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Predictability of Predictors of Corporate Failure Using Forward Logistic Regression: Evidence from Bangladesh

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Abstract

The purpose of this study is to find out the financial variables that predominantly influence the prediction of corporate failure. The study is based on forward logistic regression. The variables of the Altman Model have been utilized to test the predictability of predictors of corporate failure because this model is widely employed in this context. A total of 217 firm years of data from 2007 to 2019 have been utilized for this study. The findings of the study show that among the variables considered in this study, the ratio of Earnings before Interest & Taxes to Total Assets has the most predictive capability to predict corporate failure. Besides, the probability of failure can also be better predicted collectively by Net Working Capital Ratio, Equity-to-Liability Ratio, & Asset Turnover Ratio along with the Earnings before Interest and Taxes to Total Assets Ratio. An important finding indicates that the Retained Earnings to Total Assets Ratio is not an effective predictor when it comes to forecasting corporate failure. Through the application of Forward Logistic Regression, one can identify the most influential variables for predicting corporate failure. The decision makers can utilize the findings to identify the factors that possess the highest capability in forecasting corporate failure, thereby enabling them to take the necessary preventive measures.

Keywords: Prediction, Corporate Failure, Financial Distress, Forward Logistic Regression

JEL: E37, G3, G32, G33, M2, M4,

1. Introduction

The forecast of financial distress is essential to stakeholders of a company to help in taking preventive measures such as changing policies or re-organizing the operational and financial structure (Aruwa, 2007). The early prediction helps stakeholders in taking various decisions like investment in a company, extending credit, sanctioning bank loans, etc. Corporate failure causes a substantial cost to various stakeholders including debt providers, shareholders, suppliers, employees, auditors, customers, etc. That is why early detection can facilitate the related stakeholders in decision-making (Brabazon & Keenan, 2004). According to

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Kücher et al. (2020), adolescent and young firms fail due to the inner weaknesses. On the other hand, medium-sized and matured firms fail due to the downward trend of the economy and high competition. The study by Harjans (2018) compiled various reasons responsible for corporate failure like lack of managerial skills, overexpansion, high competition, liquidity crisis, declining economy, insufficient capital in small firms, lack of planning, improper employee staffing, etc.

Broadly, there are three methods for predicting corporate failure i.e., statistical techniques, artificially intelligent expert system techniques, and theoretical techniques (Appiah et al., 2015). According to Alareeni (2019), Altman's Multiple discriminant analysis is a widely used popular model because it has a high level of correctness in predicting corporate failure. Altman's (2018) perspective indicates that the Z-score is utilized considerably by both academics & practitioners. Due to the wide demand for its use in decision making, this model has been revised multiple times to suit diverse sectors of the corporate world. It is used by internal managers, research analytics, and external analytics (lenders, stock investor, bond investor, security analysts, rating agencies, regulators, auditors, advisors, etc.)

There are many instances of corporate failure in Bangladesh. A recent example of corporate failure in Bangladesh is the People's Leasing and Financial Services (Azim & Sharif, 2020). Besides, eight more companies are going to be delisted by the regulator due to their financial distressed position (Rahman, 2021). So, to protect stakeholder interests, it is therefore crucial to identify financially strapped companies at the earliest convenient moment. Accordingly, the objective of this study is to recognize the variables that have the greatest impact on forecasting corporate failure in Bangladesh. In this study, Forward Logistic Regression has been used to ascertain the capacity of the financial factors for predicting financial distress or corporate failure. The Forward Logistic Regression can find the most influential variables in predicting corporate failure. Here, Altman Model's variables are taken to test the predictability of predictors of corporate failure since the model is widely used in this perspective.

While there are many studies that utilized Logistic Regression to predict corporate failure, there are a limited number of studies utilizing Forward Logistics Regression for predicting corporate failures. Therefore, this study addresses this research gap by employing Forward Logistic Regression to identify the most influential predictors in predicting corporate failure. This study will contribute on corporate failure literature through identifying the most influential predictors based on the variables used in the Altman model.

This study is organized as follows: The literature review is presented in the second part, while the methodology section is addressed in the third section. The empirical results are presented in the fourth part, and lastly, the fifth section covers the study's conclusions and implications.

2. Literature Review

2.1. Corporate Failure

The synonyms used for corporate failures are financial distress, liquidation, insolvency, bankruptcy, and dissolution. Generally, failure can be defined as the position of a company when it doesn't have the ability for meeting the obligation (Almansour, 2015; Mackevicius & Sneidere, 2010). But according to Beaver (1968), corporate failure is the position when there are overdrawn bank accounts and default on loan.

The possible indicators of corporate failure can be defined as follows: capital turning into zero or negative, profits falling below projected levels, showing losses or reducing dividend payment, business closure or selling part of the business, take-over, director's resignation, reconstruction of the company, breaking of debt covenants, seeking protection by the creditors, composition with the creditors, auditor's going concern qualification, delisting from the stock exchange, nomination of a receiver, and voluntary or creditors' liquidation (Appiah et al., 2015).

One sole cause does not bring about corporate failure. Many causes may occur together for the failure of many firms (Nasir et al., 2000). The primary causes of bankruptcy are: dishonesty of competitors and business partners, superfluous charges for even unintentional tax law breaches, tax and duties rule, strong (buttressed by overseas capital) rivals arriving in the marketplace, unsteady and/or inadequate market access, lack of competence of the CEO, etc. (Klauss, 2004). Corporate failure occurs due to imperfect management decisions (Brabazon et al., 2002), lack of corporate governance (Hartman, et al., 2018), adverse environmental impact, etc.

2.2. Variables in Predicting Corporate Failures

Different models used different variables in predicting corporate failures. There is no consistency in the case of choosing variables to predict corporate failure (Appiah et al., 2015). Although the financial ratio of a non-failed firm considerably differs from the failed firm, no single ratio or variable can provide a better result in predicting corporate failure. That is why combining different ratios or determinants can produce a better result in prediction (Neophytou & Molinero, 2004; Beaver, 1966).

According to the review study of Bellovary et al. (2007), there was a use of a total of 752 diverse variables in the various prediction models in different countries. In predicting corporate failures, it is essential in considering both financial (e.g. financial ratios) & non-financial information e.g. company age, size, activity, etc. (Alfaro et al., 2008) because adding non-financial factors enhances the precision of the prediction (Altman et al., 2010). The same view is provided by Bandyopadhyay (2006) that opines that to describe default risk the notion i.e., using non-financial facts along with financial facts is very useful. The non-financial factors used in the previous studies are Age of the firm, Association with best business groups, Quality Certification from ISO, Industry dummy as Control variables. Alzayed et al. (2023) also opines that nonfinancial information, when combined with financial information, can improve the accuracy of predicting corporate failure. That study demonstrates that corporate governance factors, including institutional ownership, voting rights, and CEO compensation, serve as effective predictors as the nonfinancial factors. In the study by Nour et al. (2023), a related finding shows that factors in corporate governance—particularly the quality of external audit, institutional ownership, and the independence of the board of directors—can reduce corporate failure.

According to Brabazon et al. (2004), the most used ratios to forecast corporate failure are Earnings Before Interest & Taxes (EBIT) divided by Sales, Inventory /Working Capital, Net Income / Total Assets, Asset Turnover Ratio, Return on Investment, EBIT / Total

Assets, Return on Assets, Retained Earnings / Total Assets, Cash from Operations / Total Liabilities, Quick Assets / Total Assets, Leverage, EBITDA / Sales, Gross Profit / Sales, Net Profit Margin, Return on Equity, Fixed Assets / Total Assets, Cash / Sales, Inventory / Cost of Goods Sold, Total Liabilities / Total Assets, Cash from Operators / Sales, Working Capital Ratio, and EBIT to Interest.

Chen (2011) uses factor analysis to identify variables with strong predictive power. Initially, 37 variables were selected, including 4 non-financial and 33 financial ones. After conducting factor analysis three times, 12 variables were found to have similar characteristics and the highest predictive ability. The selected ratios were Debt/Equity, Current Ratio, Gearing Ratio, Inventory to Total Assets Ratio, Acid-Test Ratio, Cash Flow Coverage Ratio, Current Ratio, Return on Asset, Cash Flow Ratio, Debt to Equity Ratio, Return on Equity, and Earnings per Share.

According to Abdullah et al. (2008), the widely used variables are debt-to-assets ratio, total liabilities to total assets, net income to total assets, changes in net income (i.e., growth), firm size, cash flow ratios (debtor turnover, cash to current liabilities, gross cash flow ratio), receivables turnover, debt coverage, financial expenses to sales, market value to debt, total asset turnover, cash to current liabilities, and sales to current assets. A significant finding from the study of Abinzano et al. (2023) shows that the variables used to predict corporate failure can also be utilized for predicting the success or failure of the restructuring procedure.

2.3. Methods for Predicting Corporate Failure

From the year 1932 to now, diverse methods or models were applied in predicting corporate failure. A predictive model is an object which is competent enough to do predictions on new data on the basis of the patterns of the prevailing data (Nguyen, 2005). Corporate failure prediction is done by classifying the identified cases and generalizing them in other cases (Boritz et al., 1995). The most used model is discriminant analysis (Bellovary et al., 2007).

According to Brabazon et al. (2002), the first study on predicting corporate failure was done by Fitzpatrick (1932). The statistical model for predicting corporate failure began with the univariate analysis of Beaver (1966) and was succeeded by Multiple discriminant analyses of Altman (1968) (Abdullah et al. 2008).

Aziz & Dar (2006) categorize the prediction models for corporate failure into three general classifications which are Theoretical Models, Statistical Models, & Artificially Intelligent Expert System Models (AIES). The examples of statistical models are Univariate, Probit Model, Logit Model, Linear Probability Model (LPM), Multiple Discriminant Analysis (MDA), Partial Adjustment Processes, Cumulative Sums Procedures. The examples of Artificially Intelligent Expert System Models (AIES) are Case-based reasoning models, Recursively partitioned decision trees, Rough sets model, Genetic algorithms, Neural networks. The examples of Theoretical Models are Cash Management Theory, Financial Position decomposition measures, Ruin theory of Gambler, Credit risk theories (including KMV model of Moody, Credit Metrics of JP Morgan, CSFB’s CreditRisk+, KcKinsey’sCreditPortfolio View). The study by Salehi et al. (2016) contrasts various models for corporate failure prediction and finds that Artificial Neural Networks surpass the models of the Naïve Bayesian Classifier, k-Nearest

Neighbor, and Support Vector Machines in accurate prediction of corporate failure. A good understanding can be gained regarding the rank of several prediction models through the study conducted by Salehi & Mousavi Shiri (2016), where the authors have done discriminative analyses using various prediction models, including Beaver's model, Altman's model, Ca-score's model, Shirata's model, Grice's model, Zmijewski's model, Springat's model, Fulmer's model, and Ohelson's model.

The Z-score of Altman is an extensively used model to predict corporate failure (distressful status) by measuring the financial health of the firms (Hossain et al., 2020; Ali et al., 2016; Mizan & Hossain, 2014; Mizan et al., 2011; Chowdhury & Barua, 2009) and it is suitable for all industries (Mackevicius & Sneidere, 2010). The usability of Altman's Z Score is also applicable for predicting corporate failure from the perspective of Bangladeshi data (Azim & Sharif, 2020; Azim & Sharif, 2021).

In this study, the variables in the Altman Model will be tested to find out the variables that might have the most predictive capability to predict corporate failure. To serve this objective, forward logistic regression will be employed, as numerous studies have employed logistic regression (Petropoulos, et al., 2020; Son, et al., 2019; Duan, 2019), yet there is a limited study employing forward logistic regression (Bauweraerts, 2016). Hence, this study utilizing forward logistic regression will make a significant contribution to the existing literature.

3. Methodology

3.1. Data Collection

Generally, the poorly performing companies considering several criteria are declared as z category companies. Out of 46 Z-category firms listed in Dhaka Stock Exchange, 35 companies' data were collected based on the obtainability of annual reports on the websites of those firms. Data from 2007-2019 were collected based on availability. Data of 13 companies of the Over-The-Counter (OTC) market were collected based on available hardcopy from Dhaka Stock Exchange.

A total of 217 firm years' data from 2007 to 2019 has been used for this study out of which 26 firm-years of OTC companies. The number of firm-years of Z-category companies is 191 out of 142 firm-years of Manufacturing and Service providing companies and 49 firm years of Bank and Non-Bank Financial Institutions (NBFI).

3.2. Variables of the Study

The analysis is done in two stages. In the *first* stage, The Altman Z score is computed by using the Z Score as the outcome variable & the independent variables are Earnings before Interest and Taxes divided by Total Assets, Net Working Capital divided by Total Assets, Book Value Equity divided by Book Value of Total Debt or Liability, Retained Earnings divided by Total Assets, and Asset Turnover Ratio. But according to Altman (1993), there is no need to use one variable (Sales/Total Assets) when data is taken for the non-manufacturing firm (bank and non-bank financial institution). In the *second* stage, Binary Logistic Regression was done where the outcome variable is dichotomous (Failed & Non-Failed) and the independent variables remain unchanged as stated in the first phase.

The Altman Z score is computed by utilizing the Z Score as the outcome variable

3.2.1. Z-Score Calculation Procedure

Z-Score for Manufacturing and Servicing Firms=1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 1.0X5

Where, X1 = (Current assets - Current liabilities) / Total assets

X2= Retained Earnings / Total assets

X3= EBIT / Total assets

X4= Book value equity / Book value of total debt or Liability

X5=Sales / Total assets

For the above model, a company will fall into the “non-bankrupt” segment if the Z score is above 2.99. If the Z score of a firm is below 1.81, then it will be categorized as “bankrupt”. If the score falls between1.81 to 2.99, then it is the “area of ignorance” or “gray area” which indicates the uncertainty of predicting.

Z-Score for Bank and NBFI=6.56 (X1)+ 3.26 (X2) + 6.72 (X3) + 1.05 (X4)

Where, X1=(Current assets - Current liabilities)/Total Assets

X2=Retained Earnings divided by Total Assets

X3=EBIT divided by Total Assets

X4 =Book Value of Equity divided by Total Liabilities

For the formula stated above, if the Z’’-Scores is below 1.10, then it indicates a failed company. If the Z’’-Score is higher than 2.60, then it indicates a non-failed firm. The Z’’-Score between 1.10 to 2.60 implies a grey area.

3.2.2. Binary Logistic Regression

The study is based on a total of 217 firm years (out of which 142 firm-years from Z category manufacturing and servicing companies, 49 firm-years from Z category bank and non-bank financial institutions, and 26 firm-years from Over-The-Counter (OTC) companies). Two Forward logistic regressions were conducted separately because the independent variables and

Table 1. Variables and Method used for Binary Logistic Regression

Dependent Variable	Failed = 1	Dichotomous variable
	Non-Failed =0 (all grey and non-failed companies are shown as non-failed)	
Independent Variable	X1 = (Current assets - Current liabilities) /Total assets	All are scale variable
	X2 = Retained Earnings divided by Total assets	
	X3 = Earnings before interest and taxes divided by Total assets	
	X4 = Book value equity divided by Book value of total debt or Liability	
	X5 = Sales/Total assets*	
Method	**Forward Logistic Regression** (Under the Forward Logistic Regression, the system will create different models. The first model will not have any independent variable. In the subsequent model, the system incorporates the independent variable that exerts a greater influence on the dependent variable. The process continues, and at each step, another variable is added based on its impact. This method of adding an independent variable in the model step by step in each model is called Forward Logistic Regression.)	
Number of Total Cases	217 cases (firm years)	

* The variable X5 (Sales/Total assets) is not used in the 2nd Forward Logistic Regression in the case of Bank and NBFI.

Source: Author’s Model

financial information of Z category bank and non-bank financial institutions are not the same with the other two categories. The first Forward logistic regression is done using the information of 168 firm-years of the Z category manufacturing firms and OTC firms. The second Forward logistic regression is accomplished using the information of 49 firm-years of the Z category bank and Non-Bank Financial Institutions (NBFI).

4. Empirical Results

4.1. Findings on Altman Z Score of the Z category and OTC Companies

After applying the model of the Altman's Z score on the Z category and OTC firms, the following summary table has been prepared.

The above summary table shows that Z-category manufacturing and servicing companies experienced a failed position in 59% firm years, a non-failed position in 19% firm years, and a grey position in 22% firm years. On the other hand, Z-category bank and non-bank financial institutions suffered a failed position in 98% firm years and a grey position in 2% firm years but no firm years as a non-failed position. OTC manufacturing and servicing companies suffered a failed position in 92% firm years and a grey position in 8% firm years but no firm years as a non-failed position. From these findings, it can be deduced that Z-category bank and non-bank financial institutions are in an extremely debilitated position.

This study indicates that the overall percentage of failure is 72% in the Z category companies. This finding is comparable to the findings of the study by Chowdhury & Barua (2009), where 77% of companies are in failed position. In a specific scenario, 98% of Bank and Non-Bank Financial Institutions in the Z category are in failed position. This finding is similar to another finding of the study by

Table 2. Summary of Failed, Grey, and Non-failed Firm Years of Z Category and OTC Companies

Company Category	Company Nature	Number of Firm Years	Status	Percentage
Z-Category	Manufacturing and Servicing	142	Failed: 84 Non-Failed: 27 Grey: 31 Total: 142	Failed: 59% Non-Failed: 19% Grey: 22% Total: 100%
Z-Category	Bank and Non-Bank Financial Institutions	49	Failed: 48 Non-Failed: 0 Grey: 1 Total: 49	Failed: 98% Non-Failed: 0% Grey: 2% Total: 100%
OTC Company	Manufacturing and Servicing	26	Failed: 24 Non-Failed: 0 Grey: 2 Total: 26	Failed: 92% Non-Failed: 0% Grey: 8% Total: 100%
Total		217	Failed: 156 Non-Failed: 27 Grey: 34 Total: 217	Failed: 72% Non-Failed: 12% Grey: 16% Total: 100%

Source: Author's Calculation using Altman's Z Score

Hamid et al. (2016), where 93% of companies are in failed position.

The mentionable banks and non-bank financial institutions that exist in the most vulnerable position are AB Bank, Bangladesh Industrial Finance Company Limited, Fareast Finance & Investment Limited, First Finance Limited, ICB Islamic Bank Limited, People's Leasing & Financial Services Limited, and Phoenix Finance & Investments Limited. The mentionable manufacturing and serving providing companies that are in failed position based on the Z score are Alltex Industries (Bangladesh), Aramit Cement Limited, Bangladesh Services Limited, Bangladesh Thai Aluminium Limited, Bangladesh Welding Electrodes Limited, Beximco Synthetics Limited, Dacca Dyeing Limited, Delta Spinners Limited, Dulamia Cotton Spinning Mills Limited, Imam Button Industries Limited, Golden Son Limited, Libra Infusions Limited, Meghna Pet Industries Limited, Meghna Condensed Milk Industries Limited, Shinepukur Ceramics Limited, United Airways Bangladesh, Usmania Glass Sheet Factory Limited, and Zahintex Industries Limited. The mentionable OTC Companies that are in failed position based on the Z score are Monospool Paper Manufacturing Company Limited, Gachihata Agriculture Farms Limited, Rangamati Food Products Limited, Yusuf Flour Mills Limited, MAQ Paper Industries Limited, MAQ Enterprises Limited, Padma Printers and Colors Limited, Tamijuddin Textile Mills Limited, Monno Fabrics Limited, Jessore Cement Mills Limited, AL-Amin Chemical Industries Limited, and The Engineers Limited.

4.2. Logistic Regression

There are three outcomes from the Altman Z Score i.e., non-failed, failed, & grey. These three outputs have been turned into two categories that are: failed and non-failed in this study. The non-failed category includes

Table 3. Encoding of Outcome Variable

Original Value	Internal Value
Non-Failed (all grey and non-failed firm year are shown as non-Failed)	0
Failed	1

Source: Author's Analysis

Table 4. Overall Classification[a,b] in Logistic Regression (using the data of Z category Manufacturing and OTC firms)

Observed			Predicted		
			Failed &Non-Failed Status		**Percentage Correct**
			0	1	
Step 0	Failed Non-Failed Status	0	0	60	.0
		1	0	108	100.0
	Overall Percentage				**64.3**
a. Constant is comprised in the model.					
b. Cut value: 0.500					

Source: Author's Analysis

both grey and non-failed firm years. Binary Logistic Regression was done by coding 1 for the failed firm-year and 0 for the non-failed firm-year.

The study is grounded on a total of 217 firm years (out of which 142 firm-years from Z category manufacturing and servicing companies, 49 firm-years from Z category bank and non-bank financial institutions, and 26 firm-years from OTC companies).

From Table 4 - Overall classification by the logistic regression, the output indicates that the overall accurate prediction is 64.3% considering the sample data. The reason for such a percentage of correct prediction is that 108 failed firm-years are correctly shown as failed status but 60 non-failed firm-years are incorrectly shown as failed status, which is considered as Type II error in prediction. The possible cause for the Type II error is that for the analysis of logistic regression in this study, the grey firm-years are considered as non-failed firm-years but maybe in the real situation, those grey firm-years fall in the failed firm-years category.

4.2.1. Forward Logistic Regression

Table 5 presents the model summary of the logistic regression. The Nagelkerke R Square assesses the extent to which the explanatory variable in this logistic regression model accounts for the variation observed in the outcome variable. The higher the Nagelkerke R Square, the greater the level of explanation for the variation. Generally, the values exist between 0 to 1.

The model in step one shows that the Nagelkerke R Square is 0.409. The Nagelkerke R Square in models two, three, four, and five are 0.639, 0.842, 0.903, and 1.000 respectively (see Table 5). The Nagelkerke R Square value in model five indicates that the model explained the variation in the outcome variable fully but it is statistically insignificant. That is why model four is the best model with statistical significance. The significance

Table 5. Model Summary of Logistic Regression
(using the data of Z category Manufacturing and OTC firms)

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	159.605[a]	.298	.409
2	113.843[b]	.465	.639
3	59.214[c]	.614	.842
4	38.970[d]	.658	**.903**
5	.000[e]	.728	1.000
a. The estimation ended during the 6th iteration since the parameter estimates experienced a change of less than .001.			
b. The estimation ended during the 7th iteration since the parameter estimates experienced a change of less than .001.			
c. The estimation ended during the 10th iteration since the parameter estimates experienced a change of less than .001.			
d. The estimation ended during the 11th iteration since the parameter estimates experienced a change of less than .001.			
e. The estimation ended at the 20th iteration due to reaching the maximum number of iterations. No definitive solution can be found.			

Source: Author's Analysis

levels of the stepwise models can be found in Table 8.

The Hosmer and Lemeshow Test evaluates the degree to which the model fits by assessing its goodness of fit. According to the Hosmer and Lemeshow test, the null hypothesis suggests that the model sufficiently conforms to the data.

In the Hosmer and Lemeshow Test (see Table 6), if the p-value is below 0.05, we

Table 6. Hosmer and Lemeshow Test
(using the data of Z category Manufacturing and OTC firms)

Step	Chi-square	df	Sig.
1	5.117	8	.745
2	2.260	8	.972
3	8.589	8	.378
4	5.770	8	.673
5	.000	3	1.000

Source: Author's Analysis

Table 7. Classification of Failed and Non-Failed in different modelsa
(using the data of Z category Manufacturing and OTC firms)

Observed			Predicted		
			Failed Non-Failed Status		Percentage Correct
			0	1	
Step 1	Failed Non-Failed Status	0	36	24	60.0
		1	13	95	88.0
	Overall Percentage				**78.0**
Step 2	Failed Non-Failed Status	0	45	15	75.0
		1	11	97	89.8
	Overall Percentage				**84.5**
Step 3	Failed Non-Failed Status	0	52	8	86.7
		1	2	106	98.1
	Overall Percentage				**94.0**
Step 4	**Failed Non-Failed Status**	**0**	**56**	**4**	**93.3**
		1	**3**	**105**	**97.2**
	Overall Percentage				**95.8**
Step 5	Failed Non-Failed Status	0	60	0	100.0
		1	0	108	100.0
	Overall Percentage				**100.0**
a. Cut value: 0.500					

Source: Author's Analysis

can discard the null hypothesis. In the above table, the significance is greater than 0.05 in all steps. So, we are affirming the null hypothesis, which implies that all the models sufficiently conform to the data.

The classification of Non-Failed and Failed in different models have been shown in Table 7 to explain the hit ratio.

The Forward Logistic Regression technique generates various models. The 1st model will not have any independent variable. In the next model, the system incorporates the explanatory variable that has a greater influence on the outcome variable. This way it goes on step after step. This method of adding an independent variable in the model step by step is called Forward Logistic Regression.

In step 1, only one independent variable (X3) has been used and the model explained 78.0% correct variation in the dependent variable. In step 2, only two independent variables (X1, X3) have been used and the model explained 84.5% correct variation in the dependent variable. In step 3, only three independent variables (X1, X3, X4) have been used and the model explained 94.0% correct variation in the dependent variable. In step 4, the model used four independent variables (X1, X3, X4, X5) and the model explained 95.8% correct variation in the outcome variable. Notably, the X2 variable has not been automatically used in any model. That means X2 has not any adequate impact on the output. Model five at step 5 is not significant because the variables in the model have p-values greater than 0.05, indicating they are statistically insignificant. The statistical significance of each variable used in those models is shown in Table 8. Based on statistical significance, model 4 is the most effective in providing an explanation for the fluctuations observed in the dependent variable within this logistic regression.

The X3 variable representing the EBIT/TA is the most influential variable in predicting corporate failure. The finding by Bauweraerts (2016) also demonstrates that the ratio of EBIT to Total Assets is the most influential factor in predicting corporate failure.

The Table 8 shows that among the five variables considered in this study, the X3 (EBIT to total assets) is the top variable in explaining the financial distress level because individually it can explain 78.0% variation in the outcome variable. Besides, the probability of failure can also be better predicted collectively by X1([Current assets - Current liabilities]/Total assets), X3 (EBIT divided by Total assets), X4 (Book value equity divided by Book value of total debt or Liability), X5 (Sales to Total Assets).

The results suggest that the EBIT to Total Assets ratio is the most impactful variable in predicting corporate failure. The second most impactful variable is the working capital ratio, while the third most impactful variable is the debt to equity ratio.

One imperative finding is that the X2 Variable (Retained Earnings divided by Total assets) is not a good predictor in predicting corporate failure.

The findings show that out of five variables taken in this study, the most influential variable in predicting corporate failure is the ratio of EBIT to total assets. Then, the second most influential variable in predicting corporate failure is the ratio of net liquid assets to total assets. Next, the third most influential variable in predicting corporate failure is the ratio of book value of equity divided by book value of total debt. After that, the fourth most influential variable to predict corporate failure is the ratio of sales to total assets. In combination, those four variables can predict corporate failure most significantly. On the other hand, the ratio

Table 8. Variables in the Equation based on Forward Logistic Regression (using the data of Z category Manufacturing and OTC firms)

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	X3	-26.110	4.503	33.616	1	.000	.000
	Constant	1.683	.289	33.837	1	.000	5.382
Step 2[b]	X1	-7.035	1.311	28.781	1	.000	.001
	X3	-27.751	5.708	23.635	1	.000	.000
	Constant	3.209	.526	37.261	1	.000	24.754
Step 3[c]	X1	-10.117	2.616	14.954	1	.000	.000
	X3	-53.431	11.969	19.928	1	.000	.000
	X4	-3.237	.897	13.028	1	.000	.039
	Constant	10.322	2.311	19.954	1	.000	30406.229
Step 4[d]	**X1**	**-14.223**	**3.876**	**13.465**	**1**	**.000**	.000
	X3	**-62.507**	**16.693**	**14.022**	**1**	**.000**	.000
	X4	**-7.194**	**1.919**	**14.049**	**1**	**.000**	.001
	X5	**-10.006**	**2.783**	**12.923**	**1**	**.000**	.000
	Constant	**21.271**	**5.208**	**16.680**	**1**	**.000**	1729944302.568
Step 5[e]	X1	-297.826	4385.154	.005	1	.946	.000
	X2	-475.282	5375.769	.008	1	.930	.000
	X3	-938.525	15028.834	.004	1	.950	.000
	X4	-159.702	1682.294	.009	1	.924	.000
	X5	-257.642	5710.396	.002	1	.964	.000
	Constant	487.403	5112.397	.009	1	.924	4.746E+211

a. Variable(s) considered in the 1st stage: X3.
b. Variable(s) considered in the 2nd stage: X1.
c. Variable(s) considered in the 3rd stage: X4.
d. Variable(s) considered in the 4th stage: X5.
e. Variable(s) considered in the 5th stage: X2.

Source: Author's Analysis

Table 9. Model Summary of Logistic Regression (using the data of Bank and NBFI)

Model Summary			
Step	**-2 Log likelihood**	**Cox & Snell R Square**	**Nagelkerke R Square**
1	.000[a]	.181	1.000

a. The estimation ended at the 20th iteration due to reaching the maximum number of iterations. No definitive solution can be found.

Source: Author's Analysis

of retained earnings to total assets is not a good predictor of predicting corporate failure.

Since the variables of Z category manufacturing and OTC firms are different compared to the variables of Z category bank and NBFI, a separate Forward Regression Analysis has been performed for the banks and NBFI.

The model summary of the Forward Logistic Regression (see Table 9) indicates that the Nagelkerke R Square value is 1.0. which indicates that the variable taken (X3) in step one has completely accounted for the variation in the outcome variable. Thus, one single variable is solely responsible to explain the variation in the outcome variable in the perspective of the data of Bank and NBFI.

In the Hosmer and Lemeshow Test (see Table 10), if the significant value is below 0.05, we can reject the null hypothesis. In the above table, the p-value is above 0.05. So, we accept the null hypothesis i.e., the model sufficiently fits the data.

The classification of Non-Failed and Failed in different models have been shown in Table 11 to explain the hit ratio.

Under the Forward Logistic Regression, the system creates different models, by adding an independent variable in the model step by step. The output shown in Table 11shows that, in step 1, only one independent variable (X3) has been used and the model explained 100.0% variation in the outcome variable. Thus, In the Bank and NBFI dataset, a single variable (X3) has the ability to fully (100%) explain the variation in the outcome variable. Consequently, the findings imply that X1, X2, X4, and X5 don't have any adequate impact on the variation of the outcome variable in the case of the data of Bank and NBFI.

Table 10. Hosmer and Lemeshow Test (using the data of Bank and NBFI)

Hosmer and Lemeshow Test			
Step	**Chi-square**	**Df**	**Sig.**
1	.000	8	1.000

Source: Author's Analysis

Table 11. Classification of Failed and Non-Failed in different modelsa
(using the data of Bank and NBFI)

Observed			Predicted		
			Failed Non-Failed Status		Percentage Correct
			Failed	Non-Fail	
Step 1	Failed Non-Failed Status	Failed	48	0	100.0
		Non-Fail	0	1	100.0
	Overall Percentage				100.0
a. Cut value: 0.500					

Source: Author's Analysis

Table 12. Variables in the Equation based on Forward Logistic Regression (using the data of Bank and NBFI)

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	X3	379.554	69344.293	.000	1	.996	6.892E+164
	Constant	-49.481	8265.976	.000	1	.995	.000
a. Variable(s) considered on 1st step: X3.							

Source: Author's Analysis

Table 12 shows that among the four variables considered in the Forward Logistic Regression analysis utilizing the data of Bank and NBFI, the X3 (EBIT divided by total assets) is the only variable in explaining the financial distress level because individually it can explain 100% variation in the outcome variable. But the finding is not statistically significant. The possible reason for insignificant findings might be the few firm-year observations. This small amount of data on banks and NBFI may not be adequate in providing the significance level of the analysis.

The findings of Bauweraerts (2016) show seven factors with significant predictive ability: Accruals, EBIT/TA, Current Ratio, firm size, Solvency, VA/TW, and firm age. However, this study indicates that when considering data from banks and non-bank financial institutions, only one variable, namely EBIT/TA, emerges as the most influential factor in predicting corporate failure.

5. Conclusions and Implications

The purpose of this study is to identify the predictors that impact mostly in predicting the financial failures of the Z category manufacturing, OTC, and Bank & NBFI companies. Binary Forward Logistic Regression has been applied for this purpose. In the perspective of the data of Z category manufacturing and OTC firms, the single variable impact shows that the ratio of EBIT to Total Assets explained a 78.0% correct variation in the dependent variable (failed and non-failed position). In considering the combined impact, four independent variables (X1, X3, X4, X5) explained 95.8% correct variation in the outcome variable. Thus, it can be said that the possibility of failure can be better predicted by X1 ([Current assets - Current liabilities]/Total assets), X3 (EBIT to Total assets), X4 (Book value equity divided by Book value of total debt or Liability), X5 (Sales divided by Total Assets). It is also found that X2 (Retained Earnings divided by Total assets) is not a good predictor in predicting corporate failure. Thus, it can be deduced that the ratio of EBIT divided by Total Assets has the most predictable capability to predict corporate failure.

In the perspective of the data of Bank and NBFI, the X3 (EBIT divided by total assets) is the only variable in explaining the financial distress level because individually it can explain 100% variation in the outcome variable. Thus, the findings indicate that the ratio of EBIT to total assets has the highest predictability power to predict the corporate failure.

The study's **managerial and practical implications** suggest that decision-makers, such as investors, creditors, bankers, lenders, etc., can utilize the findings in their decision-making process through understanding the variables with the highest predictive capability for forecasting corporate failure. According to the findings, the most impactful variable in predicting corporate failure is the EBIT to Total Assets ratio. The study's **theoretical implication** is that forward logistic regression can be employed to identify the variables with the greatest predictive capability for anticipating corporate failure.

In this study, 5 factors used in the Altman's Z score have been taken for the analysis. Future research could be done by taking more variables and different models to increase the generalization of the findings.

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