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Analysis of Financial Distress Model with Altman, Zmijewski and CA Score in Predicting the Condition of Financial Distress in Manufacturing Public Companies in Indonesia

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Abstract

The purpose of this paper is to test the accuracy of the prediction model by Altman, Zmijewski, CA Score in predicting the condition of financial distress of manufacturing companies listed on the Indonesia Stock Exchange. The research method used in this research is descriptive and comparative method. The statistical test used in this study is the discriminant method and the Nested Test. The test results show that the CA-Score model is more accurate than the discriminant research model for each calculation of accuracy every year and for each model.

Key words

Altman Score, Zmijewski Score, Financial distress

JEL Codes: G33, L60

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1. Introduction

A country's manufacturing industry plays a key role as a development machine. The development of the manufacturing industry can be used to see industrial development nationally. This development can be seen from aspects of product quality and overall industry performance. All companies are required to be able to survive and compete in the global market by producing quality products so that consumers do not move to other similar products. Competition in the manufacturing industry is now getting tougher. The going concern principle is one of the principles that must be applied by the company and it can be explained that the company will continue to carry out its operations throughout the agreement project completion process and ongoing activities (Harahap, 2013). The company's failure to maintain its going concern can be caused by two things, first, namely economic failure and the second is financial failure. Economic failure is related to an imbalance between income and expenditure. Other causes of economic failure can also be caused by the company's capital costs which are greater than the rate of return on historical costs of investment. The company is categorized as a financial failure if it is unable to pay its obligations at maturity even though its total assets exceed its obligations (Lutfie *et al.,* 2016). Based on Government Regulation in Lieu of Law (Perpu) Number 1 of 1998 which regulates bankruptcy, debtors affected by default (default) can be ensured to be bankrupt by only two debtors (Wardhani, 2007). And every company has a risk of bankruptcy which can be experienced at any time if the company's performance does not go well. Bankruptcy is defined as the failure of the company to run the company's operations to generate profits. Profit or profit is an important means to maintain the survival of the company. The higher the profit gained is expected that the company will be able to survive, grow, develop and be resilient in facing competition. The decrease in income will have an impact on the decline in operating profit, and if it occurs in a prolonged period of time, it will have an impact on business sustainability (Syahyunan *et al.,* 2017 and Erwin *et al.,* 2018). Therefore, it is necessary to study the financial performance of manufacturing companies that go public on the Indonesia Stock Exchange, to find out whether they are experiencing financial distress or not. Indicators of bankrupt companies in the capital market are companies delisted. A company that is delisted from the Indonesia Stock Exchange means that the company is written off or removed from the list of companies whose shares are traded on the IDX. Delisting can be done at the request of the company or on the orders of the Indonesia Stock Exchange because the company cannot fulfill the obligations and rules that have been set.

The initial indication of a company experiencing bankruptcy is a condition of financial difficulties or financial distress. Companies that go public can result in the delisting of the Indonesian Stock Exchange. If the company experiences a decline in performance so that it does not meet the recording requirements, the company can be excluded from the stock exchange. The table of delisted company data above shows that in 2012 of the 4 companies listed there were 2 manufacturing companies, in 2013 from 7 companies there were 2 manufacturing companies that were delisted, in 2015 from 3 companies there were 2 manufacturing companies that were delisted and in 2017 there is 1 manufacturing company delisted by IDX. This shows that quite a number of companies from the manufacturing industry sector are delisted from the IDX. In 2015 the IDX imposed a Forced Delisting process on PT. Davomas Abadi, Tbk because the business continuity was alarming and the search for addresses for the company itself was unclear so it was officially released from the IDX in January 2015. PT. Unitex Tbk was delisted because the results of operational activities carried out by the company over the past few years resulted in negative equity and could not distribute dividends to shareholders. In 2017 PT. Sorini Agro Asia Corporindo Tbk is also delisted from the IDX due to not being able to fulfill the provisions in the IDX regulation, so the company submitted a request for delisting for the go private process. Financial distress is a step in reducing a company's financial condition before bankruptcy or liquidation occurs. To overcome and minimize the occurrence of bankruptcy, companies can monitor financial conditions by using financial statement analysis techniques (Muda and Dharsuky, 2016). Financial analysis is a very important tool to find out the company's financial position and the results that have been achieved in connection with the selection of the company's strategy that has been taken. Analysis of financial statements includes the calculation of financial ratios to assess the company's financial performance in the past, current and future possibilities (Muda *et al*., 2014). By conducting a financial analysis of the company, we can find out the weaknesses and the results that are considered quite good and the potential bankruptcy of the company (Muda *et al*., 2018). The occurrence of bankruptcy in a number of companies will definitely cause problems related to the owners and employees who have to lose their jobs. This problem can certainly be avoided if the bankruptcy process of a company can be predicted earlier, so that it can be avoided or reduced the risk of bankruptcy.

Various studies have been conducted to predict the beginning of the bankruptcy of a company. The most widely used analysis is Altman's discriminant analysis (1968). Altman examines the use of financial ratio analysis as a tool to predict corporate bankruptcy by using financial statements. The Altman model is known as The Z-Score Model, which is a score that indicates the level of possible bankruptcy of a company. In this model bankruptcy is calculated by the Multiple Discriminant Analysis approach which involves elements of financial ratios such as Working Capital to Total Asset Ratio (representing liquidity ratios), Retained Earnings to Total Assets Ratio (representing Rentability ratios), Earning Before Interest and Taxes to Total Assets Ratio (representing Profitability ratio), Market of Equity to Book Value of Total Debt Ratio (representing Leverage ratio) and Sales to Total Assets Ratio (Efficiency). Until now the Altman model is still believed to be one of the most accurate analysis tools for predicting financial distress in a company. One of the advantages of this model is that it can be used as a measure of the overall financial performance of the company.

Zmijewski (1984) introduced a model that uses the logit method by including three variables that represent aspects of profitability which are reflected by the ratio of Net Income to Total Assets, the level of debt usage explained by Total Liabilities to Total Assets, and also company liquidity symbolized by the Current Assets ratio to Current Liabilities. The CA-Score (1987) model was developed under the leadership of Jean Legault University of Quebee in Montreal, using the Multiple Discriminant Analysis step. This model uses three variables, namely Shareholder investment to Assets, EBT + financial expenses to assets, and Sales to Assets. The results of the CA-Score calculation are divided into two categories: not bankrupt and bankrupt. This research is based on research that has been done before in Indonesia, which includes research conducted in Indonesia by Nenengsih (2018) who found that the CA Score Model was the best delisting predictor compared to the Altman Modification, Springate, Zmijewski and Grover models. While the research of Layyinaturrobaniyah and Dewi (2017) shows that the Zmijewski model has more accuracy than Altman in predicting the possibility of Financial Distress in manufacturing companies in the Indonesia Stock Exchange with 68% accuracy in the period of one year before the occurrence of financial difficulties. Husen and Galuh's (2014) research also shows that the Zmijewski model is the most appropriate model used to predict financial difficulties because it has the highest level of significance compared to other models. This study also reinforces the Fatmawati (2012) study comparing zmijewski models, Altman and springate models in predicting financial difficulties, the results of the study found that the Zmijewski model was more accurate in predicting delisting companies, compared to the revised Altman models and Springate models. The Zmijewski model has a prediction accuracy of 83%, The Altman model is 36% and The Springate model is 60%.

The research results of Savitri and Norita (2014) show that the Altman model is the most effective model used to predict companies delisting from other models used, namely the Springate Model and the Zmijewski Model. The results of the study are similar to those of Hadi and Angraini (2008) who chose the Altman model as the best delisting predictor compared to the Springate model and the Zmijewski model. While research outside Indonesia which underlies this research is a study conducted by Altman *et al.* (2016) provides evidence that the z-score model in general runs quite well for most countries (accuracy is around 0.75) and its accuracy can be increased even further (above 0.90) using specific estimates that include additional variables. The results of the research conducted by Almamy *et al.* (2016) show the Altman Z score model that is better at predicting bankruptcy of companies in the UK. Samarakoon and Hasan's (2003) study concluded that the Altman Z Score model has a remarkable level of accuracy in predicting financial distress in companies in Sri Lanka with a success rate of 81%. Proof of out-of-sample shows that the Z-Score model has very good potential in evaluating the risk of corporate pressure in emerging markets. Other research recommends Altman as the best predictive model, including research conducted by Narayan (1983), explaining that the Altman model is suitable for predicting bankruptcy in manufacturing companies. Begley *et al.* (1997) stated that there was consistency in the Altman Model to predict bankruptcy in the grouped samples experiencing healthy financial distress and group of companies or predicted to be in the gray area. Hillegeist *et al.* (2001) also concluded Altman as the right model for predicting bankruptcy because it provides more significant information.

Whereas Luciana and Kristijadi (2003) have different opinions, it is said that the Altman model can no longer be used today with several reasons namely first, in forming this model only includes manufacturing companies while companies that have other types have different relationships between total capital work and other variables used in ratio analysis, the two studies conducted by Altman in 1946 to 1965 are of course different from the current conditions so that the proportion for each variable is no longer appropriate to use. Luciana and Kristijadi's research shows that the most dominant financial ratio variable in determining financial distress is the Profit Margin Ratio, which is net profit divided by sales (NI/S), Financial Leverage Ratio, namely total debt divided by total assets (CL/TA), liquidity ratio i.e. assets smoothly divided by current debt (CA/CL), and Growth Ratio, namely the ratio of growth to net income divided by total assets (GROWTH NI/TA). Pranowo, et al (2010) concluded that financial ratio variables that have a significant effect are Current Ratio, EBITDA to Total Assets, Due Date accounts payable to fund availability and Paid in capital (capital at book value). The research conducted by Aziz and Humayon (2006) found that the proportion of the use of the Multiple Discriminant Analysis (MDA) model of 30.3% was mostly used to predict financial distress compared to other models, the second was the Logit model of 21.3%, but in in fact there are still many companies that experience bankruptcy. So that this phenomenon raises the suspicion that the Altman Model cannot necessarily be used accurately to analyze the occurrence of financial distress. Azis and Humayon's research concludes that the use of logit models is more accurate than the MDA model, because the accuracy of MDA is only 85% while the accuracy of the logit model reaches 87%.

Based on the above studies, many studies have been conducted comparing financial distress prediction models to find the most accurate prediction models, the results of the study show that inconsistencies still occur so that there is no standard model for predicting financial distress conditions. This study continues the research conducted by Choerunnisa (2016) by using a different bankruptcy prediction model so that the comparison of financial ratio indicators can be more varied and can reflect the actual conditions. So the authors are interested in conducting further research in predicting the condition of financial distress with the Altman Z score model, the Zmijewski Model and the CA Score Model. There is a difference in research time, place and condition of the current manufacturing industry with manufacturing conditions in the previous study, so the author tries to test the accuracy of these models and try to build a model that comes from dominant financial ratios that can predict financial distress in manufacturing companies listed on the IDX from 2012-2017.

2. Literature review

2.1. Financial Distress

Financial Distress is an early sign before a company experiences business bankruptcy. Financial distress is a condition where a company is unable to meet current obligation payments such as trade credit and interest expense (Ross et al. 1999). This state of financial distress can be bad to be insolvency, a situation where the company cannot pay all its debts, if the company does not immediately deal with it. In practice, the condition of financial difficulties will be characterized by deteriorating liquidity ratios, solvency and profitability of a company when compared to similar companies in an industry. Companies are said to experience financial distress: (Ross *et al.,* 1999)

1) The company does not have the ability to fulfill the repayment schedule of its debt to creditors at maturity. The company is considered the default because it has violated the credit agreement or bond indenture. There are 2 conditions, namely:

a. Technical default, the company as a debtor violates the credit agreement because it is unable to pay debts that are due but the company can continue its operations if the company renegotiates with the creditor, so it rarely ends in bankruptcy.

b. Payment default, payment failure does not always mean the company cannot pay its debt. A company can be said to be a payment default if the company is late in paying its obligations that are due even for one day. If there is a grade period clause in the agreement, the payment default condition occurs after the grace period has occurred.

2) Companies in insolvency conditions, there are 2 kinds of insolvency notions:

a. Stock based insolvency occurs when the company's capital becomes negative, because the company's assets are smaller than its obligations.

b. Flow based insolvency occurs when cash flow from operating activities is insufficient to meet one or more debts that have matured.

Whereas Brigham and Gapenski (2004) define financial distress to be five, namely:

1. Economic Failure, failure in this economic sense means that the income of a company is not able to cover all the total costs including the cost of capital (Muda *et al*., 2016). Companies that experience economic failure can continue their operations as long as the investor is willing to increase the amount of capital and the owner is willing to receive income below the market average.

2. Business Failure, this failure means that the company has terminated its operations by surrendering all losses it has received to creditors. Members of this category are companies that fail and never enter formal bankruptcy and are not categorized if this company does not hand over its losses to creditors.

3. Technical Insolvency, companies that experience financial distress in this definition is companies that are unable to cover the entire current obligation that is due. This technical insolvency can describe the company's liquidity problems temporarily. If given the time maybe the company that experiences this will increase the cash, then pay the obligations and survive the failure.

4. Insolvency in Bankruptcy. A company enters this condition if the book value of total liabilities exceeds the value of its assets. This condition is more serious than technical insolvency because it is a sign of economic failure and often makes the company liquidated.

5. Legal Bankruptcy. That is the condition where the company hands over the company that failed to court.

Besides the issue of financial distress there is another important issue is the existence of a common mistake that equates financial distress with bankruptcy (bankruptcy). Financial distress is only one of the causes of a company's bankruptcy, but that does not mean that all companies experiencing financial distress will go bankrupt. Bankruptcy is the last process of a company's journey to overcome financial distress experienced by a company if it is not able to rehabilitate it. Ross, Westerfield and Jaffie (1999) define bankruptcy as follows: "bankruptcy is a legal proceeding and can be done," with a corporation with the filling in the accounting or credit with filling the petition". While financial difficulties can be defined starting from liquidity difficulties (the ability to meet short-term obligations) which are the lightest financial difficulties, to the statement of bankruptcy which is the most difficult difficulty. Thus financial difficulties can be seen as a long series ranging from the mild to the most severe. There are several factors that can predict bankruptcy, one of which is the company's financial statements. Financial statements can be used to predict financial difficulties (Sadalia *et al.,* 2017). Another source is external information. In advanced capital markets, rating agencies have developed and their information can be used to predict the possibility of financial difficulties.

2.2. Financial Distress Prediction Model

The financial distress prediction model is a model that can be used to predict the financial condition of a company before going bankrupt. The financial distress prediction model is very important for companies, investors, creditors and the government. The warning system model to anticipate financial distress needs to be developed, because this model can be used as a means to identify even to improve conditions before the company experiences more fatal conditions, namely bankruptcy or liquidation. The current prediction model of financial distress for companies going public in Indonesia, most of them only use traditional financial ratios as predictor variables. Traditional analysis ratios focus on profitability, solvency and liquidity. Companies that experience losses, cannot pay obligations or are illiquid may require restructuring. To find out the symptoms of bankruptcy, a model is needed to predict financial distress to avoid losses in the value of investment.

2.3. Discriminant Analysis Method

Cramer (2004) states Discriminant Analysis is a parametric technique used to determine the weight of the best predictor to distinguish two or more groups of cases, which do not occur by accident. Whereas Singgih (2015) states discriminant analysis is a multivariate technique which includes the dependence method, namely the existence of dependent and independent variables. Ghozali (2016) states discriminant analysis is a form of regression with dependent variables non-metric or category forms. A data analysis technique where the criterion category and the predictor are basically intervals. Cramer (2004) states that the benefits of discriminant analysis are used to see the significance of differences in two or more sample groups. Whereas according to Ghozali (2012) to find variables that distinguish significantly two groups or more. The discriminant function model is:

$$YD = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots\ldots\ldots\ldots\ldots + \beta_n X_n \quad (1)$$

Where:

Y = Dependent Variable;

β = The weighting coefficient of the discriminant function;

X = Independent Variable.

Discriminant analysis is done to predict the condition of a company by analyzing the financial statements of a company two to five years before the company is predicted to go bankrupt or bankrupt. Bankruptcy is a situation where a company experiences insufficient funds to run its business. Bankruptcy is usually associated with financial difficulties. Discriminant analysis is beneficial for companies to get early warning of bankruptcy and sustainability of their business. The earlier the company knows the potential for bankruptcy, the better for the management because management can make improvements and can provide a picture and solid expectations of the company's future value.

2.3. Altman Model Financial Distress Prediction

Altman initially selected a sample of 66 manufacturing companies consisting of 33 bankrupt companies and 33 companies that did not go bankrupt. Furthermore, there were also 22 variables (ratios) that were potential to be evaluated which were grouped into 5 groups, namely Liquidity, Profitability, Solvency and Activity, then analyzed by discriminant analysis. From the analysis, a bankruptcy prediction model is known as the Z-Score, the Z-Score formula is as follows:

Z = 0,012 X1 + 0,014 X2 + 0,033 X3 + 0,006 X4 + 0,999 X5

Where:

X_1 = Working Capital/Total Assets

X_2 = Retained Earning/Total Assets

X_3 = Earnings before Income and Taxes/Total Assets

X_4 = Market Value Equity/Book Value of Debt

X_5 = Sales/Total Assets

Z = Overall Index

and the Z-Score cut-off point is as follows:

$Z < 1.81$ means company

$1.81 < Z < 2.99$ which means company in the Gray area

$Z < 2.99$ which means the company is not bankrupt.

Altman further argued that this Z-Score model had an accuracy rate of 95% while if it was to predict bankruptcy 2 years before bankruptcy, the accuracy rate was 72%. Because many companies do not go public so they do not have market value, Altman develops an alternative model by replacing the X4 variable which was originally a comparison of the capital market value with the book value of total debt, a comparison of the value of ordinary shares and book value of total debt. This Altman model revised in 1983 will be used in this study. The revised equation is:

Z-Score = 0,717 X_1 + 0,847 X_2 + 3,107 X_3 + 0,420 X_4 + 0,998 X_5 (2)

Where:

X_1 = Working Capital to Total Assets

X_2 = Retained Earnings to Total Assets

X_3 = Earnings before Interest and Taxes to Total Assets

X_4 = Market Value Equity to Book Value of Debt

X_5 = Sales to Total Assets

3. Methodology of research

3.1. Types of research

The research method used in this research is descriptive and comparative method because it aims to get an overview and information about the prediction of the Altman Financial Distress model, the Zmijewski model and the CA-Score model test which model has the highest level of accuracy in predicting financial distress in the 756 company manufacturing companies on the Indonesia Stock Exchange for the period 2012-2017 there were 52 companies that met the sample selection criteria by purposive sampling.

3.2. Variable operationalization

Operationalization of research variables can be seen in Table 1 the following:

Table 1. Variable Operationalization

Variable	Concept	Scale	Measurement
Status of Financial Distress/Non-Financial Distress (Y)	As a determinant of whether a company belongs to a company that experiences financial distress or non-financial distress (negative net income for 2 years in a row)	Nominal	1 = Financial Distress 0 = Non-Financial Distress
WC/TA (X_1)	Calculation of working capital against total assets owned by the company, the greater the ratio, the better the company's ability to fulfill short-term obligations.	Ratio	%
RE/TA (X_2)	This ratio measures the size of a company's ability to make a profit, judging from profitability compared to operating asset turnover speed as a measure of business efficiency. The greater the ratio of the more productive assets of the company in generating retained earnings.	Ratio	%
EBIT/TA (X_3)	The ratio that measures interest income before interest and tax to total assets, is used to measure a company's ability to generate profits from assets used	Ratio	%
MVE/BVTD (X_4)	This ratio measures the ability of companies to provide guarantees to each debt through ordinary capital and preferred shares, while debt includes current debt and long-term debt.	Ratio	%
S/TA (X_5)	This ratio measures how efficiently the assets used by the company to generate sales. The greater the ratio, the better in the sense that asset use has been efficient.	Ratio	%
NI/TA (X_6)	This ratio measures a company's ability to generate profits from assets used. The greater the value shows the better the performance of the company because the return on investment is getting bigger.	Ratio	%
TD/TA (X_7)	This ratio shows the ratio between current debt and long-term debt with the sum of all assets, which shows how much of the total assets spent on debt.	Ratio	%
CA/CL (X_8)	This ratio shows the ability of a company that is symbolized by current assets to cover current liabilities. The bigger the ratio, the better it means that the company is able to cover its current debt.	Ratio	%
SI/TA (X_9)	This ratio shows the ratio of shareholder investment to the total assets	Ratio	%
EBT+FA/TA (X_{10})	Ratio that measures interest income before tax and fixed assets to total assets.	Ratio	%

3.3. Uji Nested

The Nested Model test is a diagnostic test to choose an existing model (competing model), and is a basic strategy in building complex models of simple components. Both models can be said to be nested if they have the same terms and the other is an additional term. With this nested test, researchers are expected to know which model is the most accurate that can be used in research. The Nested model can be tested using F Test, T Test, LR Test, Wald Test and LM Test. So to review the model that will be used in this study can be explained as follows:

A $= FD = \beta_0 + \beta_1 WC/TA + \beta_2 RE/TA + \beta_3 EBIT/TA + \beta_4 MVE/BVTD + \beta_5\ S/TA$

$Z = FD = \beta_0 + \beta_6 NI/TA + \beta_7 TD/TA + \beta_8 CA/CL$

$CA = FD = \beta_0 + \beta_9 SI/TA + \beta_{10} (EBT+FE)/TA + \beta_{11} S/A$

Where:

A = Prediction of Financial Distress from Altman Z Score

Z = Financial distress prediction from Zmijewski

CA = Financial distress predictions from CA-Score

When combined into:

$A \text{ vs } Z = \beta_0 + \beta_1 WC/TA + \beta_2 RE/TA + \beta_3 EBIT/TA + \beta_4 MVE/BVTD + \beta_5 S/TA + \beta_6 NI/TA + \beta_7 TD/TA + \beta_8 CA/CL$

$A \text{ vs } CA = \beta_0 + \beta_1 WC/TA + \beta_2 RE/TA + \beta_3 EBIT/TA + \beta_4 MVE/BVTD + \beta_5 S/TA + \beta_6 SI/TA + \beta_7 (EBT+FE)/TA$

$Z \text{ vs } CA = \beta_0 + \beta_1 NI/TA + \beta_2 TD/TA + \beta_3 CA/CL + \beta_4 SI/TA + \beta_5 (EBT+FE)/TA + \beta_6 S/TA$

$A \text{ vs } Z \text{ vs } CA = \beta_0 + \beta_1 WC/TA + \beta_2 RE/TA + \beta_3 EBIT/TA + \beta_4 MVE/BVTD + \beta_5 S/TA + \beta_6 NI/TA + \beta_7 TD/TA + \beta_8 CA/CL + \beta_9 SI/TA + \beta_{10} (EBT+FE)/TA + \beta_{11} S/A$

4. Results and discussions

4.1. Results

4.1.1. Altman Z-Score Model Test Results

From the financial ratio data owned by manufacturing companies listed on the Indonesia Stock Exchange in 2012-2017, it can be explained that companies that experience financial distress, gray area or gray area and non-financial distress using the Altman Model can be seen in the Table 2 below:

Table 2. Results of Altman Z-score Model Calculation

Years	Bankrupt Initial Hypothesis	Experience Financial Distress Z < 1,23	Grey 1,23 < Z-score < 2,9	Not experiencing financial distress Z- Score > 2,9
2012	26	10	22	20
2013	26	15	18	19
2014	26	15	20	17
2015	26	18	16	18
2016	26	16	18	18
2017	26	15	22	15
Total	**156**	**89**	**116**	**107**

Based on Table 2 above, it is explained that there are differences between companies that experience financial distress between the initial hypothesis and the results of the calculation of the Altman model. Where in the Altman research model pay more attention to the assets owned by the company compared to the income earned by the company, it becomes a benchmark of a company.

Table 3. Wilk's Lambda Altman Value Model

Years	*Wilk's Lambda*	*Chi-square*	Df	Sig.
2012	0,815	10,022	2	0,007
2013	0,780	12,196	2	0,002
2014	0,742	14,594	2	0,001
2015	0,849	8,085	1	0,004
2016	0,855	7,736	1	0,005
2017	0,841	8,572	1	0,003

Sequentially the values of Lambda Wilk's from 2012-2017 amounted to 0.815, 0.780, 0.742, 0.849, 0.855, and 0.841 with significance values from 2012-2017 respectively are 0.007, 0.002, 0.001, 0.004, 0.005 and 0.003 which means the results of Wilk's calculations Lambda <0.01. It can be explained that there are differences between groups of companies that experience financial distress and groups of companies that do not experience financial distress found in the results of the Altman Z-score research model.

Table 4. Emanvalues Value of the Altman Model

Years	*Eigenvalue*	*% of Variance*	*Cumulative %*	*Canonical Correlation*
2012	0,227	100,0	100,0	0,430
2013	0,283	100,0	100,0	0,469
2014	0,347	100,0	100,0	0,508
2015	0,177	100,0	100,0	0,388
2016	0,169	100,0	100,0	0,380
2017	0,189	100,0	100,0	0,399

The value of Canonical Correlation from 2012-2017 is 43.0%, 46.9%, 50.8%, 38.8%, 38.0%, and 39.9% which indicate the ability or contribution of discriminant factors that explain the financial distress and non-financial distress group of 43.0%, 46.9%, 50.8%, 38.8%, 38.0%, and 39.9%. The following are the results of the recapitulation for the validation of the Altman model, where the companies included in the gray area are categorized as non-financial distress companies.

Table 5. Recapitulation of Altman Model Accuracy Levels

Model Building Companies and Not Including Model Formers		Actual Qualifications	Number of Companies	Prediction results		% Level of accuracy
				Financial Distress	Non-Financial Distress	
2012	Total	Financial Distress	26	7	19	26,9%
		Non-Financial Distress	26	3	23	11,5%
2013	Total	Financial Distress	26	10	16	38,5%
		Non-Financial Distress	26	5	21	19,2%
2014	Total	Financial Distress	26	13	13	50,0%
		Non-Financial Distress	26	2	24	7,7%
2015	Total	Financial Distress	26	14	12	53,8%
		Non-Financial Distress	26	4	22	15,4%
2016	Total	Financial Distress	26	14	12	53,8%
		Non-Financial Distress	26	2	24	7,7%
2017	Total	Financial Distress	26	12	14	46,2%
		Non-Financial Distress	26	3	23	11,5%
Total			312	89	223	342%
Altman Model Accuracy Average						**28,5%**

From Table 5 above, we can see that the results of the discriminant model validation from 2012-2017 with the number of companies as many as 52 companies in each period of 2012-2017 show the right and accurate research using the Altman method of 30, 31, 37 , 36, 38, and 35 companies that fit the actual conditions. Thus the accuracy of the Altman model presentation can be found at 28.5%.

4.1.2. Zmijewski Model Test Results

From the financial ratio data owned by manufacturing companies listed on the Indonesia Stock Exchange in 2012-2017, it can be explained that companies that experience financial distress, gray area or gray area and non-financial distress using the Zmijewski Model can be seen in the Table 6 below:

Table 6. Zmijewski Model Calculation Results

Years	Bankrupt Initial Hypothesis	Experience Financial Distress $X \geq 0$	Not experiencing financial distress $X < 0$
2012	26	7	45
2013	26	10	42
2014	26	12	40
2015	26	14	38
2016	26	12	40
2017	26	10	42
Total	**156**	**65**	**247**

Based on Table 6 above, it is explained that there are differences between companies that experience financial distress between the initial hypothesis and the results of the calculation of the Zmijewski model. Where in Zmijewski's research model pay more attention to assets owned by the company compared to profits and debts held by the company, it becomes a benchmark of a company.

Table 7. Wilm's Lambda Model Zmijewski Value

Years	*Wilk's Lambda*	*Chi-square*	Df	Sig.
2012	0,814	10,111	2	0,006
2013	0,869	6,938	1	0,008
2014	0,776	12,401	2	0,002
2015	0,586	26,152	2	0,000
2016	0,641	21,817	2	0,000
2017	0,850	8,051	1	0,005

Sequentially the values of Lambda Wilk's from 2012-2017 amounted to 0.814, 0.869, 0.776, 0.586, 0.641, and 0.850 with significance values from 2012 - 2017 respectively are 0.006, 0.008, 0.002, 0.000, 0.000, and 0.005 which means the results of Wilk's calculations Lambda <0.01. It can be explained that there is a difference between the group of companies that experience financial distress and groups of companies that do not experience financial distress which are found in the results of the Zmijewski research model.

Table 8. Zmijewski Model Eigenvalues Value

Years	*Eigenvalue*	*% of Variance*	*Cumulative %*	*Canonical Correlation*
2012	0,229	100,0	100,0	0,432
2013	0,150	100,0	100,0	0,362
2014	0,288	100,0	100,0	0,473
2015	0,705	100,0	100,0	0,643
2016	0,561	100,0	100,0	0,599
2017	0,177	100,0	100,0	0,387

Canonical Correlation values from 2012 - 2017 are 43.2%, 36.2%, 47.3%, 64.3%, 59.9%, and 38.7% which indicate the ability or contribution of the discriminated factors which explain the financial distress and non-financial distress group of 43.2% , 36.2%, 47.3%, 64.3%, 59.9%, and 38.7%. The following are the results of the recapitulation for the validation of the Zmijewski model:

Table 9. Recapitulation of Zmijewski Model Accuracy Levels

Model Building Companies and Not Including Model Formers		Actual Qualifications	Number of Companies	Prediction results		% Level of accuracy
				Financial Distress	Non-Financial Distress	
2012	Total	Financial Distress	26	6	20	23,1%
		Non-Financial Distress	26	1	25	3,8%
2013	Total	Financial Distress	26	9	17	34,6%
		Non-Financial Distress	26	1	25	3,8%
2014	Total	Financial Distress	26	11	15	42,3%
		Non-Financial Distress	26	1	25	3,8%
2015	Total	Financial Distress	26	13	13	50,0%
		Non-Financial Distress	26	1	25	3,8%
2016	Total	Financial Distress	26	11	15	42,3%
		Non-Financial Distress	26	1	25	3,8%
2017	Total	Financial Distress	26	10	16	38,5%
		Non-Financial Distress	26	0	26	0,0%
Total			312	65	247	250%
Average Zmijewski Model Accuracy						**20,8%**

From Table 9 above, we can see that the results of the discriminant model validation from 2012 - 2017 with a total of 52 companies in each of the years 2012 - 2017 show the right and accurate research using the method of Zmijewski as many as 31, 34, 36 , 38, 36, and 36 companies that are in accordance with the actual conditions. Thus the presentation of the accuracy of Zmijewski's model can be known at 20.8%.

4.1.3. CA-Score Model Testing Results

From the financial ratio data owned by manufacturing companies listed on the Indonesia Stock Exchange in 2012-2017, companies that experience financial distress, gray area or gray and non-financial distress can be explained by using the CA-Score Model can be seen in the Table 10 below.

Table 10. Results of CA-Score Model Calculation

Years	Bankrupt Initial Hypothesis	Experience Financial Distress CA-Score >- 0,03	Not experiencing financial distress CA Score < -0,3
2012	26	38	14
2013	26	34	18
2014	26	36	16
2015	26	31	21
2016	26	36	16
2017	26	33	19
Total	**156**	**208**	**104**

Based on Table 10 above, it is explained that there are differences between companies experiencing financial distress between the initial hypothesis and the results of the CA-Score model calculation. This becomes a benchmark for a company.

Table 11. Value of Wilk’s Lambda CA-Score Model

Years	*Wilk's Lambda*	*Chi-square*	Df	Sig.
2012	0,926	3,783	1	0,052
2013	0,890	5,780	1	0,016
2014	0,764	13,190	2	0,001
2015	0,776	12,433	2	0,002
2016	0,879	6,381	1	0,012
2017	0,886	6,016	1	0,014

Sequentially the values of Lambda Wilk's from 2012-2017 amounted to 0.926, 0.890, 0.764, 0.776, 0.879 and 0.886 with significant values from 2012 - 2017 respectively 0.052, 0.016, 0.001, 0.002, 0.012, and 0.014 which means the results of Wilk's calculations Lambda <0.01. It can be explained that from 2014-2017 there were differences between groups of companies experiencing financial distress and groups of companies that did not experience financial distress found in the results of the CA-Score research model. Whereas in 2012 and 2013 there were no differences between groups of companies experiencing financial distress and groups of companies that did not experience financial distress found in the results of the CA-Score research model.

Table 12. Eigenvalues CA-Score Model

Years	*Eigenvalue*	*% of Variance*	*Cumulative %*	*Canonical Correlation*
2012	0,079	100,0	100,0	0,271
2013	0,124	100,0	100,0	0,332
2014	0,309	100,0	100,0	0,486
2015	0,289	100,0	100,0	0,473
2016	0,138	100,0	100,0	0,348
2017	0,129	100,0	100,0	0,338

The Canonical Correlation values from 2012-2017 were 27.1%, 33.2%, 48.6%, 47.3%, 34.8%, and 33.8% which showed the ability or contribution of the discriminant factors which explained the financial distress and non-financial distress group of 27.1% , 33.2%, 48.6%, 47.3%, 34.8%, and 33.8%. The following are the results of the recapitulation for the validation of the CA-Score model:

Table 13. Recapitulation of the Accuracy of the CA-Score Model

Model Building Companies and Not Including Model Formers		Actual Qualifications	Number of Companies	Prediction results		% Level of accuracy
				Financial Distress	Non-Financial Distress	
2012	Total	Financial Distress	26	14	12	53,8%
		Non-Financial Distress	26	24	2	92,3%
2013	Total	Financial Distress	26	10	16	38,5%

Model Building Companies and Not Including Model Formers		Actual Qualifications	Number of Companies	Prediction results		% Level of accuracy
				Financial Distress	Non-Financial Distress	
		Non-Financial Distress	26	24	2	92,3%
2014	Total	Financial Distress	26	11	15	42,3%
		Non-Financial Distress	26	25	1	96,2%
2015	Total	Financial Distress	26	7	19	26,9%
		Non-Financial Distress	26	24	2	92,3%
2016	Total	Financial Distress	26	11	15	42,3%
		Non-Financial Distress	26	25	1	96,2%
2017	Total	Financial Distress	26	9	17	34,6%
		Non-Financial Distress	26	24	2	92,3%
Total			312	208	104	800%
Average CA-Score Model Accuracy						**66,70%**

From Table 13 above, we can see that the results of the discriminant model validation from 2012-2017 with the number of companies as many as 52 companies in each of the period 2012 - 2017 showed the right and accurate researched using the CA-Score method of 16, 12, 12, 9, 12, and 11 companies that fit the actual conditions. That way the accuracy of the CA-Score model presentation can be known at 66.7%.

4.1.4. Combined Test Results of the Altman Z-Score Model, Zmijewski and CA-Score

The initial stage in building this linear discriminant model is to classify firms that fall into the category of financial distress and non-financial distress. Where the determination of financial distress and non-financial distress is determined by the condition of the company's equity. The category of companies that experience financial distress is those that have negative net income for two consecutive years, while the category of companies that do not experience financial distress is the opposite, which is not having a negative net income for two consecutive years. In assessing the company's financial distress and non-financial distress conditions, referring to the company's financial statements from 2012-2017, which can be grouped as follows:

Table 14. Number of Companies

No.	Years	Number of Company	Companies that experience financial distress	Companies that do not experience financial distress
1	2012	52	26	26
2	2013	52	26	26
3	2014	52	26	26
4	2015	52	26	26
5	2016	52	26	26
6	2017	52	26	26
Total		**312**	**156**	**156**

From the data of the number of companies obtained starting from 2012-2017, according to the initial hypothesis, companies that are classified as experiencing financial distress and non-financial distress are obtained. After the company is grouped into the category of financial distress and non-financial distress, a calculation is performed to find the values of 10 financial ratios using the linear discriminant function. The following is a linear discriminant function by performing the following steps.

Table 15. Combined Value of Wilk's Lambda

Years	*Wilk's Lambda*	*Chi-square*	Df	Sig.
2012	0,818	10,024	2	0,007
2013	0,721	15,856	3	0,001
2014	0,654	20,574	3	0,000
2015	0,767	12,978	2	0,002
2016	0,855	7,736	1	0,005
2017	0,841	8,572	1	0,003

Sequentially the values of Lambda Wilk's from 2012-2017 amounted to 0.818, 0.721, 0.654, 0.767, 0.855, and 0.841 with significance values from 2012-2017 respectively are 0.007, 0.001, 0.000, 0.002, 0.005, and 0.003 which means the results of Wilk's calculations Lambda <0.01. It can be explained that there are differences between groups of companies that experience financial distress and groups of companies that do not experience financial distress from the combined results.

Table 16. Eigenvalues CA-Score Model

Tahun	*Eigenvalue*	*% of Variance*	*Cumulative %*	*Canonical Correlation*
2012	0,227	100,0	100,0	0,430
2013	0,387	100,0	100,0	0,528
2014	0,528	100,0	100,0	0,588
2015	0,303	100,0	100,0	0,482
2016	0,169	100,0	100,0	0,380
2017	0,189	100,0	100,0	0,399

The value of Canonical Correlation from 2012-2017 is 43.0%, 52.8%, 58.8%, 48.2%, 38.0%, and 39.9% which shows the ability or contribution of the factors that explain the group of financial distress and non-financial distress by 43.0%, 52.8%, 58.8%, 48.2%, 38.0%, and 39.9%. After it is known that there are differences in values between groups, a linear discriminant function is formed from the data that already exists every year by using a different number of variables each month. The following results from the formation of a linear discriminant function using the stepwise selection method.

Table 17. Canonical Discriminant Function Coefficients

Years	Ratio	Function
2012	X1 (Working Capital to Total Assets (WC/TA))	2,872
	X6 (Net Income to Total Assets (NI/TA))	-1,590
	(Constant)	1,033
2013	X1 (Working Capital to Total Assets (WC/TA))	2,006
	X5 (Sales to Total Assets (S/TA))	1,256
	X8 (Current Assets to Current Liabilities (CA/CL))	-0,498
	(Constant)	-1,750
2014	X1 (Working Capital to Total Assets (WC/TA))	2,582
	X5 (Sales to Total Assets (S/TA))	1,599
	X7 (Total Debt to Total Assets (TD/TA))	-0,546
	(Constant)	-2,513
2015	X4 (Market Value of Equity to Book Value of Total Debt (MVE/BVTD))	0,671
	X6 (Net Income to Total Assets (NI/TA))	1,280
	(Constant)	-1,238
2016	X4 (Market Value of Equity to Book Value of Total Debt (MVE/BVTD))	0,607
	(Constant)	-0,011
2017	X4 (Market Value of Equity to Book Value of Total Debt (MVE/BVTD))	0,622
	(Constant)	-0,062

From the data in Table 17 generated from the stepwise selection model, it can be explained that the dominant ratios produced from 10 ratios combined Altman Z-score model, Zmijewski, and CA-Score from 2012- 2017, the ratio that affects financial distress is X1, X4, X5, X6, X7, and X8. Then we get the results of linear discriminant functions from 2012-2017 with several significant different variables in the model.

Table 18. Discriminant Functions

Years	Discriminant function
2012	$Z = 1,033 + 2,872\ X_1 – 1,590\ X_6$
2013	$Z = -1,750 + 2,006\ X_1 + 1,256\ X_5 – 0,498\ X_8$
2014	$Z = -2,513 + 2,582\ X_1 + 1,599\ X_5 – 0,546\ X_7$
2015	$Z = -1,238 + 0,671\ X_4 + 1,280\ X_6$
2016	$Z = -0,622 + 0,607\ X_4$
2017	$Z = -0,062 + 0,622\ X_4$

Where:

Z = Classification value

X_1 = Working Capital to Total Assets (WC/TA)

X_4 = Market Value of Equity to Book Value of Total Debt (MVE/BVTD)

X_5 = Sales to Total Assets (S/TA)

X_6 = Net Income to Total Assets (NI/TA)

X_7 = Total Debt to Total Assets (TD/TA)

X_8 = Current Assets to Current Liabilities (CA/CL)

Of all the discriminant functions that were late obtained from 2012-2017 consisted of 3 variables from the Altman Z-score model, 3 variables from the Zmijewski model and no variables obtained from the CA-Score model. Classification of a company experiencing financial distress and non-financial distress is done by comparing the value of Z-score and the value of ZCE as the cut-off score. The ZCE value which is the cut off Z score is calculated first using the following formula (Hair et al., 2011):

$Z_{CE} = (Z_A + Z_B)/2$

Where:

Z_{CE}= Critical cutting score between Group A and Group B

Z_A = Centroid of Group A

Z_B = Centroid of Group B

Using the formula above, ZCE can be calculated per year as follows:

Table 19. ZCE results

Years	Z_{CE}	Z_{CE}
2012	$Z_{CE} = \frac{0,467 + (-0,467)}{2}$	0
2013	$Z_{CE} = \frac{0,610 + (-0,610)}{2}$	0
2014	$Z_{CE} = \frac{0,713 + (-0,713)}{2}$	0
2015	$Z_{CE} = \frac{0,540 + (-0,540)}{2}$	0
2016	$Z_{CE} = \frac{0,403 + (-0,403)}{2}$	0
2017	$Z_{CE} = \frac{0,426 + (-0,426)}{2}$	0

If the Zscore value is <0 (negative value), then it includes companies that experience financial distress, while Zscore> 0 (positive value), including companies that do not experience financial distress. After making the model, there are 6 variables that construct linear discriminant models in determining the condition of the company whether experiencing financial distress or non-financial distress. From the financial ratio data owned by manufacturing companies listed on the Indonesia Stock Exchange in 2012-2017, companies that experience financial distress or non-financial distress can be explained using a combined model between the Altman Z-score model, the Zmijewski model, the CA-Score model can be seen in the table below:

Table 20. Company Data Experiencing the Joint Financial Distress Model

No.	Years	Number of Company	Experiencing Financial Distress (Initial Hypothesis)	Z_{CE} Combined	Data Experiencing Financial Distress	Data Not Experiencing Financial Distress
1	2012	52	26	0	5	21
2	2013	52	26	0	7	19
3	2014	52	26	0	10	16
4	2015	52	26	0	10	16
5	2016	52	26	0	10	16
6	2017	52	26	0	8	18
Total		**312**	**156**	**-**	**50**	**106**

From Table 20, it can be explained that there are differences in the number of companies experiencing financial distress when the initial hypothesis with data has been calculated using a combined model, from the data explained that by using a combined model the number of companies experiencing financial distress is more than the initial hypothesis, this can be due to all company financial ratios that are used as indicators or variables calculated in this model, so that each of the financial report values can be included in this indicator. In addition, the financial ratios that have no effect on this model are Retained Earnings to Total Assets (RE/TA), Earnings before Interest and Taxes to Total Assets (EBIT/TA), and Shareholders Investment to Total Assets (SI /TA). The most influential financial ratio is the ratio of Working Capital to Total Assets (WC/TA) and Market Value of Equity to Book Value of Total Debt (MVE/BVTD). The following are the results of validation models that have been formed by companies:

Table 21. Recapitulation of Combined Model Accuracy Levels

Model Building Companies and Not Including Model Formers		Actual Qualifications	Number of Companies	Prediction results		% Level of accuracy
				Financial Distress	Non-Financial Distress	
2012	Total	Financial Distress	26	5	21	19,2%
		Non-Financial Distress	26	3	23	11,5%
2013	Total	Financial Distress	26	7	19	26,9%
		Non-Financial Distress	26	1	25	3,8%
2014	Total	Financial Distress	26	10	16	38,5%
		Non-Financial Distress	26	0	26	0,0%
2015	Total	Financial Distress	26	10	16	38,5%
		Non-Financial Distress	26	2	24	7,7%
2016	Total	Financial Distress	26	10	16	38,5%
		Non-Financial Distress	26	2	24	7,7%
2017	Total	Financial Distress	26	8	18	30,8%
		Non-Financial Distress	26	1	25	3,8%
Total			**312**	**59**	**253**	**227%**
Combined Model Accuracy Average						**18,9%**

Based on Table 21 above, we can see that model validation shows that in 2012 as many as 28 companies were accurately predicted using a model that had been formed, while 24 companies were not accurately predicted by the model that had been formed. In 2013 as many as 32 companies were accurately predicted using the model that had been formed, while 20 companies were not accurately predicted by the model that had been formed. In 2014 as many as 36 companies were accurately predicted using the model that had been formed, while 16 companies were not accurately predicted by the model that had been formed. In 2015 as many as 34 companies were predicted accurately by using a model that had been formed, while 18 companies were not accurately predicted by the model that had been formed. In 2016 as many as 34 companies were predicted accurately by using a model that had been formed, while 18 companies were not accurately predicted by the model that had been formed, and in 2017 as many as 33 companies were accurately predicted using models that had been formed, while 19 companies were not accurately predicted by the model that has been formed. So in broad outline, we can find out the accuracy of the model from 2012-2017 which is equal to 18.9% accurate in predicting the state of the company. Thus it can be explained the difference in the accuracy of each model, here is a table of the level of accuracy of the overall research model:

Table 22. Recapitulation of Results of Levels of Accuracy of Research Models

No.	Years	Result of Accuracy Level			
		Altman	Zmijewski	CA-Score	Combined
1	2012	19,23%	13,46%	73,08%	15,38%
2	2013	28,85%	19,23%	65,38%	15,38%
3	2014	28,85%	23,08%	69,23%	19,23%
4	2015	34,62%	26,92%	59,62%	23,08%
5	2016	30,77%	23,08%	69,23%	23,08%
6	2017	28,85%	19,23%	63,46%	17,31%
Average		**28,53%**	**20,83%**	**66,67%**	**18,91%**

Based on Table 22 above, it can be explained that a model with an accuracy rate of almost 100% is a CA-Score model with a value of 66.67%. Therefore the discriminant model produced from financial ratios from the previous research model can be used to determine the company experiencing financial distress or non-financial distress.

4.1.5. Nested Test Results

Nesting is a basic strategy in building complex models of simple components. This technique is the answer to the problem that is the standard of the relationship between algebra and calculus and SQL-based operations, cannot express all desired operations in the direct hierarchy. Both models can be said to be nested if both content have the same terms and the other is an additional term. In this nested test researchers are expected to know which model is the most accurate that can be used for financial distress prediction analysis research which can be explained below:

Table 23. Nested Test Results

Years	Altman			Zmijewski			CA-Score		
	F_{test}	Sig.	Decision	F_{test}	Sig.	Decision	F_{test}	Sig.	Decision
2012	2,639	0,048	Rejected	5,094	0,002	Rejected	0,377	0,770	Accepted
2013	0,474	0,828	Accepted	0,875	0,453	Accepted	0,381	0,767	Accepted
2014	0,690	0,658	Accepted	0,996	0,426	Accepted	0,739	0,529	Accepted
2015	5,525	0,001	Rejected	0,500	0,683	Accepted	0,162	0,688	Accepted
2016	0,417	0,518	Accepted	3,847	0,049	Rejected	0,417	0,518	Accepted
2017	0,220	0,639	Accepted	0,641	0,423	Accepted	0,220	0,639	Accepted

From Table 23 it can be explained that if Sig. <0.05 then H0 is rejected. Where:

- H0 is accepted stating that the comparison model is more accurate than the model made by the researcher.

- H0 is refused to state that the research model is more accurate than the comparison model.

The Nested test results explain that the discriminant model using the stepwise selection method made by the researcher is known to be the discriminant model when the accuracy is tested with existing models (Altman, Zmijewski and CA-Score) the results are mostly accepted, or in other words the comparison model more accurate than the model that was made by the researcher.

4.1.6. Sample Out Test Results

Furthermore, the results of discriminant testing will be explained using the research model (which is used is a significant variable) from 2012 - 2017 as follows:

Table 24. Model Outcomes for Samples in 2012 - 2017

Expected Sig.	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Coef.	-0,776	-0,855	-0,996	-0,894	-0,386	-0,686
Variable						
X_1 (WC/TA)	0,562***	0,517***	0,736***	0,729***	0,576***	0,553***
X_2 (MVE/BVTD)	-	-	-	-	-	-
X_3 (S/TA)	-	-	-	-	0,470***	-
R^2	66,2%	69,5%	51,3%	52,0%	72,8%	66,9%
F_{test}	0,585	0,571	0,413	0,025	8,605	3,591
F_{Sig}	0.445	0,450	0,522	0,876	0,000	0,061

Note: * 1%; ** 5%; *** 10%

Based on Table 24 above, it can be explained as follows:

1. In the 2012 model the following equation is obtained:

Y = -0,776 + 0,562 WC / TA

The value of Fcount is 0.585 which has a significance level of 0.445> 0.05 (α = 5%), it can be concluded that the WC/TA variable has no significant effect on the dependent variable and the hypothesis is rejected. With R2 value of 66.2% which means the dependent variable is explained WC/TA variable of 66.2%, while the remaining 33.8% is explained by other variables outside the model.

2. In the 2013 model, the following equations are obtained:

Y = -0.885 + 0.517 WC/TA

The calculated F value is 0.571 which has a significance level of 0.450> 0.05 (α = 5%), it can be concluded that the WC/TA variable has no significant effect on the dependent variable and the hypothesis is rejected. With the R2 value of 69.5%

which means the dependent variable is explained WC/TA variable of 69.5%, while the remaining 30.5% is explained by other variables outside the model.

3. In the 2014 model, the equation is as follows:

Y = -0.996 + 0.736 WC/TA

Fcount value is 0.413 which has a significance level of 0.522> 0.05 (α = 5%), it can be concluded that the WC/TA variable does not significantly influence the dependent variable and the hypothesis is rejected. With the R2 value of 51.3% which means the dependent variable is explained WC/TA variable of 51.3%, while the remaining 48.7% is explained by other variables outside the model.

4. In the 2015 model the following equation is obtained: Y = -0.889 + 0.729 WC/TA The Fcount value is 0.025 which has a significance level of 0.876> 0.05 (α = 5%), it can be concluded that the WC/TA variable does not have a significant effect on the dependent variable and the hypothesis is rejected. With R2 value of 52.0% which means the dependent variable is explained by WC/TA variable of 52.0%, while the remaining 48.0% is explained by other variables outside the model.

5. In the 2016 model the following equation is obtained: Y = -0,386 + 0,576 WC/TA + 0,470 S /TA The Fcount value is 8.605 which has a significance level of 0.000 <0.05 (α = 5%), it can be concluded that the WC/TA and S/TA variables together have a significant effect on the dependent variable and the hypothesis is accepted. With the R2 value of 72.8% which means the dependent variable is explained WC / TA and S / TA variables of 72.8%, while the remaining 27.2% is explained by other variables outside the model.

6. In the 2017 model, the equation is as follows: Y = -0,686 + 0,553 WC/TA Fcount value is 3.591 which has a significance level of 0.061> 0.05 (α = 5%), it can be concluded that the WC/TA variable does not significantly influence the dependent variable and the hypothesis is rejected. With R2 value of 66.9% which means the dependent variable is explained by WC/TA variable of 66.9%, while the remaining 48.0% is explained by other variables outside the model.

5. Conclusions and suggestions

5.1. Conclusions

This study conducted a comparative analysis of the predictions of the occurrence of financial distress in manufacturing companies listed on the Indonesia Stock Exchange using financial ratios of prediction models Altman, Zmijewski and CA-Score Model. From all financial ratios used, the first conclusion can be drawn that the dominant financial ratios used by researchers to predict the occurrence of financial distress of a manufacturing company found on the Indonesia Stock Exchange are:

1. Liquidity ratio, namely Working Capital to Total Assets (WC/TA);

2. Activity Ratios, namely Market Value of Equity to Book Value of Total Debt (MVE / BVTD) and Sales to Total Assets (S/TA). These variables are factors that influence the condition of the company whether or not financial distress occurs in the company.

3. The discriminant model obtained from this study tested its accuracy on manufacturing companies listed on the Indonesia Stock Exchange from 2012 to 2017, and the discriminant model that showed the value closest to 100% was the CA-Score model with a value of 66.67%. There is a difference in the level of accuracy of each research model each year. This annual difference can be caused by the performance of a company, if there is a decrease in the level of accuracy in the following year, the company's performance decreases, and if there is an increase in the accuracy of the model, the company's performance will increase.

5.2. Suggestions

1. For company management, the dominant indicator of financial ratios that must be considered is the variable liquidity ratio as indicated by the financial ratio of Working capital to total assets because liquidity conditions are important to consider the impact of the inability of companies to fulfill their short-term obligations.

2. For investors who want to invest their funds in shares, they should get enough information about the condition of the company in question. The other dominant financial ratio is the activity ratio indicated by Market Value of Equity to Book Value of Total Debt (MVE/BVTD) and Sales to Total Assets (S /TA).

3. For creditors/banks that will provide credit facilities to manufacturing companies, financial variables or ratios that must be considered to be able to provide an initial assessment to the company is the Working capital to total asset ratio.

4. For academics or researchers, they can consider other factors besides financial ratios, for example macroeconomic conditions, and use other financial distress prediction models so that if these factors can be accurately measured, a more accurate level of financial distress prediction will be obtained.

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