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The Analysis of Altman Model and Ohlson Model in Predicting Financial Distress of Manufacturing Companies in the Indonesia Stock Exchange

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Abstract: The purpose of this research is to examine the accuracy of the Altman Model and the Ohlson Model in Bankruptcy Prediction. The research population is all companies who are listed on the Indonesian Stock Exchange. The sample of the research is 40 manufacturing companies listed on the Indonesian Stock Exchange in the period of 2010-2014 that are divided into companies with financial distress and those without financial distress. The data analysis technique is the Multiple Discriminant Analysis and Logit Analysis. The Multiple Discriminant Analysis is derived from the Altman Model while the Logit Analysis is derived from the Ohlson Model. The results show that the Ohlson Model and the Logit Analysis are more accurate than the Altman Model and the Multiple Discriminant Analysis in predicting bankruptcy of manufacturing firms in the Indonesian Stock Exchange (BEI) in 2010-2014. Also, the results of the study reveal that the ratio of retained earnings to total assets; earnings before interest and taxes to total assets; market value of equity to total liabilities; sales to total assets; and debt ratio, return on assets, working capital to total assets and net income were negative in the last two years. Hence constitutes the benchmark for consideration in determining the financial distress of a company.

Keywords: Altman Model, Ohlson Model, Multiple Discriminant Analysis, Logit Analysis, Bankruptcy

JEL Classification: G140, G330
Paper Type: Research

1. INTRODUCTION

The development of technology and the change in the economic cycle have led the business world also to continue to improve. These changes have an impact on the fierce competition experienced by all subjects in the business community (Sinambela, 2009). A company is expected not only adapt to the circumstances but also to sustain ongoing concern in the middle of the occurring changes. Besides the changes that continue to occur, one of the problems that could become a threat for a company is bankruptcy. Prihanthini and Sari (2012) argued that bankruptcy is a condition in which a company can no longer afford its operation well, because of the financial

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distress experienced by these entities has been very severe. Elmabrok and Kim (2012) found that bankruptcy or financial distress occurs when the amount of liabilities exceeds the fair value of the assets or when current liabilities exceed current assets. Bankruptcy or financial distress experienced by most companies could have an appalling impact on the world's economy (June, 2012).

Ramadhani and Lukviarman (2009) and Ghosh (2013) stated that the characteristic of a bankrupt company is a decrease in the company's financial condition that occurs for an extended period and continuously (financial distress). According to Gamayuni (2011), the causes of financial distress can be derived from internal and external factors. The internal factors can be the lack of management experience and the lack of knowledge in managing the assets and liability effectively. While the external factors can be inflation, taxes, and legal system, and the depreciation of foreign currencies. Some parties will get harmed if a company goes bankrupt. Adriana et al. (2012) explained that the parties are investors and creditors. Therefore, we need a tool or a predictive model that can be used to detect the potential of financial distress of companies.

There are many types of research of prediction models to detect financial distress that can lead to various conditions of the company before it becomes bankrupt (Endri, 2009). These researchers help potential investors and creditors in choosing the right company and not to get caught up in the bankruptcy problem. Pradhan (2011) considered that to improve the financial condition after receiving an early warning for bankruptcy depends on the utilization capacity of some areas and the availability of financial options in the company. As stated by Nidhi and Saini (2013), the company's financial situation can be assessed by using standard financial ratios. The financial distress detection tools that can be employed are the Altman Z-Score (1968) and Ohlson (1980).

In 1968, Altman did research to find a predictive model for the financial distress that is called the Multiple Discriminant Analysis (MDA). This analysis combines several financial ratios into one model as a measure of the health of a company that consists of five ratios and then is called Z-Score. Ohlson's model has a different formula and methodology from Altman (1968). This method is the logistic regression, a statistical method used to predict the probability of an occurring event by matching the data on the logistic curve function.

From the models of financial distress above, there are differences in the prediction result. Karamzadeh (2012) concluded that the Altman's model was the better predictor between the two predictors in the analysis (Altman's model and Ohlson's model). In contrast, the previous study of Moghadam, Zadeh and Fard (2010) found that the Ohlson's model was a better predictor. Muzir and Caglar (2009) study agreed with this position as their revealed that Ohlson's model was better than the Altman's model. Based on the inconsistent results, this research is made to analyse the accuracy of the two predictors in predicting financial distress.

2. LITERATURE OF FINANCIAL DISTRESS MODEL

This section explained in details about the two quite common financial distress analysis models. They are the Altman's (1968) and the Ohlson's (1980).

2.1. The Altman Z-Score (1968)

After Beaver (1966), later Edward Altman also conducted research in financial distress. Altman (1968) did what Beaver (1966) suggested at the end of his writing, which is to perform multivariate analysis. The Altman's model later becomes the most popular model to predict financial distress. The model is known as the Z-Score.

Altman (1968) used Multiple Discriminant Analysis (MDA) with five types of financial ratios such as working capital to total assets, retained earnings to total assets, earnings before interest

and tax, the market value of equity to total liabilities, and sales to total assets. This research used 66 companies in a period of 20 years (1946-1965) as samples. These samples were divided into two groups: 33 companies that were considered in distress and 33 other companies that were considered not to be in distress. These companies that were considered to be in distress were companies who filled bankruptcy petition by National Bankruptcy Act Chapter X. Altman (1968) only used manufacturing companies as his samples. The reason behind it is the same as Beaver (1966) that the data is available only from Moody's Industrial Manual which only contains data on manufacturing firms.

The Altman's study was able to obtain 95% prediction accuracy for the data of one year before distress, and 72% for the data of two years before distress. In addition, the companies with low profitability are potential to face financial distress. Until now, the Z-Score is still more widely used by researchers, practitioners, and academics in accounting than the other prediction model. The equation of the Altman's research is:

$$Z = 1.2\ X_1 + 1.4\ X_2 + 3.3\ X_3 + 0.6\ X_4 + 1.0\ X_5$$

Where,

X_1 = *Working Capital/Total Assets*
X_2 = *Retained Earnings/Total Assets*
X_3 = *Earnings before Interest and Taxes/Total Liabilities*
X_4 = *Market Value of Equity/Total Liabilities*
X_5 = *Sales/Total Assets*

With criteria (Kumari & Chaudhry, 2012):

a) *Z-Score*> 2.99 as healthy public company (non-distress)
b) 1.81 <*Z-Score*< 2.99 as grey zone
c) *Z-Score*< 1.81 as unhealthy public company (distress)

2.2. The Ohlson Model (1980)

Ohlson (1980), who was inspired by previous studies, also conducted a study about financial distress. However, there are some modifications that he did in his study compared with previous ones. Ohlson used data from the year 1970 to 1976 of 105 manufacturing companies that went bankrupt and 2058 companies that were not bankrupt during the period.

Besides the number of samples used, there are other differences from the data source. If Altman (1968) and Beaver (1966) used data from Moody's Manual, then Ohlson (1980) got the data from the financial statement issued for taxes (10K-Financial Statement). The service he used is Compustat. Ohlson used logit statistical method. Ohlson believed the method could cover the weakness in Multiple Discriminant Analysis method employed by Altman.

Ohlson's model has 9 (nine) variables consisting of several financial ratios. The model is:

$$O = -1{,}32 - 0{,}407\ X_1 + 6{,}03\ X_2 - 1{,}43\ X_3 + 0{,}0757\ X_4 - 2{,}57\ X_5 - 1{,}83\ X_6 + 0{,}285\ X_7 - 1{,}72\ X_8 - 0{,}521\ X_9$$

Where,

X_1 = *Size* (LOG (*Total Assets/GNP Index*))
X_2 = *Debt Ratio* (*Total Liabilities/Total Assets*)
X_3 = *Working Capital to Total Assets*
X_4 = *Current Liabilities to Current Assets*
X_5 = *Total Liabilities Exceeds Total Assets (OENEG)*
X_6 = *Return on Assets*
X_7 = *Funds Provided by Operations to Total Liabilities*
X_8 = *Net Income was Negative for The Last Two Years (INTWO)*

X_9 = *Delta Net Income Divided by the Sum of the Absolute Net Income (CHIN)*

Criteria of distress:

a) O-*Score*< 0.38 as non-financial distress companies
b) O-*Score* > 0.38 as financial distress companies

2.3. Logit Analysis

Logit regression analysis is used to analyse the effect of a number independent variables on dependent variables which are categorical variables (binomial, multinomial, or ordinal) and also to predict the value of a dependent variable (in the form of categorical variable) based on the value of the independent variable. SPSS provides three logistic regression procedures:

a) Binary logistic regression: a logistic regression where the dependent variable is dichotomous variables or binary variable
b) Multinomial logistic regression: a logistic regression where the dependent variable is categorical variable comprising of more than two values
c) Ordinal logistic regression: a logistic regression in which the dependent variable is a variable with the ordinary scale

Logit analysis is a special form of regression in which the dependent variable is non-metric and is divided into two parts or groups (binary), although the formulation may include more than two groups. In general, the interpretation of the logit analysis is very similar to the linear regression.

The logistic regression model used in this research (Moghadam, Zadeh and Fard, 2010) was derived from Ohlson's model and the model is:

$$\mathrm{Ln}\frac{P_1}{1-P_1} = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4$$

Notes:

$\mathrm{Ln}\frac{P_1}{1-P_1}$ = Dummy variable (P_1 = 1 for non-financial distress company and 1-P_1 = 0 for financial distress company)
β_1 = Constant
X_1 = *Debt Ratio* (*Total Liabilities/Total Assets*)
X_2 = *Working Capital to Total Assets*
X_3 = *Return on Assets*
X_4 = *Net Income was Negative for The Last Two Years (INTWO)*

2.4. Multiple Discriminant Analysis (MDA)

Multiple Discriminant Analysis (MDA) is a statistical technique used to predict and explain the strong relation influence on the category in which the object has certain dependent variables (nominal or non-metric), and the independent variables are metrics. The purpose of MDA is to identify the minimum number of discriminant function that can maximize the difference between the groups that exist.

Multiple Discriminant Analysis is a formal methodology that is used to reduce the ratio as to enhance the representativeness of the selected financial ratios as variables. This analysis model can be used to:

1) Predict the company's bankruptcy
2) Evaluate the company's prospect
3) Assess the feasibility and reasonableness of an organizational plan in deciding alternatives

The prediction models of MDA (Moghadam, Zadeh and Fard, 2010) which derived from Altman's Model is:

$$Z\text{-}Score = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4$$

Notes:

a = Intercept
b = coefficient
X_1 = *Retained Earning to Total Assets*
X_2 = *Earnings Before Interest and Taxes to Total Assets*
X_3 = *Market Value of Equity to Total Liabilities*
X_4 = *Sales to Total Assets*

3. RESEARCH HYPOTHESIS

Karamzadeh (2012) concluded that the Altman's model is the better predictor between the two predictors in the analysis (Altman's model and Ohlson's model).This is because the Altman's model has more percentage of accuracy than the Ohlson's. Therefore, the hypothesis of this research is:

H1: The Ohlson's Model is more accurate than Altman's Modelling predicting the financial distress of manufacturing companies listed on the Indonesian Stock Exchange in 2010-2014

Since the MDA Analysis is derived from the Altman Model and the Logit Analysis stems from the Ohlson model. Therefore the second hypothesis of this research is:

H2: The Logit Analysis is more accurate than the Multiple Discriminant Analysis in predicting the financial distress of manufacturing companies listed on the Indonesian Stock Exchange in 2010-2014

4. RESEARCH METHODOLOGY

The population in this study is all the manufacturing companies listed on the Indonesia Stock Exchange. The research sample is determined by predetermined criteria. The standards in this research consist of general and specific criteria. General criteria are the criteria that must be met by all samples as follows:

a) The financial statements (income statement, retained earnings statement, balance sheet, and cash flow) are available for the 5 years period (2010-2014).
b) Stock price data is accessible on the last trading date

Specific criteria are used to determine whether a company is experiencing financial distress or not. Specific criteria must be met to categorize the samples. The samples are divided into 2 (two) categories, companies that are experiencing financial distress and companies that are not experiencing financial distress. The specific criteria for the samples belonging to the category 1 (financial distress) are:

a) The company has a *Retained Loss* (negative equity). Negative equity means total liability exceeds its total assets. This is consistent with the definition of financial distress by Luciana (2006)
b) The company has negative net income for the last two years. This is in conformity with the definition of financial distress by Luciana (2006)

The specific criteria for the samples belonging to category 2 (non-financial distress) are:

a) The company does not have negative equity, or does not have negative net income for the last 2 years

b) Derived from the same year with the sample at category 1

The data used in this research is secondary data. Secondary data is the data obtained indirectly from the research object. The data obtained by the researcher are a financial statement of the company, one, two and three years before the company underwent distress. The data which is taken is manufacturing companies listed on the Indonesian stock exchange in the period 2010-2014. Because the financial distress prediction was made three years earlier, then the period of the financial distress was 2013-2014.

This research adopted independent sample t-test and the calculation of the Altman's Model and Ohlson's model to test the Hypothesis H1. The method is to compare the classification accuracy of the Altman's model and Ohlson's model. Then test the significance by using the independent sample with at-test.

This research used the Multiple Discriminant Analysis and the Logit Analysis to compare the percentage of the classification accuracy to test the Hypothesis H2. All of the test using statistical analysis tool of IBM Statistical Packages for the Social Science for windows version 22 (SPSS ver.22).

5. RESEARCH RESULT AND ANALYSIS

This section will compare the Altman's Model and Ohlson's Model for hypothesis 1. The MDA analysis and Logit Analysis will be compared for hypothesis 2.

5.1. The Comparison of Altman's Model and Ohlson's Model

The Altman's model has a cut-off value of 2.99 for the public manufacturing companies (Kumari and Chaudhry, 2012). It means that if the score obtained by a company exceeds 2.99, the company is predicted as not experiencing financial distress. Otherwise, if the score of the company is less than 2.99, then the company is predicted as experiencing financial distress.

Table 5.1. The Calculation of the Altman's Model

Year	Actual		Total	Predicted		Grey	Accuracy	
	Distress	Non-Distress		Distress	Non-Distress	Zone	Number	%
1 year before	20	20	40	18	7	4	25	63%
2 years before	20	20	40	16	8	10	24	60%
3 years before	20	20	40	17	7	11	24	60%
Total	60	60	120	51	22	25	73	-
Mean	-	-	-	-	-	-	-	61%

From the average of three years before financial distress above, the overall model of Altman can predict that are 51 companies that are experiencing financial distress from total 60 samples categories of financial distress and 22 companies that are not experiencing financial distress from the total 60 samples categories of non-financially distress company. Therefore, it can be concluded that the level of accuracy of Altman's model as a whole is about 61% of the number of correct predictions is 73 samples.

The Ohlson's model has a cut-off value of 0.38, which means if the company has a score more than 0.38, then the company is predicted to experience financial distress in the future. Otherwise, if the score is less than 0.38, it is predicted that it will not experience financial distress in the future.

Table 5.2. The Calculation of the Ohlson's Model

Year	Actual		Total	Predicted		Accuracy	
	Distress	Non-Distress		Distress	Non-Distress	Number	%
1 year before	20	20	40	11	15	26	65%
2 years before	20	20	40	14	17	31	78%
3 years before	20	20	40	12	18	30	75%
Total	60	60	120	37	50	87	-
Mean	-	-	-	-	-	-	73%

From the average of three years before financial distress above, the overall model of Ohlson can predict there are 37 companies that are experiencing financial distress from total 60 samples categories of financial distress and 55 companies that are not experiencing financial distress from total 60 samples categories of non-financial distress. Therefore, it can be concluded that the level of accuracy of Ohlson's model as a whole is about 73% of the number of correct predictions is 87 samples.

Table 5.3. The Comparison of Altman's Model and Ohlson's Model

Year	Accuracy	
	Altman	Ohlson
1 Year Before	63%	65%
2 Years Before	60%	78%
3 Years Before	60%	75%
Average	61%	73%

The test of HypothesisH1was done by using independent sample t-test for both models.

Table 5.4. Independent Sample T-test of Altman's Model and Ohlson's Model

		Levene's Test for Equality of Variances		t-test for Equality of Means			
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference
Altman	Equal variances assumed	8.504	.004	7.561	118	.000	-3.357138036
	Equal variances not assumed			7.561	90.624	.000	-3.357138036
Ohlson	Equal variances assumed	29.480	.000	4.482	118	.000	3.091568168
	Equal variances not assumed			4.482	67.045	.000	3.091568168

The table 5.4 showed that the model of Altman and Ohlson significantly differentiate categories of financial distress companies with non-financial distress companies. However, since the accuracy of Ohlson's Model is bigger. Therefore the conclusion of the hypothesis in this study are as follows:

Ho_1: The Ohlson's Model is not more accurate than the Altman's Modelling predicting the financial distress on manufacturing companies listed on the Indonesian Stock Exchange in 2010-2014

Ha_1: The Ohlson's Model is more accurate than the Altman's Modelling predicting the financial distress on manufacturing companies listed on the Indonesian Stock Exchange in 2010-2014

From the result of the calculation on both the Altman's model and Ohlson's model can be concluded that HO_1 is rejected. This is consistent with the research by Moghadam, Zadeh and Fard (2010) which said that the Ohlson's model is more accurate than the Altman's model in predicting financial distress.

5.2. The Comparison of Multiple Discriminant Analysis and Binary Logit Analysis

The test of discriminant analysis and binary logit analysis were conducted in order to identify the variables that are able to differentiate groups, using variables that have been identified to construct the equation or function to calculate new variables or index that explain the differences between groups, and use these variables to develop new feature or how to categorize the group in future. Then the MDA and logit analysis will be compared to seek the accuracy and test the second hypothesis.

5.2.1. Multiple Discriminant Analysis

This research used the Multiple Discriminant Analysis and the calculation of the Altman's model as the data. Step one, determine what variables are the most efficient in differentiating between the companies that are categorized as experiencing financial distress, grey zone, and non-financially distressed. Mahalobis distance was used for the stepwise procedure to determine which variables have the greatest accuracy.

Table 5.5. Wilks' Lambda Multiple Discriminant Analysis (MDA) Model

Step	Number of Variables	Lambda	df1	df2	df3	Exact F Statistic	df1	df2	Sig.
1	1	.829	1	2	117	12.035	2	117.000	.000
2	2	.706	2	2	117	11.004	4	232.000	.000
3	3	.499	3	2	117	15.923	6	230.000	.000
4	4	.345	4	2	117	20.020	8	228.000	.000
5	5	.321	5	2	117	17.297	10	226.000	.000
6	4	.325	4	2	117	21.507	8	228.000	.000

Table 5.6. Selected Variable for Forming Discriminant Model

Step		Tolerance	Sig. of F to Remove	Min. D Squared
6	EBIT/TA	.976	.001	2.630
	MARKET VALUE/TL	.729	.000	.380
	SALES/TA	.812	.000	1.404
	RE/TA	.868	.000	2.100

Table 5.5 and Table 5.6 show the variable that has been chosen from five variables in the model that can be inserted in the discriminant's equation. The equation of discriminant starts from variables that have the greatest statistical F number and the highest Min.D Square. F value for variable Working Capital to Total Assets is the smallest in the group, so at the final stage, variable Working Capital to Total Assets is not selected. High Mahalanobis indicates a high accuracy.

From the result of Wilk's Lambda test, variables *Earnings before Interest and Taxes to Total Assets*, *Market Value of Equity to Total Liabilities*, *Sales to Total Assets*, *Retained Earning to Total Assets* have a significant value of less than 0.05 which is 0.000. Therefore, from the five variables, there are four variables that are significant, *Earning before Interest and Taxes to Total Assets*, *Market Value of Equity to Total Liabilities*, *Sales to Total Assets*, and *Retained Earning to Total Assets*. Step two, determine the equation model. From the canonical discriminant function, produce the coefficient to determine the equation model.

Table 5.7. Discriminant Function

Variable	Function
RE/TA	.515
EBIT/TA	2.847
MARKET VALUE/TL	.529
SALES/TA	1.324
(Constant)	-1.879
Unstandardized coefficients	

Table 5.7 shows there are four variables that are made as discriminant function. They are *Earning before Interest and Taxes to Total Assets*, *Market Value of Equity to Total Liabilities*, *Sales to Total Assets*, and *Retained Earning to Total Assets*. The function is:

$$Z_1 = -1{,}879 + 0{,}515\ X_1 + 2{,}847\ X_2 - 0{,}277\ X_3 + 1{,}324\ X_4$$

Step three, canonical correlation test to measure the relationship between the value of the discriminant and the group. Canonical correlation is identical to R^2 (R-Square) on a regression which measures the variation between groups that can be explained by discriminant variables. The Canonical correlation measures how strong the discriminant function.

Table 5.8. Level of Accuracy

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1.755[a]	93.7	93.7	.798

a. First 2 canonical discriminant functions were used in the analysis.

Table 5.8 shows that the discriminant function can explain the variation of 93,7%. So it can be said that the variable *Earnings before Interest and Taxes to Total Assets*, *Market Value of Equity to Total Liabilities*, *Sales to Total Assets*, and *Retained Earning to Total Assets* can explain the variation between groups of financial distress and non-financial distress.

Table 5.9. Classification Result

Distress/non-distress			Predicted Group Membership			Total
			1.00	2.00	3.00	
Original	Count	Distress	52	16	1	69
		Greyzone	0	24	1	25
		Non Distress	0	9	17	26
	%	Distress	75.4	23.2	1.4	100.0
		Greyzone	.0	96.0	4.0	100.0
		Non Distress	.0	34.6	65.4	100.0

a. 77.5% of original grouped cases correctly classified.

Step four, the classification result is used to assess how well the discriminant function is Discriminant function on table 5.9 shows the average of classification accuracy for MDA is 78,93%

$$Average = \frac{75{,}4 + 96 + 65{,}4}{3} = 78{,}93\%$$

5.2.2. Binary Logit Analysis

Binary logistic regression is the logistic where the dependent variables are dichotomous variables or binary variables. This research uses the stepwise method to analyse the most influential independent variable to dependent variable. The dependent variable has two categories, the financial distress company = 0, and the non-financial distress company = 1. This research using the calculation of Ohlson's model as the data within total 120 data.

This logit analysis will use Wald test. The purpose of this test is to determine what variables are most efficient in differentiating between companies categorized as experiencing financial distress and those not experiencing financial distress. Table 5.10 and Table5.11 show that the significance of the variables entered into the equation is less than 0.05, and the significance of the variables removed from the equation is more than 0.05.

Table 5.10. Wald Test Result

Variable	B	S.E.	Wald	df	Sig.	Exp(B)
TLTA	-1.939	.867	5.005	1	.025	.144
WCTA	4.670	1.799	6.735	1	.009	106.652
NITA	16.537	4.953	11.148	1	.001	15196356.946
INTWO	-5.142	1.963	6.861	1	.009	.006

Table 5.11. Variables Removed from the Equation

		Score	df	Sig.
Variables	Size	.134	1	.715
	CLCA	.193	1	.660
	OENEG	.095	1	.757
	FUTL	.212	1	.645
	CHIN	.727	1	.394

The table 5.10 shows that there are four significant independent variables: *Debt Ratio*, *Working Capital to Total Assets*, *Return on Assets*, and *Net Income were Negative for The Last Two Years* (INTWO). The function of Logit analysis is:

$$\text{Ln}\frac{P_1}{1-P_1} = 1{,}01 - 1{,}939\ \text{TLTA} + 4{,}67\ \text{WCTA} + 16{,}537\ \text{NITA} - 5{,}142\ \text{INTWO}$$

The Cox and Snell R Square and Nagelkerke R Square can be interpreted as R Square on multiple regression. Table 5.12 shows that Cox and Snell R Square is 0.525, which means that all four independent variables (Debt Ratio, Working Capital to Total Assets, Return on Assets and Net Income were Negative for The Last Two Years (INTWO)) in logit analysis and can explain financial distress by 52,5%. While Nagelkerke R Square can explain financial distress by 70%, better than using Cox and Snell R Square.

Table 5.12. Cox & Snell R Square and Nagelkerke R Square

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
77.116[c]	.525	.700

Table 5.13. Classification Result

		Predicted		
		Distress/ Non distress		Percentage
Observed		.0000	1.0000	Correct
DISTRESS	.0000	45	15	75.0
NON DISTRESS	1.0000	4	56	93.3
Overall Percentage				84.2

By using four variables in this model, variables Debt Ratio, Working Capital to Total Assets, Return on Assets and Net Income were Negative for The Last Two Years (INTWO) shows that the overall accuracy of a prediction model for logit analysis is 84,2%.

5.2.3. Multiple Discriminant Analysis and Logit Analysis Classification Result

Table 5.14. Table Multiple Discriminant Analysis and Logit Analysis Classification Result

	Accuracy (%)
Multiple Discriminant Analysis	78,93%
Logit Analysis	84,2%

Ha_2: Logit Analysis is more accurate than Multiple Discriminant Analysis in predicting the financial distress on manufacturing companies listed on the Indonesian Stock Exchange in 2010-2014

$H0_2$: Logit Analysis is not more precise than Multiple Discriminant Analysis in predicting the financial distress on manufacturing companies listed in Indonesian Stock Exchange in 2010-2014

The Table 5.14 shows that the Logit Analysis has a greater accuracy than the Multiple Discriminant Analysis. Therefore, $HO_2$is rejected. This is consistent with Moghadam, Zadeh and Fard (2010) which said that the Logit Analysis is more accurate than the Multiple Discriminant Analysis.

6. CONCLUSION AND RECOMMENDATION

6.1 Conclusion

Based on the result, this study concluded that the Ohlson's Model is more accurate than the Altman's Model in predicting financial distress on manufacturing companies listed on the Indonesian Stock Exchange in 2010-2014. This is relevant with Moghadam, Zadeh and Fard (2010) which said that the Ohlson's model is more accurate in predicting financial distress than the Altman's model. However, it is not relevant with Karamzadeh (2013) which said that the Altman's model is more accurate than the Ohlson's model in predicting the financial distress.

Moreover, the result of this study also concluded that the Logit analysis model is more accurate than the Multiple Discriminant Analysis in predicting financial distress on manufacturing companies listed on the Indonesian Stock Exchange in 2010-2014. This is relevant with Moghadam, Zadeh and Fard (2010) which said that the Logit analysis model is more accurate than the Multiple Discriminant Analysis in predicting financial distress.

The result also concluded that the variables *Retained Earning to Total Assets*, *Earning before Interest and Taxes to Total Assets*, *Market Value of Equity to Total Liabilities, Sales to Total Assets* are significant to financial distress. While variable *Working Capital to Total Asset* in *Multiple Discriminant Analysis* model is not significant to financial distress.

Variables *Debt Ratio, Return on Assets, Working Capital to Total Assets*, and *Net Income were Negative for The Last Two Years* (INTWO) in *Logit Analysis* model are significant to financial distress. While variables *Current Liabilities to Current Assets, Total Liabilities Exceeds Total Assets* (OENEG)*, Funds Provided by Operations to Total Liabilities* (FUTL), *Delta Net Income Divided by The Sum of The Absolute Figures of Nominator (CHIN)* are not significant to financial distress.

Based on the conclusion above, it can provide information for investors and creditors in making investment decision with more attention to ratio *Retained Earning to Total Assets*, *Earning Before Interest and Taxes to Total Assets*, *Market Value of Equity to Total Liabilities, Sales to Total Assets* in Multiple Discriminant Analysis, and *Debt Ratio, Return on Assets, Working Capital to Total Assets*, and *Net Income was Negative for The Last Two Years* (INTWO) in Logit Analysis. Investors would be better use the Ohlson's Model and Logit analysis in predicting financial distress because they have a higher accuracy than the Altman's Model and the Multiple Discriminant Analysis.

6.2. Recommendation

There are some limitations that require improvement in this research. These limitations include 1) The number of samples is limited to manufacturing companies, 2) The models used are only 2 (two), but there are some other models that have been found, 3) The criteria financial distress is still not fixed to differentiate between financially distressed companies and non-financially distressed ones.

Based on the limitations described above, there are some suggestions for the future research. Future studies are expected to consider a broader sampling, for example, using a sample of other companies than manufacturing companies, such as banking or services. So, it can provide a broader view of the financial distress model in other industrial fields. Future studies are expected to use other financial distress prediction models that are rarely used but affect financial distress. Future studies are also expected to add more criteria for financial distress so that the result will be more accurate.

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