THE COMPARISON OF DISCRIMINANT ANALYSIS AND LOGISTIC REGRESSION TO SEE THE FACTORS AFFECTING THE CONDITIONS OF FINANCIAL DISTRESS IN MANUFACTURING COMPANIES LISTED IN INDONESIA STOCK EXCHANGE (ISE)

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Abstract
Penelitian ini bertujuan untuk mengetahui pengaruh seperangkat rasio keuangan untuk mengelompokan perusahaan-perusahaan manufaktur di Bursa Efek Indonesia (BEI) masuk kategori FD dan Non FD dengan menggunakan Analisis Diskriminan dan Regresi Logistik, dan membandingkan kedua metode tersebut. Penelitian ini menggunakan sampel 107 perusahaan yang laporan keuangannya lengkap dari tahun 2010-2014. Kriteria perusahaan masuk kelompok FD sebagai variable dependent adalah nilai Earning Per Share (EPS) negatif atau Jumlah Aktiva (TA) < Jumlah Kewajiban (TL) dan 24 rasio keuangan sebagai variable independent. Hasil penelitian menunjukkan rasio keuangan Equity to Total Assets (ETA), Return on Equity (ROE), Return on Asset (ROA), Retained Earning to Total Assets (RETA), dan Pre Tax Profit to Total Assets (PPTA) adalah rasio keuangan yang mampu memprediksi Kelompok FD dan Non-FD. Dengan regresi Logistik, rasio keuangan yang dominan untuk memprediksi kelompok FD dan Non-FD adalah ETA, ROA, dan RETA. Kekuatan Prediksi Regresi Logisitik relatif lebih baik dari analisis diskriminan.
Kata Kunci :

Introduction

The 2008 global financial crisis hit the world economy due to the subprime mortgage crisis in the United States has a broad impact on the political and economic life of the countries in the world. The economic crisis caused the bankruptcy of public enterprises in various corners of the world, especially in USA, Europe, Asia and countries other.

The global community of the world's financial crisis affected the Indonesian economy, especially in the capital market, reflected by the turmoil in the capital markets and money markets. The impact of the global economic crisis in Indonesia's capital market did not spread to other sectors, due to the contribution of relatively small capital market in the Indonesian economy. This means the global economic crisis did not impact significantly on the overall Indonesian economy because Indonesia's economy is more dependent on the domestic economy.

This research used various analytical methods, Multi Discriminant analysis (MDA), refers to Altman (1968) logistic regression, and multinomial logit using financial ratios as independent variables. Muliaman et.al (2003) used the method of MDA and Logistic Regression to establish Bankruptcy Indicators in Indonesia. The samples were 32 companies, comprising of 16 active companies on the exchange and the 16 delisted companies from the Jakarta Stock Exchange (JSE).

The study to predict the company's FD and Non FD in Indonesia uses the Total Assets less Total Liabilities (TA <TL) or an Earning Per Share (EPS) of negative as an

indicator (Umi et. Al 2013), and 24 financial ratios on research Al-Khatib & Al-Horani (2012) on the stock market Jordan as independent variables.

Objective

This study aims to:

1. Find the influence of a set of financial ratios to classify the companies listed on the ISE categorized FD and Non FD using discriminant analysis and logistic regression methods.
2. Compare the results of the comparison of FD and non- FD category to companies listed on the ISE between models discriminant analysis and logistic regression.

Literature Review

Bankruptcy and Financial Distress

Bankruptcy is another term that describes the company's performance is negative and generally used in a way that is more technical. Bankruptcy is more critical in terms of bankruptcy and usually indicates a chronic rather than a temporary condition. When a company meets the situation, its total liabilities exceed the fair valuation of the total assets. The real net worth of the company, therefore, is negative. Technical bankruptcy is easily detected, while the more serious condition of bankruptcy requires a comprehensive assessment analysis, which is usually not done until the liquidation of the assets (Altman & Hotchkiss 2006). Bankruptcy represents the situation in which company is unable to settle its liabilities (to banks, suppliers, employees, tax authorities, etc) and therefore, according to law, company enters the bankruptcy procedure (Pervan et.al 2011). Leverage increases are accompanied by increased potential for default and bankruptcy. These structures raise the importance to financial economists, managers, and legal scholars of understanding how firms deal with financial distress (Hotchkiss et.al 2008)

Financial distress is a condition in which the company cannot meet nor pay off financial obligations to creditors. FD prediction models are usually composed on financial information – financial ratios of solvency, activity, profitability, investment, and leverage (Sarlija and Jeger, 2011). FD conditions increase when companies have high fixed costs, illiquid assets, or revenues are sensitive to economic downturns. FD predicts failure before insolvent financial companies that actually happened. Platt & Platt (2002) define FD as a stage of decline in financial condition that occurs prior to the bankruptcy or liquidation.

FD is a condition when the company is unable to meet or pay off its financial obligations to creditors (Ahmad et. al, 2014). The occurrence of the company's financial difficulties resulted higher fixed costs, illiquid assets or income are highly sensitive to the economic recession. If this situation lasts in a long time, it leads to the bankruptcy of the company. According to Ross et.al (2012) FD is a cash flow the company's operating is not able to cover or meet current obligations, FD can bring a company fails (corporate failure) at the end of its contract to do restructuring of financial the company. Jostarndt (2007) states companies that belong to the category of FD are a company that repeatedly experienced shortages interest coverage. A year in which there is deficiency interest coverage in the initial referred to as the year 0 in time of trouble. There are three different factors causing the company's inability to cover its debt obligations: (1) the excessive influence; (2) industry slump; and (3) poor performance of special operations company. Beaver (1966) defines failure as the company's inability to pay its financial obligations at maturity.

Previous Research

Research to predict the FD and the bankruptcy of the company developed since the late 1960s. Research on FD and bankruptcy attracted many researchers in the field of finance. Research on failure prediction models quantitatively companies was first conducted by Beaver (1966). In his study, Beaver creates five groups of financial ratios and made a univariate analysis connecting each ratio to find which ratio best used as a predictor. However, further research after Beaver followed Altman (1968), suggested a multivariate technique, known as Multivariate Discriminant Analysis (MDA). Altman found five ratios combined to see the difference between bankrupt and not bankrupt companies.

Five types of ratios used Altman are working capital to total assets, retained earnings to total assets, EBIT to total assets, market value of equity to book value of total debts, and sales to total assets. In his research, the ratio of working capital to total assets is used to measure the liquidity of the company's assets relative to total capitalization. The ratio of retained earnings to total assets is to measure the cumulative profitability. EBIT to total assets ratio is to measure the actual productivity of the assets of the company. The ratio of market value of equity to book value of total debts is to measure how much the company's assets may be impaired before the debt amount is greater than its assets and becoming the company failure. Sales ratio to total assets is to measure the ability of management in the face of competitive conditions. Altman formulated the form of equations known as the formula Z-score, Z-score is a combination of several financial ratios considered to predict the occurrence of the bankruptcy.

Ohlson (1980) used a logit analysis to predict the FD and the bankruptcy, a method to avoid the technical limitations of Multi Discriminant Analysis (MDA). In the logit analysis, assumption multivariate normal distribution is ignored. Given this assumption, the limitations of the statistical tests for financial distress and defaults on MDA method can be overcome by Logit. Logit called the conditional probability model because logit provides a conditional probability of the observation that comes within a group. Another consideration to choose logit partly is because logit model has a statistical advantage. Logit Model needs to be modified to ensure the validity coefficient parameter to influence the group generated by the data panel. In this study took 105 bankrupt companies in America 1970-1976 and based on three types of the 2058 of non bankrupt companies. The results of the study is to conclude the strength of the model depends on when the financial ratios required information available, where in some previous studies is not observed.

Especially for the Asian region, many researchers continue to study the financial sector in the various stock exchanges. Research carried out by a variety of methods was to predict the FD and bankruptcy. Zeytmoglu & Akarim (2013) apply the MDA on the stock exchanges of Istanbul (ISE) with the criteria of the FD company refers Altman Z score to find the company's success and not success, there are 20 financial ratios used as independent variables include liquidity, operations, liability management and profitability. Taking a sample of 115 companies trading 2009-2011, successful research results showed 88.7%, 90.4% and 92.2% of companies were successful and not successful in 2009, 2010 and 2011.

Puagwatana & Guwardana (2005) predict failure businesses in the technology industry in Thailand with logistic model. By using the five financial ratios as independent variables refer to the model of the variables used in the Model Altman. In this research Total Liability is not counted because of a lack of data Market Value Equity (MVE), on the model of Altman's modified by adding Net income (loss)/amount of share. The dependent variable predicted from failed opportunities between 0 and 1. If the chance $\geq$ 0.5, then the company is classified healthier, the other is unhealthy. The results showed the model predicted 77.8% of the company's financial health technology in Thailand.

In Iran, a study to predict the financial crisis undertaken by Hassani & Parsadmehr (2012) was the sample data taken from productive enterprise data in the Tehran Stock Exchange from 2002 to 2009 as many as 73 companies. Grouping of successful companies and unsuccessful refers to article 141 code of commercial with the help of Simple Tobin's q yielded 19 successful companies and 54 companies did not succeed. Financial ratios are used as independent variables there are 14 financial ratios. Using logistic regression as a method of analysis, research shows the debt to equity ratio, net profit to net sale ratio and working capital to asset ratio is a factor that affects the success or failure of companies in Iran. The resulting prediction accuracy is 81.49%.

Olson models applied research conducted by Wang & Campbell (2010) samples were taken from the company on the stock exchange Shanghai Stock Exchange Market (SHSE) from 1998-2008. The number of non delisted companies are 11194 companies and 36 companies from the first year to delisting 40 companies from the second delisting year. It involved 1336 companies. The results showed the model's accuracy above 95% depending on the selected cutting point.

Ahmad et.al (2014) identified the company experienced FD in Malaysia. In this study the development model of MDA by Altman (1968) used as the statistical techniques. The number of companies sample was 30 listed companies on the Malaysian stock exchange. Companies experiencing financial distress were classified on the Z-score. By having ratios Liquidity Current Ratio and Debt Ratio as independent variables, the results showed there is real significant relationship between the two variables with a Z-score to determine FD companies in Malaysia.

Lin & Mc Clean (2000) compared the statistical technique models of Linear Discriminant Analysis (DA) and Logistic Regression (LR) and methods of machine learning, namely: Neural Network (NN) and decision tree (C4-0) to predict financial distress. The sample data were taken from the structure of financial data from the UK (United Kingdom). Companies are divided into two groups: FD and non FD companies. By using 37 financial ratios including profitability, profit margins, efficiency, leverage, liquidity ratio, productivity and items per share and with a total result of 337 companies studied company consisted of 48 companies failed and 289 companies did not fail the period 1991-1999, the results showed accuracy better machine compared with statistics on the overall accuracy. Researchers propose the use of a hybrid algorithm combining statistical and machine learning.

Ko et.al (2001) used the method Composite Rule Induction System (CRIS) to predict the financial distress of the company by taking a sample of companies in Taiwan, by taking a sample of 19 of FD companies and 34 of FD companies. The results of the study conclude CRIS models can be used as a tool to predict FD in Taiwan, with a better accuracy than the logit model.

Liang (2003) conducted a study on the FD in China to increase the sample size to compare between Multi Discriminant Analysis (MDA) and logistic regression, particularly in the larger sample size. Both have high flexibility with a combination of data from the financial statements and stock market prices. The results of logistic regression analysis were considered as the best techniques to classify and predict the condition of FD companies registered in China.

Pongsatat et.al (2004) reported the results of the study by comparing the Ohlson Logit models and four models to predict bankruptcy Altman variants of large and small companies in Thailand. The sample of 60 bankrupt and 60 non-bankrupt companies were examined during the period 1998 to 2003. The results concluded each method had its predictive capability when applied to a Thai company; there was no significant difference in the predictive ability of each good for companies with assets of large and small assets in Thailand.

Al-Khatib & Al-Horani (2012) conducted a research to study the role of a set of financial ratios in predicting financial difficulties public company in Amman Stock Exchange in the period from 2007 to 2011, using logistic regression and discriminant analysis results indicate the Return on Equity (ROE), Return on Assets (ROA) and some other ratio can predict the financial difficulties of public companies in Jordan The number of companies surveyed in this study is 18 FD companies, and 38 non FD companies.

Umi et.al (2013) conduct FD research related to the balance of data between two classification using SVM method and Discriminant Analysis as an analytical tool for manufacturing companies that go public in Indonesia. Gauges of FD used are the value of total assets less total liabilities of the company or a negative EPS.

Data And Method

Materials used in this research is financial statement data of manufacturing companies listed on the ISE obtained from the Indonesian Capital Market Directory (ICMD), www.idx.co.id and information summary of the company's performance manufactures listed on ISE. In this research, manufacturing companies can present the complete financial statements in the period 2010-2014 chosen as a sample. Of the 141 companies that the population in this study, there are 107 companies that have complete financial statements in the period 2010-2014.

Dependent variable in this research refers to research Umi et.al (2013): The company had Total Assets less the value of Total Liabilities (TA <TL) or the value of Earning Per Share (EPS) is negative. If TA <TL or EPS <0 : Financial Distress (FD (Y=0)); others Non Financial Distress (Non FD (Y=1)).

The independent variablel refers to reseach by Al-Khatib & Al-Horani (2012), the financial ratios are:

1. Liquidity: **CR** (Current Ratio), **CLTFA** (Current Liabilities to Total Fixed Assets).
2. Profitability: **PPTA** (Pre-tax Profit to Total Assets), **NPM** (Net Profit Margin), **ROA** (Profit After Tax to Total Assets), **ROE** (Profit After Tax toTotal Equity), **ATPWC** (After Tax Profit to Working Capital), **WCE** (Working Capital to Equity).
3. Solvency: **RETA** (Retained Earnings to Total Assets), **CLE** (Current Liabilities to Equity), **ETA** (Equity to Total Assets), **ETL** (Equity to Total Liabilities), **DR** (Debt Ratio), **DE** (Debt to Equity), **LTDE** (Long-term Debt to Equity Ratio), **FAE** (Fixed Assets to Equity).
4. Activities: **AT** (Asset Turnover), **SE** (Sales to Equity), **SWC** (Sales to working capital), **RT** (Receivables Turnover).
5. Investment: **BVP** (Book Value Per Share), **DPS** (Dividend Per Share).
6. Size: **LTA** (Logarithm of Total Assets), **LAT** (Logarithm of Asset Turnover).

Data processing and data analysis:

1. **Data Processing:**
Collect data of financial statements, a summary of the performance of listed companies and the Factbook as many as 141 manufacturing companies listed on the Stock Exchange as the study population. Check the completeness of financial reporting data, a summary of the performance of listed companies and manufacturing companies Fact book to 141 in 2010-2014. Establish 107 companies in the research samples to provide the required information on this research a value of EPS and 24 financial ratios required in the study period 2010-2014.
2. Data Analysis
Method analysis used discriminant analysis and logistic regression to compare both results as follows:
   1) Normal multivariate test in this study was conducted using Chi Square plot (Johnson & Wichern 2002) with the help of Minitab software Macro.
   2). Factor analysis is used to calculate the adequacy of the sample and variable selection. The adequacy of the sample is calculated using Kaiser-Meyer-Olkin Measures of Sampling Adequacy (KMO-MSA)> 0.5 as a reference. Selection variable is done for selecting 24 variables used to predict manufacturing company FD and non-FD by using the value of diagonal anti-image correlation matrix. If the anti-image correlation value matixs <0.5, variable excluded from the model (Hair et.al, 2010).
   3) Discriminant analysis is done by using method stepwise by adding variables one by one, and at each step. The procedure stops when F partial largest among the variables provided for in failed exceeding the threshold value has been determined. Model prediction discriminant function is:
   $Z = \alpha + w_1x_1 + w_2x_2 + w_3x_3 + \cdots + w_ix_i$
   Where
   α=constant; Z = Discriminant Value; $w_1, w_2, \ldots, w_i$: Coefficient discriminant function; $x_1, x_2, \ldots x_i$= Financial Ratio.
   4) Logistic regression mathematical model of this research are:
   $(p\frac{(x)}{1-p}(x)) = e^{\beta_0+\beta_1x_1+\beta_2x_2+\,..\beta_px_p}$
   Where
   $\beta_0, \beta_1, \beta_{2,}.., \beta_p$ is the unknown parameters; $x_1, x_{2,}.., x_p$ is financial ratios as independent variables (predictors); $(\frac{p(x)}{1-p(x)})$ is a group opportunities Non FD, Logistic regression models used by the author is a method forward stepwise Likelihood Ratio.
   5) Comparing discriminant analysis with logistic regression to predict the FD and Non FD companies listed in Indonesia Stock Exchange 2010-2014.

Discriminant analysis and logistic regression were done with the help of SPSS version 21 Software.

Results And Discussions

Multivariate Normal Test

The Multivariate Normal Test in this study was calculated using graph Chi Square plot by using statistical software Minitab macros.

Table 1. The Results Of Normal Multivariate Test

Year	Value t	Criteria	Conclusion
2010	0.701	0.500	Multinormal
2011	0.729	0.500	Multinormal
2012	0.701	0.500	Multinormal
2013	0.710	0.500	Multinormal
2014	0.710	0.500	Multinormal

Note: * p<0.05

The Normal Multivariate Test Data of independent variables was conducted using graph, dd plot by plotting the remnant of data sorted by cumulative. From Table 1 the data of 24 independent variables used by the author distribute normal multivariate each year.

Variable Selection

Selection process variables were calculated by Principal Component Analysis, Measurement of the sample adequacy refers to the value of Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy. Of the 24 independent variables of this study were used as the initial basis of variables, KMO value each period in Table 2.

Table 2. Test KMO Measure of Sampling Adequacy and Bartlett

Size		2010	2011	2012	2013	2014
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.720	0.711	0.721	0.665	0.690
Bartlett's Test of Sphericity	Approx. Chi-Square	2272.885	2422.464	2450.64	3264.805	3419.288
	df	105	120	105	105	91
	Sig.	0.000*	0.000*	0.000*	0.000*	0.000*

Note: * p<0.05

Based on the value of KMO obtained, the number of samples used in this study was valid. By using the Bartlett test the approach on the distribution Chi Square with significance level = 5% (0.05). The significant value in each period in this study entirely is <0.05, It indicates the sample used in future studies is valid.

Of the 24 financial ratios become the beginning variable of the study, the results of the factor analysis is to select variables shown in value of anti-image correlation financial ratios of each period. Variables valid financial ratios in 2010 are: CLE, LTA, ROA, ROE, ATPWC, RETA, ETA, DR, DE, LTDE, FAE, AT, SE and RT. In the period 2011 are CLE, LTA, LTA, PPTA, ROA, ROE, ATPWC, RETA, ETA, ETL, DR, DE, LTDE, FAE, AT and SE. In the period from 2012, is CLE, LTA, PPTA, ROA, ROE, DPS, RETA, ETA, DR, DE, LTDE, FAE, AT, SE, LAT. Period of 2013, is CLE, WCE, PPTA, ROA, ROE, DPS, RETA, ETA, DR, DE, LTDE, FAE, AT, SE, and SWC. In the period from 2014, the variables valid financial ratios are CLE, PPTA, ROA, ROE, RETA, ETA, DR, DE, LTDE, FAE, AT, SE, SWC, and RT.

The Result of Discriminant Analysis

Using software SPSS version 21, Zscore discriminant function values in Table 3 is a discriminant function per year. In the periode 2010-2014, the value of model constant coefficient was negative, the score indicate the occurrence of FD. The value discriminant functions in 2010:

$$Zscore=-1.001 +1.645(ETA)+0.014(ROE)+0.042(ROA)$$

ETA Variable coefficient indicates the increase in the ratio of ETA by 1 unit while other independent variables remain constant, so there will be an increase in the value Zscore of 1.645, the coefficient ROE indicating if there is an increase ROE by 1%, then Zscore value will increase by

0.014, ROA coefficient indicate if there is an increase ROA of 1%, then the value Zscore will increase by 0.042.

The values of discriminant function in 2011:

Zscore = -0.683 + 0.903(ETA) + 0.685(RETA)+0.05(ROE)+3.224(PPTA)

ETA variable coefficient indicated if there is an increase ratio of ETA, the value Z score will increase by 0.903. RETA variable coefficient indicated that the increase in financial ratios RETA of one unit increase by 0.685 Z score, ROE variable coefficient meant that the increase in ROE 1% can increase Z score value of 0.05, and the coefficients PPTA meant that the increase in the ratio of one unit PPTA increase Z score by 3.224.

Table 3. Discriminant function Z score

Year	Variable	Function 1
2010	ROA	0.042
	ROE	0.014
	ETA	1.645
	(Constant)	-1.001
2011	PPTA	3.465
	ROE	0.004
	RETA	0.660
	ETA	0.891
	(Constant)	-0.698
2012	ROA	0.077
	ETA	1.804
	(Constant)	-1.251
2013	ROA	0.037
	ROE	0.012
	RETA	0.909
	(constant)	-0.285
2014	ETA	1.702
	(constant)	-0.761

Value discriminant function Zscore in 2012:

Zscore = -1.251 + 1.804(ROA) + 0.077(ETA)

ETA variable coefficient meant the increase in financial ratios ETA for one unit increase the value Zscore by 1.804, where ROA is fixed. ROA variable coefficient meant that any change ROA of 1%, there will be an increase in the value of Zscore 0.077 where ETA is fixed.

Values in the discriminant function 2013:

Zscore = -0.285+ 0.909(RETA) + 0.012(ROE) + 0.037(ROA)

RETA variable coefficient indicated the increase in financial ratios RETA of one unit increase by 0.909, where two other variables are constant. Variable coefficient ROE meant if there is an increase ROE, then the value increase by 0.012 with a record of two other variables are constant, variable coefficient ROA meant the increase in financial ratios ROA of one unit will increase the value Zscore to 0.037.

The value of discriminant function in 2014:

Zscore = -0.761+ 1.702(ETA)

Values model constant coefficient discriminant analysis above indicated if the financial ratios ETA zero, then the resulting Zscore is -0.761. ETA variable coefficient meant if there is an increase ratio of ETA, the value Zscore increase by 1.702.

The Results of Logistic Regression

The logistic regression models produced based on year financial statements in Table 4. In the data processing for a model, variables entered simultaneously into the model and selected gradually by Step wise LR method. Using a significance level $\alpha = 5\%$, in 2010 found the significant value of ROA, thus it can be concluded the ROA variables significantly predicted group FD and Non FD companies listed on ISE. Odd Ratio variable ROA is 1.867 indicated if the independent variable ROA increased by one percent, the value of the odds ratio increase by 1.867, meaning the tendency of companies enter the group of Non FD is equal to 1.867, in other words, the tendency of companies enter the group of Non FD likely to 1.867 compared with the incoming group FD if there is an increase ROA one percent. Odd Ratio variable ETA indicated if the independent variable ETA increase by one unit the value odds ratio increase by 111.744, meaning the tendency of the company belong to a group of Non FD equal to 111.744, in other words, the tendency of companies enter the group of Non FD 111.744 compared with the likely entry of any changes FD group ETA. Thus the logistic regression model year 2010 is:

$$\left(\frac{p}{1-p}\right) = e^{-0,630 + 4.716(\text{ETA}) + 0.624(\text{ROA})}$$

Odd Ratio variable RETA meant if the company increased by one unit RETA the tendency of companies enter the group Non FD equal to 9.405 or the tendency of a company Non FD increase by 9.405 when compared with the FD company in 2011. Thus the regression model produced in 2011 are:

$$\left(\frac{p}{1-p}\right) = e^{1.752 + 2.163(\text{RETA})}$$

In 2012, found the significance value ROA = 0.004 <0.05, indicating the ROA variables significantly predicted group FD and Non FD manufacturing companies in ISE. Value odds ratio indicated the change in the value of ROA of one per cent would increase the chances of the company belong to a group of Non FD amounted to 2.827 compared to if the incoming FD group, meaning the tendency of a company experiencing Non FD increase by 2.827 when compared with the company experienced FD in 2011 if ROA increased. Logistic Regression Model 2012 can be written:

$$\left(\frac{p}{1-p}\right) = e^{1.305 + 1.039(\text{ROA})}$$

Table 4 Results of Logistic Regression Model parameter Estimation per year during the 2010-2014 periods

Year	Step	Variable	B	S.E.	Wald	df	Sig.	Exp(B) (odd ratio)
2010	*Step* 2[b]	ROA	0.624	0.208	9.015	1	0.003*	1.867
		ETA	4.716	1.477	10.198	1	0.001*	111.744
		Constant	-0.630	0.709	0.789	1	0.374	0.533
2011	*Step* 1[a]	RETA	2.241	0.569	15.530	1	0.000*	9.405
		Constant	1.583	0.296	28.641	1	0.000*	4.869
2012	*Step* 1[a]	ROA	1.039	0.362	8.240	1	0.004*	2.827
		Constant	1.305	0.519	6.319	1	0.012*	3.687
2013	*Step* 2[b]	ROA	2.464	0.888	7.706	1	0.006*	11.757
		ETA	9.210	3.504	6.908	1	0.009*	9999.192
		Constant	-3.780	1.664	5.161	1	0.023*	0.023
2014	*Step* 1[a]	ETA	3.321	0.997	11.108	1	0.001*	27.701
		Constant	-0.269	0.478	0.316	1	0.574	0.764

Note: * p<0.05

From a logistic regression model year of 2013 there were two significant variables, namely ROA and ETA, thus each of these variables separately could predict the group FD and Non FD in 2013. Odd Ratio variable ROA gave the sense if the independent variable ROA increased by one percent. the value of odd ratio increase by 11.757, meaning that the tendency of the company belong to a group of Non FD equal to 11.757. Odd Ratio variable ETA meant if the independent variable ETA increase by one unit the value odds ratio increase by 999.192 times, meaning the tendency of the company belong to a group of Non FD equal to 999.192. Thus the logistic regression model year 2013 is:

$$\left(\frac{p}{1-p}\right) = e^{-3.780 + 9.210(\text{ETA}) + 2.464(\text{ROA})}$$

In 2014, a significant variable is ETA, meaning that in 2014 a significant variable can classify company FD and Non FD is ETA. Value odds ratio of 27.701 indicating the change in the value of ETA by one percent would increase the chances of the company belong to a group of Non FD amounted to 27.701 compared to if the incoming FD group, meaning the tendency of a company experiencing Non FD would be increased by 27.701 if compared with the company experienced FD in 2011 when ETA increase. Logistic Regression Model 2014 can be written:

$$\left(\frac{p}{1-p}\right) = e^{-0.269+3.321(\mathrm{ETA})}$$

Comparison of Discriminant Analysis and Logistic Regression

Comparison of predicted results Discriminant Analysis and Logistic Regression in Table 5. In 2010 showed the predicted results with the FD group using logistic regression analysis (77.78%) is better than the discriminant analysis (66.67%), it contributes to the prediction error where the prediction error for discriminant analysis FD group greater than logistic regression. Non FD group prediction accuracy for discriminant analysis (100.00%) is better than logistic regression (98.88%) in 2010. In 2011, the predicted results with the FD group discriminant analysis (54.55%) better than the logistic regression (40.91%), but the predicted results Non FD group the two models of the same year. Slightly different results occurred in 2012, in which the predicted results FD group both models is equal to the amount of 85.71%, found the predicted results Non FD group with logistic regression model (100.00%) better than the discriminant analysis in that year (96.51%).

In 2013 the predicted results of FD group with logistic regression model (85.71%) were better than the discriminant analysis (67.86%), on the other hand predicted results Non FD group with discriminant analysis (98.73%) is better than by logistic regression (97.47%). In 2014, there was a large difference prediction results both models, in which the predicted results FD group, the results of discriminant analysis (45.15%) better than the logistic regression (29.63%), on the other hand predicted results Non FD group with logistic regression (98.75%) better than the discriminant analysis (85.00%). From the calculation of the average value during the period 2010-2014, it was found that to predict the FD group, discriminant analysis predicted results relatively better than logistic regression, on the other hand to predict Non FD group predicted outcome logistics relatively was better than the discriminant analysis.

Table 5. Comparison Results Classification Discriminant Analysis and Logistic Regression Model

Year	Financial Status	Variable	Discriminant Analysis		Variable	Logistic Regression	
			n	%		N	%
2010	FD	ROA, ROE, ETA.	12	66.67%	ROA, ETA	14	77.78%
	Non FD		89	100.00%		88	98.88%
	Classification Errors FD		6	33.33%		4	22.22%
	Non FD Classification Errors		0	0.00%		1	1.12%

Next Table

Year	Financial Status	Variable	Discriminant Analysis n	Discriminant Analysis %	Variable	Logistic Regression N	Logistic Regression %
2011	FD	PPTA, ROE. RETA, ETA	12	54.55%	RETA.	9	40 91%
	Non FD		83	97.65%		83	97.65%
	Classification Errors FD		10	45.45%		13	59.09%
	Non Classification Errors FD		2	2.35%		2	2.35%
2012	FD	ROA, ETA	18	85.71 %	ROA	18	85.71%
	Non FD		83	96.51%		86	100.00%
	Classification Errors FD		3	14.29%		3	14.29%
	Non FD Error Classification		3	3.49%		0	0.00%
2013	FD	ROA, ROE, RETA	19	67.86%	ROA, ETA	24	85.71%
	NonFD		78	98.73%		77	97.47%
	Classification Errors FD		9	32.14%		4	14.29%
	Non Classification Errors FD		1	1.27%		2	2.47%
2014	FD	ETA	13	48.15%	ETA	8	29.63%
	Non FD		68	85.00%		79	98.75%
	FD Classification Errors		14	51.85%		19	70.37%
	Non FD Classification Errors		12	15 . 00%		1	1.25%
Average	FD			64.59%			63.95%
	Non FD			95.58%			98.55%

Seen from the predicted value FD discriminant analysis (64.590%) is better than the logistic regression (63.95%). Non FD group predicted results, prediction results of logistic regression (98.50%) is better than discriminant analysis (95.58%).

Based on the predictive power, a comparison between the predictive power of discriminant analysis and logistic regression in Table 6 shows the power predictive logistic regression model is generally better than the discriminant analysis. The average value of the predictive power of the logistic regression is greater than the discriminant analysis (90.64%> 88.80%).

Table 6. Comparison of Strength Prediction Model with Logistic Regression and Discriminant Analysis

Year	Predicted Strength	Strength Prediction
2010	94.40%	95.30%
2011	88.80%	85.00%
2012	94.40%	97.20%
2013	90.70%	94.40 %
2014	75.70%	81.30%
Mean	88.80%	90.64%
Std	0.07	0.01

From Table 7 shown variable most dominant financial ratios to predict FD and Non FD group both with discriminant analysis method and ETA, further ROA and ROE, the next is RETA and PPTA. With variable logistic regression model financial ratios is the most dominant ROA and ETA, then the variable RETA 1 times, two other variables do not have a role to predict the FD and Non FD groups by using logistic regression.

Table 7. Frequencies Financial ratios that can predict the group FD and Non FD

Codes	Variable	Discriminant Analysis	Logistic Regression
ROA	Return on assets	3	3
RETA	Retained Earnings / total assets	2	1
PPTA	Pre Tax Profit to total assets	1	0
ETA	Equity to total assets	4	3
ROE	Return on Equity	3	0

Discussion

The results of discriminant analysis showed the influencing factors to predict manufacturing companies belong to the FD and FD Non group in 2010-2014 dominated by the value of ETA, the next the big ROA and ROE, followed by RETA and PPTA, By using a logistic regression model, the variable most dominant financial ratios to find which group belong to FD and Non FD Company is ETA, ROA and RETA. If classified more specifically, the five financial ratios into the group's profitability ratios, represented by ROA, ROE and the PPTA and the solvency ratio represented by ETA and RETA.

The influence of ROA and ROE to find the FD and Non FD group corresponding to the research Al-Khatib & Al-Horani (2012) who found the ROA and ROE , two dominant financial ratios, financial difficulties predicting public company in Jordan. Because the ROA shows the ability of the company with all the money is to gain a profit and ROE is a part of the profit derived from its own capital often used by investors in the purchase of a stock.

ROE ability to predict the group FD and Non FD model discriminant analysis shows if the value of ROE increased the chances of the company belong to a group of Non FD increases. ROE value negatively on the company FD group showed poor performance of the company caused by the value of net profit or equity firm negative in the study. The results of this analysis showed the greater percentage of ROA and ROE, the finance company will likely be better thus increasing the company's ability to pay its obligations to its creditors and investors. Results of other studies show that the ROA and ROE is a decisive factor to group FD and Non FD. Liang (2003) stated that the ROA as an indicator of the return on investment is the most important factor to predict FD and Non FD in Stock Exchange China with logistic regression and discriminant analysis. ROE as an indicator of capital investment has a contribution to the logistic regression.

PPTA showed a comparison between profit before tax to total assets as part of the profitability ratios, the difference with the ROA is the absence of a reduction of the tax liability results of its operating profit, thus the greater the company's operating profit increase its net income improving opportunity for the company to get in on a group of Non FD companies. From the analysis in this study, the role of the PPTA to predict group FD and Non FD occurred the discriminant analysis 2011.

Solvency ratio contributing to define FD and Non FD groups is ETA and RETA. As a ratio shows the company's ability to meet all its obligations both short term and long term, the role of the solvency ratio is needed to increase the leverage of a company into a better direction or toward a group of Non FD. RETA has had a role to predict corporate bankruptcy in previous research, Altman (1968); Altman et.al (1977) with multi models discriminant analysis established that RETA is one of the indicators in the Altman Z score and Zeta analysis

RETA is a partial or total profit from the company that is not distributed by the company to shareholders in the form of dividends to total assets. Total undistributed earnings can be used by companies for additional capital or to increase the company's capital. If the profit is not shared, the greater it will improve the company's financial performance. Thus, if the ratio of RETA is getting better. then the chances of the company to enter the group of Non FD will be even greater, it is consistent with the results of this study, in which the positive effect RETA variable to predict group FD and Non FD companies listed on the Stock Exchange. RETA role to predict the ability of FD and Non FD occurred in 2011, both with discriminant analysis and logistic regression. In 2013, RETA can predict group FD and Non FD with Logistic Regression.

ETA ratio shows its own capital obtained investors who sourced from total assets of the company. Thus, the greater the value of ETA shows the bigger the performance of the company grows; it indicated for improvements in the company's ability to pay its obligations to investors and creditors. The positive effect on the ratio of ETA to predict group FD and Non FD on manufacturing companies in ISE based on the results of this research possibly due to the higher ratio of ETA, the company opportunity to sign the Non FD group will be even greater. The results are consistent with research Zeytmoglu & Akarim (2013) using financial ratios to predict financial failure in Istanbul stock exchanges (ISE) with Discriminant Analysis, the research states in the three years of the study (2009, 2010 and 2011) found the ratio ETA is one of the financial ratios that most influences to discriminate successful and unsuccessful companies in Istanbul stock exchange, where the influence give is a positive influence.

From the comparison of predictions of a group of FD and Non FD companies between Discriminant Analysis and logistic regression provide results on the average, the predicted results of logistic regression analysis higher than discriminant analysis. The results of this analysis in accordance with the results of research Pongsatat et al (2004) comparing Ohlson and Altman method to predict bankruptcy of large and small companies in Asia; the second method represents a logistic regression analysis and discriminant analysis. The results showed there was no significant difference between the two methods of predictive capability when applied in enterprises in Thailand. Results of research shows there are significant differences between the two methods include Liang (2003) who found the results of logistic regression analysis significantly better than the discriminant analysis to predict the FD on companies registered in China. Similar results were obtained by Muliaman et.al (2003), showing that the ability to predict the logistic regression is more accurate than the discriminant analysis,

Conclusions

1. With Discriminant analysis, financial ratios Equity to Total Assets (ETA), Return on Equity (ROE), Return on Assets (ROA), Retained Earnings to

Total Assets (RETA) and Pre Tax Profit to Total Assets (PPTA) is a financial ratio that affect the grouping of companies in the category FD, and Non FD manufacturing companies in ISE with reference to the criteria FD EPS or TA <TL

2. With logistic regression analysis, financial ratios that affect the grouping of companies in the category Non FD and FD is the ratio of Equity to Total Assets (ETA), Return on Assets (ROA) and Retained Earnings to Total Assets (RETA).
3. Results of the analysis showed the power predictive logistic regression model is generally better than the discriminant analysis.

Bibliography

Ahmad K., Basheer H.M.A., Hassanudin M.T.T., Yousuf M.H., and Nurun N. 2014. *Identifying Financial Distress Firms: A Case Study of Malaysia's Government Linked Companies*. International Journal of Economics. Finance and Management, Vol 3 No. 3, pp. 141-150.

Al-Khatib, H. B, and Al-Horani, A. 2012. *Predicting Financial Distress of Public Companies Listed in Amman Stock Exchange.* Europan Scientific Journal., Vol 8, No. 15, pp. 1-17.

Altman, E. I. 1968. *Financial Ratio. Discriminant Analysis and The Predication of Corporate Bankruptcy*. The Journal of Finance, Vol 23, No. 4, pp. 589-611.

Altman, E.I., Haldeman, G., and Narayanan, P. 1977. *Zeta Analysis: A New Model to Identify Bankruptcy Risk of Corporations*. Journal of Banking and Finance, pp. 29-54.

Altman, E. I and Hotchkiss, E. 2006. *Corporate Financial Distress and Bankruptcy*. John Wiley & Sons. Inc. Hoboken. New Jersey.

Beaver, W.H. 1966. *Financial Ratios as Predictors of Failure.* Journal of Accounting Research, pp. 71-111.

Hair, Jr. J.F., Black, W.C., Babin, B.J. & Anderson., R. E. 2010. *Multivariate Data Analysis.* Seventh Edition. Pearson Prentice Hall, New Jersey, USA.

Hassani, M., and Parsadmehr, N. 2012. *The Presentation of Financial Crisis Forecast Pattern (Evidence from Teheran Stock Exchange).* International Journal of Financing and Accounting, pp. 142-147.

Hotchkiss, E., John, K., Mooradian, R.M. & Thorburn, K.S. 2008. *Bankruptcy And The Resolution Of Financial Distress.* Handbook of Empirical Corporate Finance, Volume 2. Elsevier B.V., pp. 1-53.

Johnson, R.A., and Wichern, D.W. 2002. *Applied Multivariate Statistical Analysis*. Pearson Prentice Hal, New Jersey, USA, pp. 185-189.

Jostarndt, P. 2007. *Financial Distress. Corporate Restructuring and Firm Survival: An Empirical Analysis In German Panel Data*. DUV In Cooperation MIT Gabler, Germany.

Ko, L. J, Blocher, E.J, and Lin, P.P. 2001. *.Prediction of Corporate Financial Distress: An Application of the Composite Rule Induction System*. The International Journal of Digital Accounting Research, Vol. 1, No. 1, pp. 69-85.

Liang, Q. 2003. *Corporate Financial Distress Diagnisis in China: Empirical Analysis Using Credit Scoring Models*. Hitotsubashi Journal of Commerce and Management 38, pp.13-28.

Lin, F.Y., and McClean, S. 2000. *The Prediction of Financial Distress Using Structured Financial Data From The Internet.* International Journal of Computer Science & Security, Vol. 1, No.1, pp. 43-57.

Muliaman, D. H., Wimboh, S. and Ita, R. 2003. *Indikator Kepailitan di Indonesia: An Additional Early Warning Tools Pada Stabilitas Sistem Keuangan*. Penerbit Bank Indonesia. Jakarta, pp. 1-31.

Ohlson, J. A. 1980. *Financial Ratios and the Probabilistic Prediction of Bankruptcy*. Journal of Accounting Research (spring), Vol. 18 No. 1, pp. 109-131.

Pervan, I, Pervan, M., and Vukoja, B. 2011. *Prediction Of Company Bankruptcy Using Statistical Techniques – Case Of Croatia*. Croatian Operational Research Review (CRORR), Vol. 2, pp. 158-167.

Platt, H. D., and Platt, B.M. 2002. *Predicting Corporate Financial Distress: Reflection on Choice-Based Sample Bias.* Journal of Economic and Finance, Vol. 26 No. 2, pp.184-199.

Pongsatat, S., Ramage, J., and Lawrence, H. 2004. *Bankruptcy Prediction for Large and Small Firms in Asia: A Comparison of Ohlson and Altman*. Journal of Accounting and Croporate Governance, Vol 1, No. 2, pp. 1-13.

Puagwatana, S., and Gunawardana, K.D. 2005. *Logistic Regression Model for Business Failures Prediction of Technology Industry in Thailand*. Proceeding of International Confenrence on Computer and Industrial Management, ICIM, Bangkok, Thailand, pp.1-4

Ross, S., David. H., Randolph, W., Jeffrey, J., and Bradford, J. 2012. *Finanza Aziendale*. McGraw-Hill, New York, USA.

Sarlija, N., and Jeger, M. 2011. *Comparing Financial Distress Prediction Models Before And During Recession*. Croatian Operational Research *Review* (CRORR), Vol. 2, pp. 133-142.

Umi, Z. N., Santosa, B., and Wiratno, S. E. 2013. *Model Prediksi Financial Distress Pada Perusahaan Manufaktur Go Public di Indonesia*. Prosiding Seminar Nasional Manajemen Teknologi XVIII Program Studi MMT-ITS, Surabaya, 27 Juli 2013, pp. 1-8.

Wang, T., and Campbell, M. 2010. *Financial Ratios and the Prediction of Bankrupcy: The Ohlson Model Applied to Chinese Publicly Traded Companies*. The Journal of Organizational Leadership & Business, pp. 1-15.

Zeytmoglu,. E., and Akarim, Y.D. 2013. *Financial Failure Prediction Using Financial Ratios: An Empirical Application on Istambul Stock Exchange.* Journal of Applied Finance & Banking, Vol 3, No. 3, pp. 107-116.