Discriminant Analysis of Insurance Companies in Indonesia

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Abstract. This study aims to identify a financial distress condition for insurance companies using existing methods such as the Altman Z-score and Ohlson O-score and also approach a new discriminant model using the data from 2017 to 2021. In order to improve the quality of estimation and forecasting of the financial state of insurance companies in Indonesia, a discriminant model should take account into the local characteristic of the insurance business. The discriminant model uses existing variables from the Altman model with an additional three variables employed by the Indonesian regulations in order to identify the financial state. The research included 124 Indonesian insurance companies. The research finds a discriminant model of insurance companies in Indonesia with three dominant variables net working capital, return on total assets, and current ratio. The application of the model allows you to determine whether the insurance company in Indonesia has a satisfactory or unsatisfactory financial condition. To the author's best knowledge, previous research using sharia insurance companies' data finds the alternative discriminant model with the same variable as the Altman model.

Keywords: Discriminant Analysis · Financial distress · Insurance companies

1 Introduction

Financial distress may bring failure and bankruptcy to a firm. A firm with liabilities greater than its assets will produce negative cash flow. This repetitive condition will bring the firm to financial distress where the firm is unable to meet repay its outstanding debt. Finally, the firm will be forced into a legal condition called bankruptcy. The firm has two options after filing bankruptcy, either selling its assets or selling the firm to others [1, 2].

Ainul [3] states that insurance premiums and investments have a positive effect on asset growth, while claims have a negative effect on asset growth.

Insurance companies business mainly earn profit from premiums, however, they have to manage their investment and underwriting portfolio to provide additional profit for the stakeholders. There is a risk transfer from policyholders to insurers while the policyholders are paying a certain amount of premium in trade for it. Higher risk means more premiums are paid by the policyholders. The insurers themselves will not absorb all the risk they took, but it will be shared with another insurer who is willing to share

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the risk. When it comes to a claimable event, the insurer will be obliged to provide compensation to the policyholders [4].

Due to the pandemic in 2020, the world facing the biggest economic crisis since 2008. The market performance significantly drops in the 1st quarter of 2020 with the 30% price drop of IHSG [5]. This condition also hits hard on insurance companies' financial statements, especially the investment return. Premiums earned by insurance companies in Indonesia continue to decline to −9% until August 2020. Finally, life insurers suffer greater losses than general insurers due to their investment portfolio performance. Devi [6] finds that the finance sector experiencing a decrease in liquidity and profitability ratio. Some of them are forced to face bankruptcy due to insolvency. With the rise of health risks, consumers face some difficulties to choose the right insurer, especially when the national literacy of insurance is only 19,4% [4]. As far as we know the major case of default experienced by Jiwasraya, Bakrie Life, Bumiputera, and Kresna Life has worsened the consumer's trust in the insurance industry.

This research will provide the best model to predict insurance companies' bankruptcy in Indonesia. This research also helps insurance companies to identify financial distress earlier. This information is critical for stakeholders to prevent any serious damage to the firm and maintain firm sustainability. Regulators are also aware of every insurance company's condition. They must act fast before the firm files bankruptcy and finally, policyholders are no longer covered by insurance. This condition is the worst-case scenario of financial distress.

This research was conducted using the population of Indonesian insurance companies. There are 53 life insurance companies and 71 general insurance companies. Exclusion for insurance companies that have no data available in the research period either new entry firms or the firm no longer runs the business. This excludes a total of 5 companies. Finally, the research will provide the best multiple discriminant analysis models using 119 insurance companies' data from 2017–2021.

Previous research [7, 8] predicts the bankruptcy of insurance companies using the Altman Z-score which is commonly used for non-manufacturers or emerging markets. The results give the best accuracy for European markets but the model did not provide the same accuracy level for other regions. There is no available model for Indonesian insurance companies with insurance-specific variables such as investment return ratio, underwriting ratio, or net premium per asset ratio.

The objective of this research is to find the best model to predict the bankruptcy of insurance companies in Indonesia using multi-discriminant analysis. This research also provides additional information about the accuracy of the existing Altman Z-score and Ohlson O-score to predict Indonesian insurance companies' bankruptcy. Finally, the research provides an alternative solution for stakeholders to review the financial condition of the firm.

1.1 Financial Distress

The Organization for Economic Co-operation and Development (OECD) reports that the COVID-19 pandemic has resulted in the threat of a major economic crisis marked by the cessation of production activities in many countries, falling levels of public consumption, loss of consumer confidence, and falling stock exchanges that ultimately lead to uncertainty [9].

Piatt [10] describe financial distress as a firm condition with financial deviation and stress leading to bankruptcy. Prediction of financial distress describes a firm condition where the business cannot meet its debt obligation and petition for either debt restructuring or debt liquidation.

The emergence of firm financial distress can be acknowledged long before it occurs. For starters, the firm is unable to meet its debt or the firm cash flow is less than the outstanding debt. This condition explains that the firm will not be able to pay its debt at that time.

Altman [1] explained that a firm failure and bankruptcy are the final result of financial distress. A firm with financial distress will have a negative cash flow due to its debt. Alternatively, firms with financial distress that conducts a business that is no longer able to support sustainability will need to restructure their asset. There are also other factors that lead to financial distress such as company bad performance, high financial leverage, lack of technology innovation, liquidity and financing problem, new entry business, deregulation, and unexpected liability.

Ross [11] explains the steps a company can take when facing financial distress, including: (1) Selling key assets, (2) Merge with another company, (3) Reducing capital expenditure, research and development, (4) Issuing new securities, (5) Negotiations with banks and other creditors, (6) Replacing debt with equity, or (7) File for bankruptcy.

Some companies will benefit from financial distress by restructuring their assets. Leveraged recapitalization can change a firm behavior and force it to eliminate unrelated businesses. Firms utilizing levered recapitalization will increase their debt so that it can have an impact on the firm cash flow and are forced to sell their side business. Financial distress conditions also often result in new organizational forms and operating strategies.

Finally, financial distress can be considered an early warning for a firm problem. Firms with more debt will experience financial distress earlier than companies with less debt. Firms that experience financial distress early will have more time to prepare improvement and reorganization strategies, while firms that experience financial distress later more often end up in liquidation.

1.2 Discriminant Analysis

Klecka [12] explains discriminant analysis as a statistical technique that allows the researcher to study the differences between two or more groups of objects with respect to several variables simultaneously. In the social sciences, there are a wide variety of situations in which this technique may be useful.

2 Method

Sample of the data observed included all current Indonesian insurance companies of 124 companies. There is an initial validation that excludes the companies with no available valid annual financial information within the 2017–2021 period. Data collection is made from the OJK reporting system. The data collection consists of current assets, current liabilities, total assets, total liabilities, retained earnings, earnings before income taxes, equities, gross national product price level index, net income, funds from operation, and solvency ratio.

All the data collected will proceed with the Altman Z-score and Ohlson O-score equation. Furthermore, the Z-score and O-score are compared with the real condition interpreted by the solvency ratio in the same year. This provides the accuracy level of each Z-score and O-score.

This research also builds a new model made with additional variables to Altman Z-score. The variable is specific to insurance companies. The data are processed through SPSS using a multi-discriminant analysis method, resulting in a model to predict bankruptcy for Indonesian insurance companies.

The Z-score developed by Altman is a model of Multi Discriminant Analysis which is used to estimate the bankruptcy of a company by using the discriminant function to financial ratios. Altman has also developed a model so that it can be used and applied according to the criteria or type of company.

The original model of Altman Z-score [13] is defined by the equation:

$$Z = 1.2\,X1 + 1.4\,X2 + 3.3\,X3 + 0.6\,X4 + 1.0\,X5 \tag{1}$$

where Z-score > 2.99 is declared as a safe zone, Z-score between 1.81 to 2.99 is declared as an grey zone, and Z-score < 1.81 is declared as a distress zone. This model is designed based on a sample of publicly owned manufacturing companies whose assets and liabilities do not exceed $25 million. This model cannot be used for predicting financial industries' conditions due to differences in accounting for the firm's revenue/loss.

Altman [14] made adjustments to the original equation so that the Z-score calculation could accommodate limited companies. The adjusted equations are as follows:

$$Z = 0.717X1 + 0.847X2 + 3.107X3 + 0.420X4 + 0.998X5 \tag{2}$$

Furthermore, Altman [15] revised the Z-score model so that it can be used for all industrial, manufacturing and non-manufacturing companies. This latter model was first used by Mexican and other Latin American companies.

$$Z = 3.25 + 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4 \tag{3}$$

Altman found X5 variable has a different sensitivity to each type of industry.

Altman Z-score which uses multivariate discriminant analysis is considered to have several weaknesses. The first weakness is the limitation of MDA assumptions, where one of the assumptions is that the two groups must have identical variance-co-variance matrices. The second weakness is that the technique of determining the cut-off value is considered a reason for weak intuition interpretation. The third weakness is that macroeconomic factors that may have an influence on the accuracy of the model have not been taken into account, and the last weakness is that if it is used for small companies (assets less than one million euros), it is important to analyze small companies carefully because the financial statement data in this group may be of poor quality, due to missing values or unstable financial ratios.

Ohlson [16] stated that the MDA approach such as the Altman model is a popular technique used in bankruptcy prediction research using vectors of predictors. However, several problems were found in this study, including some statistical requirements imposed on the nature of the distribution of the predictors, the results of which the MDA model test is a score with little intuitive interpretation because the MDA model is basically ordinal in rank, and there are problems related to the alignment of procedures. Which is usually used in MDA.

The use of logit analysis eliminates all problems in the MDA model. Ohlson formulated an O-score that predicts failure in one year, which consists of nine variables two of which are dummy variables. This model is usually used to predict the probability of the occurrence of an event by fitting the data to the logit function of the logistic curve. In full the O-score equation is as follows:

$$\begin{aligned} \mathrm{O-score} = & -1.32 - 0.407\mathrm{Y1} + 6.03\mathrm{Y2} - 1.43\mathrm{Y3} + 0.0757\mathrm{Y4} \\ & -2.37\mathrm{Y5} - 1.83\mathrm{Y6} + 0.285\mathrm{Y7} - 1.72\mathrm{Y8} - 0.521\mathrm{Y9} \end{aligned} \tag{4}$$

Y1 = SIZE = log (total asset/GNP price level index)
Y2 = TLTA = total liabilities/total assets
Y3 = WCTA = working capital/total assets
Y4 = CLTA = current liabilities/current assets
Y5 = OENEG = 1 if liabilities > total assets, others 0
Y6 = NITA = net income/total assets
Y7 = FUTL = funds provided by operations/total liabilities
Y8 = INTWO = 1 if net income was negative for last two years, others 0
Y9 = CHIN = (NIt – NIt-1)/(|NIt| + |NIt-1|), NI = net income

The results of the O-score calculation can be interpreted that a company is in distress if the O-score is less than 0.038.

3 Result and Discussion

As previously mentioned the sample process through initial validation which result in total of 580 data observation and eliminating 15 invalid data, see Table 1. These invalid data are a result of corporate actions such as mergers and acquisitions which result in the change of the firm's name. Including the firm which has revoked the license. Initial validation shown in Table 1.

Table 1. Initial Validation.

	Life Insurer	General Insurer	Total Data
Population	55	76	131
Invalid Data	7	8	15
Valid Data	48	68	116
Total Data Observed			580

Table 2. Altman Model Accuracy.

Life Insurer			
Z-Score	Predicted	Real	Accuracy
Healthy	229	230	227
Grey	4	–	–
Distress	7	10	6
Total	240	240	233
General Insurer			
Z-Score	Predicted	Real	Accuracy
Healthy	338	333	332
Grey	2		–
Distress	0	7	–
Total	340	340	332

3.1 Altman Model Accuracy

After the initial validation, the data are processed through the Altman model to predict the firm condition whether it is healthy or distress. The result shows good accuracy of 97.08% in compared to risk-based capital condition, see Table 2. Altman model only able to predict 6 out of 10 distress life insurance companies. Unfortunately worst result for the general insurance, which unable to predict all 7 distress companies. But almost successfully predict the healthy condition. Overall the Altman model accuracy reach 97.41%, details see Table 2.

3.2 Ohlson Model Accuracy

In compared to Altman, the Ohlson model only get 41.67% of accuracy with 1 out of 10 distress life insurance companies are predicted Table 3.

As for the general insurer, Ohlson model are only able to predict 29.41% with 0 out of 7 distress general insurance companies are predicted. Overal the Ohlson model accuracy is 34.48%.

3.3 Discriminant Analysis Model

The result of the accuracy level of Altman and Ohlson, this research acknowledges that the Altman model is more reliable in predicting the financial condition of insurance companies. The Ohlson model indicates that every increase in liabilities means the companies are more healthy, which is uncommon for the insurance business. While in Altman the indicators are net working capital, earnings, and equity.

Research variable shown in Table 4.

In response to the existing Altman model, researchers are approaching the discriminant analysis using the same variable and three additional variables, such as (1) current

Table 3. Ohlson Model Accuracy.

Life Insurer			
Z-Score	Predicted	Real	Accuracy
Healthy	108	230	99
Invalid	10	–	–
Distress	122	10	1
Total	240	240	100
General Insurer			
Z-Score	Predicted	Real	Accuracy
Healthy	107	333	100
Invalid	6	–	–
Distress	227	7	0
Total	340	340	100

Table 4. Research Variable.

Variable	Description
Z	dummy variable, healthy: 1, distress: 0
X1	Net Working Capital Ratio
X2	Retained Earnings to Total Asset Ratio
X3	Return on Total Assets
X4	Equity to Liabilities Ratio
X5	Current Ratio
X6	Investment Adequacy Ratio
X7	Solvency Ratio

ratio, (2) investment adequacy ratio, and (3) solvency ratios. All available variables are used in the process as described in Table 4.

The current ratio is a result of current assets divided by current liabilities. Investment adequacy ratios are calculated by the total of investment and cash divided by the total of own retention technical reserve, claim, and other liabilities to the insured. The solvency ratio is the result of the difference between admitted assets and liabilities, divided by risk-based minimum capital.

All the research variables are input to the SPSS program, running multiple discriminant analyses with a step-wise method to find the most significant variable. The program stops when there is no significant variable available, resulting in choosing 3 out of 7 variables to best discriminate the data. The 3 variables are X1, X3, and X5.

Table 5. Eigenvalue and Wilks Lambda.

Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
.656	100	100	0.629
Wilks Lambda	Chi-square	df	Sig.
0.604	290.64	3	0

Table 6. Functions at Group Centroids.

Y	Function
0	0.089
1	−7.313

Eigenvalue of the analysis showing 65.6%, with the canonical correlation of 62.9% which can be translate into determining coefficient of 39.56% (Table 5).

Chi-square are describing a significance level of the estimated model. This research estimated a level of 60.4% associated with the wilks lambda, and a Chi-square of 290.64.

The result of the analysis estimated the model of Z-score function:

$$Z = -1,138 + 3,882X1 + 6,777X3 - 0,007X5 \tag{5}$$

X1 = Net Working Capital Ratio, X3 = Return on Total Assets, and X5 = Current Ratio.

According to the formula (5) the variable of net working capital ratio and return on total asset have positively impact on financial condition of the insurance companies, while the current ratio shows negative impact. This condition happens due to the abnormal condition of pandemic era in 2020–2021.

The function has a cut-off score calculated from the function at group centroids (Table 6):

$$Z_{\text{cutoff}} = \frac{573(0,089)+7(-7,313)}{580} = -0,0003345 \tag{6}$$

It means that if the Z-score are above the cut-off score then the companies are categorized as healthy, and score are below the cut-off score then the companies are categorized as distress.

4 Conclusion

The result of the multi discriminant analysis for financial distress shows dominant variable to predict insurance company condition which are Net Working Capital Ratio, Return on Total Assets, and Current Ratio. This three variable can be assumed as an early warning system indicator for an insurance company. With the most significant variable in describing the financial healthiness is the return on total assets.

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