FINANCIAL DISTRESS: AN EMPIRICAL STUDY ON THE LISTED COMPANIES IN DHAKA STOCK EXCHANGE

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Abstract

The study, by applying logistic regression, develops a financial distress prediction model that provides early warning signal and identifies those financial ratios that are significantly poor in the distressed firms. Certain characteristics that are commonly found among financially distressed firms are disproportionate use of financial leverage, chronic shortage of cash and other liquid current assets, and excessive level of current liabilities. A total of one hundred and fifty companies mainly from manufacturing sectors, listed in Dhaka Stock Exchange, have been chosen as samples. Financial status of the firm – a categorical and dichotomous dependent variable – has two dimensions: namely financially distressed or financially non-distressed. As for independent variables, nineteen different financial ratios have been chosen. Financial data of the period between 2013 and 2018 has been collected from annual reports of the sample companies. The model has found that three predictors namely: Profit Margin, Fixed Charge Coverage Ratio, and Cash Flow from Operations to Net Income, are significantly poor in financially distressed companies.

Keywords: Financial Distress, Logistic Regression, Financial Ratio, Dhaka Stock Exchange

1. Introduction

The study of financial distress produced considerable interest among researchers due to its importance to the investors, creditors, corporate managers, and taxation authorities. Researchers defined the term 'Financial Distress' in many different ways as some saw it as the inability of a firm to meet its short term obligations due to cash flow shortage (Beaver, 1966), while others viewed it as a situation when a firm sought legal protection from the creditors (Altman, 1968). The causes of financial distress range from inefficient management of financial activities, inappropriate marketing and production strategies to even some macroeconomic issues such as economic recession, high interest rates, and credit crunch in the financial markets (Baldwin and Glezen, 1992). Nonetheless, certain characteristics are common among financially distressed firms: high levels of debt, frequent defaults on credit, poor levels of cash, and, most importantly, negative net income.

Since the beginning of the twenty-first century, a large number of corporations from both the developed and the developing economies have fallen into the peril of financial distress. Especially the countries from the developing economies have experienced slowdown in their economic growth due to financial distress that

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occurs in many firms every year. Previous studies (Chowdhury and Barua, 2009) in Bangladesh have found that a large number of Z-category shares in Dhaka Stock Exchange (DSE) are in financial distress. Z-category shares are those which fail to pay dividend due to profitability or those whose accumulated loss after adjustment of revenue reserve is negative.

Firms can avert such turmoil by forecasting imminent financial distress and by identifying causes of the distress for adopting corrective measures. At this junction, the current study finds a scope to play a contributing role. This paper aims to develop a prediction model that would forecast the financial distress one year before the occurrence. In addition, the model would also identify financial ratios of distressed companies that are significantly underperforming than those of the financially non-distressed ones in Dhaka Stock Exchange (DSE).

2. Literature Review

Altman (1968), the pioneer of the study on financial distress prediction, applied multivariate discriminant analysis to develop a prediction model and a composite index called 'Z-score' in his seminal paper. Even today, Z-score index is popular among investors and corporate managers for investment and managerial decision making. Later, Edmister (1972) developed Altman's (1968) model by adding three distinct dimensions: solving the multicollinearity problem among financial ratios that are used as independent variables; fitting the time series of financial ratios in his dataset; and, for the first time, using small size firms as samples.

However, the arbitrary assumption that independent variables are normally distributed remained a major limitation of prediction models that used discriminant analysis. Due to this limitation, discriminant models were not valid when applied to a different set of samples or when the sample composition changed. To overcome this limitation, Logistic Regression was applied by Ohlson (1980) in the study of financial distress prediction. Logistic Regression does not assume normal distribution of independent variables and is more robust than Multivariate Discriminant Analysis.. Zavgren (1983) enhanced and modified the study of Ohlson (1980) by improving the predictability of his (Ohlson, 1980) model. While using non-probability and pair-matched design in sample selection, Zavgren matched two groups of firms (bankrupt and non-bankrupt) by asset size and industry type. Reducing sampling bias and improving the selection criteria of independent variables by using factor analysis were two important contributions of his study.

Gilbert, Menon, and Schwartz (1990) argued that previous researchers only considered the firms that existed in two extreme ends of financial situations and ignored the firms in between. They opined that firms that suffered financial distress and adopted turnaround strategy to survive bankruptcy would provide more valuable insight if they were taken into sample. Therefore, Gilbert, Menon, and Schwartz (1990) used a mixed sample consisted of three groups: (1) bankrupt firms (2) financially distressed firms that survived, and (3) non-bankrupt and healthy firms. They developed two models, the first one was based on bankrupt and non-bankrupt firms, while the second one was from bankrupt firms and the firms which turned around to survive financial distress. Their results showed that the first model outperformed the second model in terms of the accuracy of classification. Gilbert, Menon, and Schwartz (1990) attributed this declining accuracy to overlapping financial characteristics between bankrupt and financially distressed firms.

Apart from developing prediction models, researchers also explored the causes of financial distress. Desai and Montes (1982) showed the relationship between financial distress and macroeconomic variables such as money supply and bank rate while Hudson (1986) and Brownbridge (1998) found that unemployment rates, interest rates, and personal consumption expenditure in the economy could significantly affect corporate bankruptcy. In a different study, Hudson and Cuthbertson (1993) recognized the influence of unemployment rate, new borrowing, and profit margin on corporate bankruptcy. Rodway (1991) and McDonald (1995) found that changes in real interest rates and in output growth could significantly affect financial distress.

Among Bangladeshi scholars, Abdullah (2015) studied the financial health of the banking sector in Bangladesh by using Altman Z-score model to see which banks could be categorized as bankrupt according to the model's estimated value. His research found that Banks that were operated according to the Islamic rules showed better performance than non-Islamic banks. He estimated the changing Z-scores of twenty nine banks over several consecutive years and found that state-own banks showed gradual improvement of their financial performance. In a similar study, Ahmed and Alam (2015) also found that majority of private banks in Bangladesh, according to Altman Z-score model, belonged to the financially distressed zone.

Therefore, most of the studies about financial distress in the context of developing countries over-relied on Z-score model for the categorization and prediction of bankruptcy and overlooked the limitations of multivariate discriminant analysis. The applicability of Z-score model is, at best, suitable as an initial test of a firm's probability of bankruptcy. Without further extension and analysis, the model cannot be used to identify specific financial areas that are problematic, and, therefore, does not help much for taking corrective measures. Moreover, in the context of Bangladesh, no study has yet been done to predict the financial distress of DSE listed firms in the manufacturing sectors, neither has been any research to identify the areas of financial performance that contribute to such distress. To fulfill these gaps, the current study seeks to construct a prediction model that foretells the financial distress of firms in DSE, particularly those in the manufacturing sectors, at least one year before. At the same time, the model would also tell which areas of financial performance are significantly poor in the distressed firm.

3. Methodology

The purpose of this study is to develop a model that predicts, one year in advance, the probability a firm's falling into financial distress and, in doing so, identifies those financial ratios whose values are significantly different between financially distressed and financially non-distressed companies in Dhaka Stock Exchange. The companies are classified into financially distressed and financially non-distressed categories on the basis of their values of Earnings Per Share (EPS). Elloumi and Gueyie (2001) are among the notable scholars who used negative EPS as a defining character of financial distress. Besides, many regulators around the world, such as China securities Regulatory Commission (Fact Book 2014 – Shanghai Stock Exchange), emphasize on the negative profitability as an indicator of financial distress.

(i) Variable Description and Data Sources

The dependent variable here is categorical (i.e. the financial status of a firm) and dichotomous. The dichotomous variable 'the financial status of a firm' has two dimensions: a) the status of the firm is financially distressed and, b) the status of the firm is not financially distressed. A numerical value of '0' is assigned to financially distressed firms and'1' to financially non-distressed ones for expressing this dichotomous variable in the binary state.

As for the independent variables, this study uses six categories of financial ratios namely liquidity ratios, cost ratios, profitability ratios, efficiency ratios, leverage ratios, cash flow ratios. Researchers (Altman, 1968; Tamari, 1978; Gibson, 1982; White, Sondhi, and Fried, 1994; Poston, Harmon, and Gramlich, 1994; and Hossari and Rahman, 2005) used financial ratios to develop prediction models of financial distress as financial ratios, quite accurately, represent the financial status of a firm. In this study, the liquidity ratios consist of current ratio, quick ratio, and cash ratio. The cost ratios include three variables: fixed charges coverage ratio, fixed costs to total assets, and variable costs to total assets. The profitability ratios are comprised of profit margin, Basic earning power (BEP), return on total assets (ROA), and return on common equity (ROE). The variables which are included in efficiency ratios are accounts receivable turnover, inventory conversion period, average obligation period, and fixed assets turnover. The leverage ratios consists of two variables namely debt ratio, and debt to equity ratio. Finally, the cash flow ratio includes three variables – cash flow from operations to net income, cash flow coverage ratio, and operating cash flow to current liabilities.

(ii) Data Collection and Sample Size

A total of one hundred and fifty companies listed in Dhaka Stock Exchange have been chosen as the original samples. Among them, seven companies belong to Cement sector, five companies belong to Ceramics sector, thirty nine companies belong to Engineering sector, three companies are from Jute sector, another three from Paper and Printing sector, thirty two companies are from Pharmaceuticals and Chemicals sector, six from Tannery sector, and fifty five companies are taken from Textiles sector. These companies, listed in DSE, broadly represent the manufacturing sectors of Bangladesh.

Between 2013 and 2018, the values of EPS of the original samples have been arranged in descending order. The top 50 EPS with positive values have been included in a set that is recognized as financially non-distressed companies. In choosing the values, if the same company shows up multiple times, then the highest value of EPS and the associated year have been kept in the sample. In a similar fashion, the bottom 50 EPS with negative values have been included in a separate set defined as financially distressed companies. Here as well, the repetition of companies has been omitted by choosing the highest value of EPS among the multiple occurrences. In case the same company appears in both top and bottom charts of EPS, the associated year for the lower EPS has been considered. Thus, financial ratios of 100 different companies, 50 of which are financially distressed and 50 financially non-distressed, are taken for data analysis.

All data have been collected from annual reports of the sample companies. The data for the independent variables or the values of the financial ratios have been collected one year prior to the year whose EPS value has been selected in the sample. To illustrate this point, Alltex Industries Limited, between 2013 and 2018, had the lowest EPS (-7.97) in 2018. Therefore, for the analysis, the financial ratios of 2017 have been used.

4. Analysis of Data

The study applies logistic regression to develop the prediction model. Logistic Regression is a suitable regression model when the dependent variable is categorical and dichotomous, as in this study, while predictor variables can be of any type, such as categorical, ordinal, interval, or ratio. Besides, a great flexibility of logistic regression is that it does not require the independent variables to be normally distributed or linearly related or of equal variance within each group. The model of this study has been constructed as follows:

$$\log_e\left[\frac{p}{1-p}\right] = a_0 + a_1x_1 + a_2x_2 + \cdots + a_nx_n$$

$$\text{or, } \log_e\left[\frac{p}{1-p}\right] = \sum_{i=0}^{k} a_ix_i$$

$$\text{or, } p = \frac{e^{\sum_{i=0}^{k} a_i x_i}}{1+e^{\sum_{i=0}^{k} a_i x_i}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where,

p = Probability of having financial status without any distress or probability of financial non-distress. Probability values close to 0 would refer to firms which are financially distressed and values close to 1 would refer to firms which are financially non-distressed. x_i= Independent variables or the financial ratios of a firm.

a_i= Parameter to be estimated.

The null hypothesis of the model is that the coefficients of the independent variables are simultaneously equal to zero or, in other words, the independent variables of this study are not relevant for the logistic regression model. Failure to reject this null suggests that removing or adding these predictor variables to the model does not improve its predictability of dependent variable. The prediction efficiency of the regression model, along with its explanatory power for explaining the variability in the dependent variable, will also be tested.

The model is expected to see how accurately the probability of a firm's falling into financial distress can be predicted based on the values of financial ratios. The model is also expected to identify the financial ratios that are significantly different between financially distressed firms and financially non-distressed firms, and the financial ratios whose poor performances can be attributed to the financial distress.

4.1 Empirical Results and Interpretations

Table 1 presents the mean values and standard deviations of the independent variables for both financially distressed firms and financially non-distressed firms. In addition to presenting group statistics, the table also assists in forming an intuition on areas of financial performance that are relatively poor in financially distressed firms. The negative values of profitability ratios (i.e., profit margin, basic earning power, return on equity etc.) indicate that financially distressed firms are suffering from negative net income.

Table 1: Group Statistics

Independent Variables	Mean		Standard Deviation	
	Distressed	Non-Distressed	Distressed	Non-Distressed
Cash Ratio	0.15	0.97	0.16	0.76
Current Ratio	0.92	2.41	0.51	1.52
Quick Ratio	0.33	1.37	0.28	1.07
Cash Flow From Operations To Net Income	-0.35	1.34	2.14	1.10
Cash Flow Coverage Ratio	-0.21	0.48	0.35	0.45
Operations Cash Flow To Current Liabilities	-0.05	0.40	0.17	0.46
Fixed Costs To Total Assets	0.08	0.05	0.05	0.03
Variable Costs To Total Assets	0.05	0.07	0.04	0.05
Fixed Charges Coverage Ratio	-1.12	2.08	5.61	1.34

Accounts Receivable Turnover	29.64	38.13	76.32	80.38
Inventory Conversion Period	143.44	99.39	171.26	130.34
Average Obligation Period	138.69	61.89	106.00	31.89
Fixed Asset Turnover Ratio	0.75	1.38	0.75	0.76
Return On Common Equity	-0.02	0.13	0.11	0.12
Basic Earning Power	-0.73	0.74	0.09	0.04
Return On Total Assets	-0.16	0.11	0.31	0.07
Profit Margin	-0.34	0.14	1.18	0.08
Debt Ratio	0.46	0.20	0.28	0.09
Total Debt To Equity Ratio	1.44	0.56	4.78	0.39

Omnibus test (Table 2) of model coefficients presents the significance level of the model using chi-square method. The test tells us whether the model that includes all the independent variables significantly differs from the model that includes only the constant term or intercept. The omnibus test can also be seen as a test that shows how capable the independent variables are in predicting the dependent variable. Inclusion of independent variables to the model is justified if the significance level is less than0.05. On the contrary, if the significance level is larger, for example, more than 0.10, it would mean that exclusion of independent variables from the regression model is justified. As we see from the table 2, the significance level is below 0.05 and implies that at least one of the predictors is significantly related to the dependent variable. Based on this result, null hypothesis can be rejected and it can be suggested that including the independent variables can meaningfully and significantly improve the predictability of the model.

Table 2: Omnibus Test of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	34.5	19	0.016
	Block	34.5	19	0.016
	Model	34.5	19	0.016

Table 3 presents three statistics namely -2 Log Likelihood, Cox and Snell's R^2, and Nagelkerke's R^2 to assess the fitness of the model. -2 Log Likelihood measures the efficiency of the prediction of the regression model that includes all independent variable. The lower the value of this statistic, the better the model. Here, the value of -2 Log Likelihood '0' means very high strength of predictability of the model. Cox and Snell R^2 and Nagelkerke R^2 represent how much variation in the dependent variable is explained by the model. Generally the coefficient of determination, or the R^2, in Ordinary Least Square (OLS) Regression analysis measures how well the regression model can predict the value of dependent variable based on the values of independent variables. It is a measure of the strength of the model showing percentage of variation in the data set explained by the regression. The R^2 value ranges from 0 to 1 where a value of 1 refers to 100% explanatory power of the model or perfect predictability. In Logistic Regression, Cox and Snell's R^2 mimics the OLS

R^2 based on the log likelihood of the final model (after including the predictor variables) and the log likelihood for the basic intercept only model. The ratio of these two log likelihoods mirrors the improvement of the full model over the intercept-only model. The smaller the ratio, the greater the improvement, and the higher the value of Cox and Snell's R^2. However, a limitation of the Cox and Snell's R^2 statistic is that the value cannot reach to 1.0 even though the model has perfect predictability. To overcome this limitation, Nagelkerke R^2 adjusts the Cox and R^2in a manner so that the possible value can extend to 1.0. The high values of Cox and Snell's R^2 (0.75) and Nagelkerke R^2 (1.0) in this research indicates a strong goodness-of-fit and variance explanatory power of the model.

Table 3: Measures of model fit

Step	-2 Log likelihood	Cox & Snell R^2	Nagelkerke R^2
1	0.000	0.750	1.000

Table 4 shows logistical coefficient for the predictor variables, standard error of the logistical coefficient, Wald Statistic and its associated significance level. Wald Statistic follows a chi-square distribution and tests the significance of the logistic regression coefficient based on the asymptotic normality property of maximum likelihood estimates.

Mathematically,

$$Wald = \left(\frac{B}{S.E.}\right)^2$$

Where,
B = logistical coefficient for the predictor variable
S.E. = Standard error of the logistical coefficient

A Statistically significant Wald Statistic means the associated parameter or predictor variable has significant influence in the model. Here, a cut-off point of 0.05 level is used to identify statistically most significant variables. Step 0 is for the intercept-only model and step 1 onward are for the full model after including all predictor variables. As we see in the intercept-only model, the coefficient value of the constant is 0 with a Wald Statistic of 0 which is statistically insignificant. After improving the model by Forward Stepwise method of Logistic Regression, we find that only three predictor variables are statistically significant at less than 0.05 level. They are Profit Margin (PM), Fixed Charge Coverage Ratio (FCCR), and Cash Flow from Operations to Net Income (CFO).

Table 4: Variables in the Equation

		B	S.E.	Wald	df	Sig.
Step 0	Constant	0	0.18	0	1	1
Step 1	PM	16.75	4.12	16.53	1	0.00
	Constant	-1.93	0.78	6.12	1	0.00
Step 2	PM	30.24	7.16	17.84	1	0.00
	CFO	-1.94	1.2	2.61	1	0.02
	Constant	-3.14	0.86	13.33	1	0.00
Step 3	PM	38.5	13.82	7.76	1	0.01
	FCCR	-42.28	17.6	5.77	1	0.02
	CFO	-5.68	2.27	6.26	1	0.04
	Constant	-2.86	1.28	4.99	1	0.15

Their logistical coefficients are 38.50, -42.28, and -5.68 respectively. It suggests that these three predictors have significant influence on the company in falling into financial distress. After putting the logistical coefficient values in model equation (1), we get the probability of a company falling into financial distress as follows:

$$p = \frac{e^{38.50\text{PM}-42.28\text{FCCR}-5.68\text{CFO}}}{1 + e^{38.50\text{PM}-42.28\text{FCCR}-5.68\text{CFO}}}$$

Table 5: Classification results

		Observed	Predicted Group Membership			Percentage Correct	
				0	1		
Step 1	Financial distress	0		50	0		100
		1		0	50		100
	Overall Percentage						100

The classification matrices in table 5 estimate the probability of occurring financial distress in a firm given the values of its chosen financial ratios. The table presents how many cases are correctly and incorrectly classified from the independent variables. As we see, the accuracy of prediction in this model is 100 percent with correct classification of all financially distressed and financially non-distressed companies. The model can be applied to predict the probability of falling into financial distress by using the appropriate values of PM, FCCR, and CFO of any firm. For example, the values of PM, FCCR, and CFO of Alltex Industries Limited in 2018 were -0.1967, 0.0753, and -0.4249 respectively. Putting these values in the above model gives us a probability value of '0' which implies that this firm has zero probability to possess a financial status free from financial distress.

Correspondingly, Saiham Textile Mills Limited had the values of PM, FCCR, and CFO as 0.4488, 0.0511, and 0.1788 in 2018 that predicts a high probability of this firm to be free from financial distress.

5. Conclusion

The current study develops a financial distress prediction model by applying logistic regression on one hundred and fifty listed companies in Dhaka Stock Exchange. The relevant predictors in the model have been found as Profit Margin (Net Income / Sales), Fixed Charge Coverage Ratio [(Earnings Before Interest and Taxes + Fixed Charges before Tax / (Fixed Charges before tax + Interest)], and Cash Flow from Operations to Net Income. These model predictors – PM, FCCR, and CFO – are also informative as to the elements in the financial statements that might be contributing to the financial distress. Poor values of these ratios can result from excessive level of costs, especially fixed costs, in the operations. Interest expenses and rents, two of the most important components of fixed costs, are generally very high in manufacturing industries due to high capital intensity. When a firm struggles to cover such costs with its operating revenue, it may eventually fall into financial distress. The model, developed in this study, can provide an early signal of financial distress as the values of the above predictors deteriorate. Therefore, this paper suggests that firms pay attention to improve the above ratios and minimize the fixed charges to avoid financial distress.

Whether the distress prediction models, based on the samples of one stock exchange, can be applied to other stock exchanges, the Altman's Z-score model can serve a good defense. Altman's Z-score model (Altman, 1968) was developed with the firms in USA during the period between 1946 and 1965, but the model is applicable in other countries even today. Chowdhury and Barua (2009) applied Altman's Z-score on the companies listed in Dhaka Stock Exchange and found the accuracy of predictability of the model. However, the model in this study may not be able to predict the financial distress of the service sector as accurately as the manufacturing sector. Besides, a model based on matched pairs of samples in terms of firm size, technology level, scope of operations may provide even better insight than the current model. The only challenge in the formation of such pairs is that the sample size may become too small to feed into a reliable model. Further research may overcome such limitations and may identify sector specific solutions to avert financial distress.

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