum, maximum, and average values, the financial stress method using Altman has a minimum value of -94.27, a maximum of 250.81, and an average of 4.66. The value of the Springate method is from -27.63 to 1749.29, with an average value of 8.11. The Springate method has a minimum value of -27.63, a maximum value of 1749.29, and an average value of 8.11. The Zmijewski method has a minimum value of -159.90, a maximum value of 1597.14, and an average value of 3.15. While the minimum value of the Grover Method is -50.98, the maximum value is 272.18, and the average value is 2.30.

b. Hypothesis Testing

Table 4. Comparison of Regression Results

	Altman	**Springate**	**Zmijewski**	**Grover**
Chi-Square	86,842	10,174	4,732	55,811
Nagelkerke R-Square	0,267	0,031	0,018	0,236
Prediction accuracy	79,8%	58,2%	82,3%	89,9%
Wald	43,259	3,613	1,275	23,396
Coefficient	-0,386	-0,063	0,006	-1,163
Significance p-value	0,000	0,057	0,259	0,000

*)sig at 0,1

The hypothesis was tested using logistic regression with dummy variables. Regression tests were performed using the statistical program Statistical Package for Social Sciences. Table

2 shows the following results: The significant value of the Altman model is 0.000, which is smaller than the cut value of 0.1. Therefore, Altman's model has a significant influence in predicting the financial problems of manufacturing companies listed on the Indonesia Stock Exchange. The significant value of the Zmijewski model is 0.259, which is smaller than the cut value of 0.1, so it can be concluded that the Zmijewski model does not have a significant influence in predicting the financial difficulties of manufacturing companies listed on the Indonesia Stock Exchange. The significant value of the Springate model is 0.057, so it can be concluded that the Springate model has a significant influence in predicting the financial difficulties of manufacturing companies listed on the Indonesia Stock Exchange. With a significant value of 0.000, which is smaller than the cut value of 0.1, it can be concluded that Grover's model has a significant influence in predicting the financial problems of manufacturing companies listed on the Indonesia Stock Exchange.

In predicting financial difficulties, it was seen that Altman with 26.7 percent with a prediction accuracy of 79.8 percent and Springate with 3.1 percent with a prediction accuracy of 58.2 percent, Zmijewski with 1.8 percent with a prediction accuracy of 82.3 percent, and Grover with 23.6 percent with a prediction accuracy of 89.9 percent could explain the accuracy level of the company's financial difficulties. Comparison of methods shows that Grover's model has the greatest accuracy value in predicting the company's financial condition quickly. Therefore, of the four hypotheses made, the fourth hypothesis of Grover's model predicts financial difficulties better than the hypothesis of Altman, Springate, and Zmijewski is accepted, and the other third hypothesis is rejected.

Accuracy analysis of all models for prediction of financial distress

The results of accuracy analysis for all models are shown in Table 4 comparison results using logistic regression for Altman, Springate, Zmijewski, and Grover models show that Grover's model has the highest level of significance compared to other models. The coefficient of determination, or the ability of the model to explain financial difficulties, for Grover is 89.9%. Grover's model can predict financial hardship more strongly than any other available method. In this essay, it will be explained how this model is able to provide more accurate and useful predictions for individuals and companies facing financial difficulties. First, Grover's model is based on deep learning algorithms that have proven efficient in financial data analysis. The model uses Natural Language Processing (NLP) technology to study patterns and trends hidden behind available financial data. By conducting a deeper analysis of the data, Grover's Model can identify early indicators of financial hardship that other methods may have missed. In addition, Grover's model is also able to utilize a larger amount of data than other methods. Through deep learning techniques, this model can process and analyze data on a larger and more complex scale. In the complex world of finance, there are many factors that affect financial conditions, such as global economic developments, changes in government policies, and market fluctuations. By considering these factors in its analysis, Grover's Model can provide more accurate predictions and help individuals as well as companies anticipate possible financial difficulties.

In addition, Grover's Model can also identify trends and patterns related to financial difficulties. This model can study and recognize the same or similar patterns in historical financial data. Using this technique, Grover's Model can identify financial difficulties early, so that individuals and companies can take the necessary actions to avoid or minimize their negative impacts. Another uniqueness of the Grover Model is its ability to better interpret financial data. This model can produce more detailed insights and analysis of financial conditions, thus providing a maximum understanding of financial difficulties that may be faced. With a better understanding, individuals and companies can make smarter and higher quality decisions in the face of difficult financial situations. In conclusion, Grover's model is a better method of predicting financial hardship than any other available method. The model uses deep learning and NLP technologies to produce more accurate predictions and leverage larger amounts of data. In addition, the Grover Model is also able to identify trends and patterns related to the level of financial distress and provide a better understanding of difficult financial situations. Therefore, the Grover Model can be a useful tool in overcoming and anticipating financial difficulties for both individuals and companies.

CONCLUSIONS, IMPLICATIONS, SUGGESTIONS, AND LIMITATIONS

The degree of significance and coefficient of determination indicate the accuracy of Grover's model. As a result, it rejects H1, H2, and H3 but does not reject H4. This suggests that Grover's model is the best for predicting financial problems that may occur in the future. The study used logistic regression with 580 samples from 145 manufacturing companies listed on the Stock Exchange from 2016 to 2020. In addition, the model suggests that the variables present in the model are better suited for predicting financial difficulties: working capital or total assets, profit before interest and taxes or total assets, and return on assets (ROA). A decrease in ROA indicates that the company is experiencing a decrease in profits or operational efficiency, debt problems, a decrease in asset value, fiercer competition, unprofitable investments, and changes in the business structure. Therefore, they can continue to experience more severe financial hardship until the company is delisted from the Stock Exchange and ends up in bankruptcy. In addition, this study can provide additional references that can support Grover's model for predicting the financial problems of companies listed on the Indonesia Stock Exchange. The number of samples combined is based only on the number of certain assets of the manufacturing company in the same approach with different measurement methods. Therefore, alternative methods such as the Owen, Zavgren, or Taffler models are used for future research.

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