PREDICTING CORPORATE FAILURE: A STUDY ON SELECTED BANGLADESHI COMPANIES

A thesis submitted to the Department of Accounting & Information systems in partial fulfillment of the requirement of the Master of Philosophy

Submitted by
Md. Azim
Roll: 1401
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Session: 2017-2018
Program: MPhil
Department of Accounting & Information Systems
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Department of Accounting & Information Systems
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4th December 2023

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LETTER OF TRANSMITTAL

4th December 2023

Dr. Md. Jamil Sharif
Associate Professor
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Subject: Submission of thesis on Predicting Corporate Failure: A Study on Selected Bangladeshi Companies

Sir,

It is a great delight for me to submit the thesis report on “Predicting Corporate Failure: A Study on Selected BangladeshiCompanies” in partial fulfillment of the requirement of the Master of Philosophy.

I have tried my level best to prepare this thesis. It is my original work under your guidance and supervision.

I hope that you will find this thesis worth reading. Please feel free to ask any query that you would like me to interpret.

Thank you very much for your direction and supervision.

Sincerely yours,

……………
Md. Azim
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Session: 2017-2018
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DECLARATION

I, Md. Azim, Researcher of MPhil Program, Department of Accounting and Information Systems, University of Dhaka do hereby declare that the work incorporated in this thesis entitled “Predicting Corporate Failure: A Study on Bangladeshi Selected Companies” is my original work under the guidance and supervision of Dr. Md. Jamil Sharif, Associate Professor, Department of Accounting & Information Systems, University of Dhaka.

The elements incorporated in this thesis have not been submitted for any award of any other Degree or Diploma in any institution or university.

I have authentically acknowledged and referred to the researchers wherever the works of them have been cited in the text of this thesis.

I have followed all the applicable ethics that encompasses academic honesty and integrity. No falsified data have been included in this thesis.

I comprehend that any infringement of the above will cause punitive action by the university, including canceling the degree, if conferred.

……………
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CERTIFICATE

This is to certify that the thesis entitled "Predicting Corporate Failure: A Study on Selected Bangladeshi Companies" is a genuine work of Md. Azim, Researcher of MPhil Program, Department of Accounting and Information Systems, University of Dhaka.

He has accomplished his study and completed the thesis for the degree of Master of Philosophy under my supervision and guidance.

I, therefore, endorse that Md. Azim is permitted to submit his thesis for the degree of Master of Philosophy (MPhil) under the Department of Accounting and Information Systems, University of Dhaka.

……………………....

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EXECUTIVE SUMMARY

The prediction of financial distress holds significant importance for the stakeholders of a company, as it helps them to proactively implement preventive measures such as policy adjustments or restructuring both operational and financial frameworks. The timely prediction serves as a catalyst for informed decisions encompassing investments, credit extensions, bank loan approvals, and more. The occurrence of corporate insolvency imposes considerable costs upon diverse stakeholders, including debt providers, shareholders, suppliers, employees, auditors, customers, and others. Therefore, early detection plays a crucial role in enabling these stakeholders to make well-informed choices that drive effective decision-making processes. Henceforth, the focal point of this research resides in the prediction of corporate insolvency within the business entities of Bangladesh.

The significance of this study is that it demonstrates the necessity of using prediction models to forecast the financial condition of entities classified under the Z category and OTC. It also emphasizes the importance of implementing alternative measures to protect the interests of various stakeholders. This is crucial because general investors are unaware of the true financial health of companies transferred to the Z category or OTC, as explained by the BSEC. Simply designating firms as Z category or OTC is insufficient. Despite being classified as Z category by the regulator, these firms do not experience any impact on trading and there is no reflection in stock prices. Instead, there is an upward movement in the prices of certain low-quality securities, which poses a risk to general investors when price corrections occur. Consequently, the capital market can become unstable. Additionally, there have been instances where the regulator was unable to trace certain companies in the OTC, which is detrimental to general investors. Therefore, utilizing a failure prediction model for distressed firms is necessary to initiate effective actions that protect the interests of general investors.

When a firm reaches a distressed level that warrants insolvency declaration, there must be a robust infrastructure for bankruptcy, enabling immediate filing to mitigate losses associated with restructuring procedures or the bankruptcy process. Otherwise, if there is a delay in the bankruptcy or restructuring procedure, it creates three impacts (Grigaraviˇcius, 2003). First, it increases direct and indirect spending related to bankruptcy. Second, it decreases the recovery potentials of the indebted firms. Third, it reduces the reimbursements of obligations to creditors. Hence, it is imperative for the distressed firm to promptly initiate the bankruptcy appeal during the initial stage of their indebtedness; otherwise, these issues will exacerbate. To avert failure, it is crucial for the Chief Executive Officer to grasp the nature and facets of failure comprehensively. Subsequently, corrective measures need to be implemented to prevent such failure. Mistakes should be acknowledged, and precautionary actions should be taken to safeguard the organization from future errors.

Based on the news report from bdnews24 (Only 2 out, 2006), it was revealed that a mere two out of thirty-three delisted companies opted to repurchase stocks from the public between 1994 and 2006. This particular situation serves as a testament to the fact that only a small fraction, six percent to be precise, of shareholders were able to reclaim their investments through buyback arrangements initiated by the sponsor or director. Consequently, a staggering 94% of shareholders find themselves in a precarious position, their interests in these delisted companies left unaddressed. Hence, this thesis contends that the governing authority ought to adopt a more proactive approach rather than simply designating such firms as Z category or OTC. Instead, the authority should employ a failure prediction model to identify companies facing severe financial distress and take necessary steps to liquidate them forcibly. Following the mandatory liquidation, the funds recovered should be promptly redistributed to the shareholders and other stakeholders who are rightfully entitled to receive their dues.

This study contributes in three aspects by addressing the following three gaps. First, the inclusion of OTC companies in predicting corporate failure fills a gap in this field of research, as no prior study has utilized data from OTC companies. Second, this study also addresses the gap of incorporating the recent data of Z category companies, as the previous study by Chowdhury & Barua (2009) only covered data up to 2009. In contrast, our study includes the most recent data of Z category firms, spanning up to 2019. Third, this study addresses the research gap by utilizing forward logistic regression to identify the most influential predictors in predicting corporate failure. The reason for choosing this method is the limited number of studies conducted using it. Therefore, this research will make a valuable contribution to the existing literature.

There are two primary aims of this study: 1. To find out whether there are any financially unhealthy firms in the Z category and OTC companies; 2. To identify the predictors that impact the financial failures of the Z category and OTC companies. There are two secondary aims of this study: 1. To understand the financial characteristics of the Z category and OTC companies; 2. To determine whether the characteristics of financially unhealthy companies in the Z category and OTC differ significantly from those in financially healthy positions.

As a data collection method, primary data is adopted. For this purpose, the author contacted the particular stakeholders of Bangladesh Securities and Exchange Commission (BSEC) and Dhaka Stock Exchanges (DSE) for the data of failed or liquidated companies. But the concerned officers of both the offices do not maintain any data related to those companies. Both the authorities keep only data of active companies whose shares are trading on the market i.e., the stock exchange of Bangladesh. Later the author asked for the data of Over-The-Counter (OTC) companies because the annual reports are not available on the website of the OTC companies. Finally, the author decided to continue this study using the data of OTC companies because no study was done on the companies in the Over-the-Counter (OTC) trading platform. Besides using the data of OTC companies, this study will also include the data of Z-category companies. Although there was a previous study (Chowdhury &Barua, 2009) on Z-category companies, this study will consider the recent data for those companies.

As a means of collecting data, the researcher has employed primary data collection methodology. For that purpose, the author reached out to the specific stakeholders associated with the Bangladesh Securities and Exchange Commission (BSEC) and the Dhaka Stock Exchanges (DSE) in order to obtain data pertaining to companies that have experienced failure or liquidation. But, it was discovered that the officials in both offices do not preserve any records pertaining to such companies. Instead, they exclusively preserve data on active companies whose shares are actively traded on the Bangladeshi stock exchange market. Then, the author requested the data concerning Over-The-Counter (OTC) companies, as the annual reports of these companies were not available on their respective websites. Consequently, the author resolved to proceed with the study utilizing data from OTC companies, primarily due to the absence of previous research conducted on companies operating within the Over-the-Counter (OTC) trading platform. In addition to utilizing data from OTC companies, this study will also incorporate data from Z-category companies. While a prior study (Chowdhury & Barua, 2009) did examine Z-category companies, this present study will focus on the most recent data available for Z-category companies.

To collect data, a sample of 35 companies was taken out of 46 Z-category companies. The selection was based on the availability of annual reports on the websites of those companies. Data from 2007 to 2019 were collected, considering their availability. Additionally, data from 13 companies in the OTC market were collected through hardcopy records obtained from Dhaka Stock Exchange. In total, the study utilized a dataset comprising 217 firm years, with 26 firm-years originating from OTC companies. Among the Z-category firms, there were 191 firm-years of data, with 142 firm-years belonging to manufacturing and service providing companies, while the remaining 49 firm-years pertained to bank and non-bank financial institutions (NBFI).

In the analysis section of this study, the financial characteristics of the Z category and OTC companies are determined through the calculation of descriptive statistics. Subsequently, Altman's (1968) model is employed to calculate the Z score in order to determine the presence of failed, grey, and non-failed positions within the Z category and OTC companies. Subsequently, the application of One Way ANOVA and Independent Samples T-Test helps in identifying significant differences in the mean values of the financial position predictors among the failed, grey, and non-failed statuses. Finally, through the utilization of Forward Logistic Regression, the factors or predictors with the greatest impact on the financial failures of the Z category and OTC companies are determined.

This research reveals that the overall failure rate among companies categorized as Z is 72%. These findings align with the results of a previous study conducted by Chowdhury and Barua (2009), which reported a 77% failure rate among companies. In a more specific context, an alarming 98% of Bank and Non-Bank Financial Institutions in the Z category are experiencing failure. This finding mirrors the conclusions drawn from a study conducted by Hamid et al. (2016), where a substantial 93% of companies were found to be in a failed position.

In order to fulfill the first primary objective of the study in assessing the financial health of firms categorized as Z and those traded over-the-counter (OTC), the results reveal significant insights. Manufacturing and servicing companies in the Z category encountered a failed financial position in 59% of firm years, while 19% of firm years were classified as non-failed and 22% as grey. Conversely, Z category banks and non-bank financial institutions experienced a failed financial position in 98% of firm years, with a mere 2% categorized as grey and none falling under the non-failed category. Regarding OTC manufacturing and servicing companies, 92% of firm years faced a failed financial position, while 8% were deemed as grey. Similar to Z category financial institutions, no firm years were classified as non-failed. These findings unequivocally indicate that Z category banks and non-bank financial institutions are entrenched in an exceedingly weakened state.

In order to attain the second primary objective of this study, which involves identifying the predictors with the greatest impact on predicting financial failures of Z category and OTC companies, the application of Forward Logistic Regression has yielded significant findings. It has been observed that when considering the single impact, a substantial 78.0% correct variation in the dependent variable (i.e., failed and non-failed positions) can be explained by the ratio of Earnings before Interest and Taxes to Total Assets. When the combined impact is taken into account, the dependent variable's correct variation is explained by four independent variables (X1, X3, X4, X5), amounting to 95.8%. Thus, it can be deduced that the prediction of failure can be enhanced by considering the following variables: X1 (Current assets minus current liabilities 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), and X5 (Sales divided by total assets). Furthermore, it has been determined that X2 (Retained Earnings divided by total assets) does not serve as a reliable predictor when it comes to forecasting corporate failure.

The findings derived from the secondary objectives of this study, which aimed to explore the financial characteristics of Z category and OTC (Over-the-Counter) companies, reveal imperative insights. When examining the gross financial data of Z category companies, the descriptive statistics demonstrate that the minimum balance of Retained Earnings, Earnings before Interest and Taxes, and Book Value of Equity are all situated in negative territory. Furthermore, the mean value of Retained Earnings also showcases a negative figure. Conversely, when analyzing the ratios-based descriptive statistics of Z category companies, we observe that the mean value of the net working capital ratio and the Retained Earnings/Total assets ratio both exhibit negative figures. Remarkably, the descriptive statistics for OTC companies exhibit similar trends to those of Z category companies.

In order to address another secondary objective of the study, which involves discerning notable distinctions in the attributes between financially unstable companies classified under the Z category and OTC, and those in a sound financial position, two statistical tests were employed: the Independent Samples T-Test and One Way ANOVA. The results indicate that when applying the Altman Z score to Z category Bank and NBFI companies as well as OTC companies, only two outcome groups, namely "failed" and "grey," were observed, with no instances of non-failed firm years being identified. To compare the means of these two groups, the Independent Samples T-Test was utilized. Based on the findings from the Independent Samples T-Test, it was determined that only one ratio, specifically EBIT/Total assets, exhibited significant differences when comparing the "failed" and "grey" firms. On the other hand, the outcomes of the one-way analysis of variance (ANOVA) reveal the following mean values for X1: -0.0773 for Failed firms, 0.4152 for Non-Failed firms, and 0.2605 for Grey firms. Consequently, it can be inferred that Failed firms tend to exhibit a negative mean value for the net working capital ratio. Similarly, the mean values for X2 are as follows: -0.3204 for Failed firms, 0.1915 for Non-Failed firms, and 0.1043 for Grey firms. Hence, it can be deduced that failed firms tend to display a negative mean value for the Retained Earnings/Total assets ratio. Moreover, the mean values for X3 are 0.0008 for failed firms, 0.0725 for Non-Failed firms, and 0.0786 for Grey firms. Thus, it can be inferred that the mean value of the Earnings before interest and taxes/Total Assets ratio for failed firms tends to be considerably lower compared to Non-Failed firms. Similarly, the mean values for X4 are 0.9879 for failed firms, 10.9985 for Non-Failed firms and 1.6087 for Grey firms. Consequently, it can be deduced that the mean value of the Book value equity/Book value of total debt or Liability ratio for failed firms tends to be significantly lower compared to Non-Failed firms. However, in terms of X5 (Sales/Total assets), there are no significant differences observed among Failed, Non-Failed, and Grey firms. Hence, this finding indicates that only one ratio, specifically Earnings before interest and taxes divided by Total assets, exhibits significant differences when comparing Failed and Grey firms. It is worth noting that no firm-year falls under the category of "Non-Failed" within the OTC companies.

In conclusion, the study asserts that the mere classification of certain firms into either the Z category or OTC category falls short in addressing the underlying issues. The findings of the study indicate a staggering failure rate of up to 98% and 92% for firms in the Z category and OTC category, respectively. Consequently, it becomes imperative to employ a failure prediction model in order to identify extremely distressed firms and implement proactive measures to safeguard the interests of general investors and other stakeholders. When a firm reaches a state of distress that necessitates an insolvency declaration, it becomes crucial to establish a robust infrastructure for bankruptcy proceedings. This would enable swift filing, thereby mitigating losses associated with the restructuring or bankruptcy procedures. Based on the findings of the study, it is recommended that employing Forward Logistic Regression can effectively uncover the key variables that play a significant role in predicting corporate failure. These insights can be invaluable for decision makers, enabling them to identify the factors with the greatest predictive power for corporate failure.

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LIST OF ABBREVIATIONS

Abbreviations	Full Form
AIES	Artificially Intelligent Expert System
ANCOVA	Analysis of Covariance
ANN	Artificial Neural Networks
ANOVA	Analysis of Variance
ATB	Alternative Trading Board
BSDM	Balance Sheet Decomposition Measures
BSEC	Bangladesh Securities and Exchange Commission
CBR	Case-Based Reasoning
CEO	Chief Executive Officer
CRIS	Composite Rule Induction System
CSFB	Credit Suisse First Boston
DEA	Data Envelopment Analysis
DSE	Dhaka Stock Exchanges
EBIT	Earnings before Interest and Taxes
EBITDA	Earnings Before Interest, Taxes, Depreciation, and Amortization
GA	Genetic Algorithms
GDP	Gross Domestic Product
IMM	Integrated Multi-Measure
IRTS	Interest Rates Term Structure
KMV	Kealhofer, McQuown and Vasicek
LOGIT	Logistic Model
LPM	Linear Probability Model
MDA	Multiple Discriminant Analysis
MDS	Multidimensional Scaling
NBFI	Non-Bank Financial Institutions
NN	Neural Networks
OLS	Ordinary Least Squares
OTC	Over-the-Counter
ROA	Return on Assets
ROE	Return on Equity
SME	Small and Medium-Sized Enterprises

CHAPTER ONE
INTRODUCTION

1.1 Background of the Study

Corporate failure or financial distress means a company's incapability to meet financial obligations. Reasons for financial distress are excess leverage, low profitability, illiquidity, managerial inability, and other external factors such as high competition due to industry saturation, unfavorable economic situations, deregulation of industries, etc. (Gyarteng, 2019).

The prediction 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 in various decisions like the investment in a company, extending credit, sanctioning bank loan, etc. Corporate failure inflicts a substantial cost on 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).

In the perspective of Bangladesh, the study of Hossain et al., (2020) on the chemical, pharmaceutical, and textile sectors evaluates companies' financial health using the model of Z-score by Altman (1968). There are 28% of entities in distress positions in the pharmaceutical and chemical industry. On the other hand, 30% of entities are in a distressed position in the textile industry. The study of Mizan & Hossain (2014) on the cement industry finds that out of 7 companies, only two companies (Confidence Cement and Heidelberg cement) were in good financial health and the other three (Lafarge Surma Cement, Aramit Cement, and Meghna Cement) were not in good financial condition. The study of Mizan et al. (2011) on the pharmaceutical industry shows that only two companies (IBN SINA Pharmaceutical and Square Pharmaceutical) were in good health out of the six companies taken as the sample. The study on the pharmaceutical industry (taking five companies as a sample) was done by Islam & Mili (2012) using the Z score of Altman and finds that maximum entities are in an average position considering the financial health.

The study of Ali et al. (2016) on the textile industry finds that 50% of companies are in a distress zone considering financial health. The study by Chowdhury &Barua (2009) on the Z category entities of Dhaka Stock Exchange (DSE) using Altman's Z-score shows that forty-one (77.36%) companies out of fifty-three are in a distress position. The study of Hamid et al. (2016) applying the Z score of Altman on the Non-Bank Financial Institutions (NBFI) of Dhaka Stock Exchange shows that 93% of the sample (15) companies in 2015 were in distress zone. The study of Masum &Johora (2015) on the ceramic industry (taking four companies as a sample) applying the Z score of Altman shows that the overall position of the entities was in the gray zone (moderate level of distress position). The study of Rahman et al. (2020) on the banking industry (taking eighteen banks as a sample) using Altman Z score shows that four banks were in a distress position in 2017. The study was also done using the Bayesian Neural Network, Support

Vector Machine, Artificial Neural Network(ANN), and found that the Support Vector Machine performs lower compared to the other two techniques.

The Z-score of Altman is a widely used model to predict corporate failure (distressful status) by measuring the financial health of the companies (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).

From the perspective of Bangladesh, most studies predicting corporate failure have focused on companies in specific sectors. One study (Chowdhury & Barua, 2009) was conducted on the Z category, but none have explored companies on the Over-the-Counter (OTC) trading platform. This study will specifically examine some OTC companies, alongside recent data from Z category companies.

The significance of the study lies in demonstrating the necessity of utilizing predictive models to forecast the financial condition of entities categorized under Z and OTC. This will also highlight the importance of adopting alternative measures, such as liquidation or restructuring, to safeguard the interests of various stakeholders. The general investors are not aware of the real financial health from the BSEC's declared reasons for transferring a company to Z category or OTC. Therefore, simply declaring some firms as the Z category or OTC category is not enough. Although the firms are declared as Z category by the regulator, there is no effect on the trading because there is no reflection in the stock prices. Rather there is an increasing movement in the prices of some junk securities that are detrimental for the general investors when there will be a price correction. As a result, the capital market can fall into unstable situations. There were instances where the regulator could not trace few companies in the OTC, which is harmful to the stakeholders. That is why the failure prediction model could be employed for detecting the extremely distressed firms, and effective actions, such as liquidation or restructuring, could be taken to protect the interests of the related stakeholders. At least some stakeholders would receive a portion of their interests from the remaining resources after liquidation. However, if the necessary actions are not taken and the company remains untraceable, the interests of the stakeholders are ignored. According to Grigaraviˇcius (2003), when a firm reaches the distressed level in which it is essential to be declared insolvent, there should be effective infrastructure for bankruptcy so that filing could be done immediately to reduce losses associated with the restructuring procedures or bankruptcy procedure. If there is a delay in the bankruptcy or restructuring procedure, it creates three impacts. First, it increases direct and indirect spending related to bankruptcy; second, it decreases the recovery potentials of the indebted firms; third, it reduces the reimbursements of obligations to creditors. That is why it is essential to file an appeal for bankruptcy for the distressed firm in the initial stage of their indebtedness; otherwise, problems will be aggravated. To avoid failure, the Chief Executive Officer should comprehend the nature and aspect of the failure. Then there should be corrective measures to prevent the failure. Mistakes should be recognized and there should be precautious actions to protect the organization from future mistakes (Mukridakis, 1991).

In the perspective of contribution of this study, the use of data from OTC companies is a new contribution through this thesis because no study on prediction of corporate failure was done using the data of OTC companies. Another contribution is that the use of forward logistic regression will show the most significant factors that affect the z score of Altman's model. Previous there were studies using Logistic Regression but no study was done using Forward Logistic Regression. Considering the findings of the study, the study will also emphasize on using failure prediction model by the regulators to detect the extremely distressed companies for taking effective actions, such as liquidation or restructuring, to protect the interests of the related stakeholders. Because simply declaring the Z category or OTC category based on some characteristics presently using by the regulators are not enough to protect the interest of the stakeholders of the extremely distressed companies.

This study makes several contributions. One contribution is the utilization of data from OTC companies, a novel inclusion in this thesis. No prior studies on predicting corporate failure have employed data from OTC companies. Another significant contribution is the application of Forward Logistic Regression which reveals the most impactful factors influencing the Z score of Altman's model. While Logistic Regression has been used in previous studies, the unique use of Forward Logistic Regression sets this research apart from the perspective of Bangladesh. The study highlights the importance of employing the failure prediction model by regulators to identify extremely distressed companies. This proactive approach allows for effective actions, such as liquidation or restructuring, for protecting the interests of relevant stakeholders. Merely categorizing companies into the Z category or OTC category based on certain characteristics, as currently done by regulators, proves insufficient in protecting the interests of stakeholders in extremely distressed companies.

1.2 Statement of the Problems

The order (Reference: SEC/CMRRCD/2009-193/08) of Bangladesh Securities and Exchange Commission (BSEC) directs that a firm will be considered as Z category share for the following reasons: i) if the firm fails in declaring cash dividend for the last two years consecutively, ii) if the firm does not hold Annual General Meeting within a specified time, iii) if the firm is not in production or operation for six months consecutively (excluding the period of expansion, rehabilitation, modernization, and balancing), iv) If the firm makes a report of net operating loss for two years consecutively, v) If the firm makes a report of negative cash flows from operation for two years consecutively, vi) if the negative balance of retained earnings of the firm is higher than the paid-up capital, vii) if the firm fails to comply with any rules, laws, regulations, provision, directives, orders, notifications, listing requirements. Another notification (No: SEC/CMRRCD/2009-193/07/Admin/106) regulates that the board of directors should be reconstructed in forty-five working days after the declaration of the Z category. If the new reconstructed board fails to improve the financial and operational performance within four years after the reconstruction date, the firm might be delisted from the stock exchanges.

After getting delisted from the automated trading system, the firm's securities could be traded in the over-the-counter (OTC) facilities of the stock exchange. Recently the securities traded in over-the-counter (OTC) would be traded in the Alternative Trading Board (ATB) which is an alternative trading facility provided by the stock exchange. On 28th December, 2020, there was a directive from the BSEC which permits that a delisted firm or the firm in the OTC or ATB can apply for an exit plan for selling the securities if there is any available offeror who could apply for buying the securities under the exit plan. An offeror for buying the firm of OTC or ATB indicates a sponsor or a promoter shareholder or a director of the applicant who makes the offer for buying the securities under the exit plan.

The offer price for purchasing the securities could be any of the following, whichever is higher: face value; or last trade price on or before the date of suspension of trade/delisting; issue price at the time of initial public offer; or Net Asset Value per share; or the volume-weighted average price for last one year.

On 8 September 2021, the BSEC postponed trading of the Beximco Synthetics because the sponsors and directors of the company expressed their intention to buy back the shares. The company deposited over Tk 27.88 crore in an escrow bank account on March 20, 2022, to buy back the shares. Beximco Synthetics Ltd protracted the time for share surrender till 30 May 2022.

But, according to the report of bdnews24 in 2006, only two out of thirty-three delisted firms bought back shares from the public from 1994 to 2006. This scenario indicates that only six percent of shareholders got back their investment through buyback by the sponsor or director i.e., 94% of shareholders' interest in the delisted companies are in stranded positions. The regulators should take initiative to forcefully liquidate those companies. After forceful liquidation, the recovered money should be returned to shareholders and other stakeholders who are entitled to receive their dues.

According to Chowdhury &Barua (2009), maximum companies under the Z category list of the Dhaka Stock Exchange are in a financially distressed position but the decision-makers especially the board of directors are not concerned to take preventive measures to protect from the further deterioration of the financial status. Therefore, the regulator, especially the Bangladesh Securities and Exchange Commission (BSEC), should devise a different classification for Z-category firms that are in a very poor or outright failed position, as determined by the prediction model.

The problem is that, although the firms are declared as Z-category by the regulator, there is no effect on trading because there is no reflection in the stock prices. Rather there is an increasing trend in the price of some securities that are detrimental for some of the general shareholders when there will be a price correction. According to Mahmud (2019), the share of junk companies in the OTC or the share of Z category companies has shown abnormal rising in price even though there is no price sensitive information or earning growth. Consequently, the capital market can encounter situations of instability. That means declaring a firm as the Z category or OTC is not the solution. In some cases, stockholders lose their full investment as a whole that is harmful to the general investors as well as undesirable to the regulators. In some cases, the regulator could not trace companies in the OTC. According to Grigaraviˇcius (2003), when a firm reaches the distressed level at which it is essential to be declared insolvent, there should be an effective infrastructure or system in place so that filing can be done immediately to reduce losses associated with the restructuring procedures or bankruptcy procedure. If there is a delay in the bankruptcy or restructuring procedure, it creates three impacts that are mentioned in the previous section of this study. That is why it is essential to file an appeal for bankruptcy for the distressed firm in the initial stage of their indebtedness; otherwise, problems will be aggravated. In such a scenario, the regulator can use the models of prediction in predicting the financial condition of the entities under the Z category & OTC and take alternative measures for protecting the interests of the various stakeholders.

Considering the scenario stated so far, this study contributes in three aspects by addressing the following three gaps. First, the inclusion of OTC companies in predicting corporate failure fills a gap in this field of research, as no prior study has utilized data from OTC companies. Second, this study also addresses the gap of incorporating the recent data of Z category companies, as the previous study by Chowdhury & Barua (2009) only covered data up to 2009. In contrast, our study includes the most recent data of Z category firms, spanning up to 2019. Third, this study addresses the research gap by utilizing Forward Logistic Regression to identify the most influential predictors in predicting corporate failure. The reason for choosing this method is the limited number of studies conducted using it. Therefore, this research will make a valuable contribution to the existing literature.

1.3 Research Questions

The research questions of the study are as below:

Q1: Are the Z-category and OTC companies in financially unhealthy positions?

Q2: What factors contribute to the occurrence of financial failures within companies?

Q3: What are the distinct characteristics of companies in the Z category and those operating over-the-counter (OTC)?

Q4: Do the attributes of financially unhealthy companies classified under the Z category and OTC differ considerably from those in a healthy financial standing?

1.4 Objectives of the Study

There are two primary goals and two secondary goals of this study:

1. To find out whether there are any financially unhealthy firms in the Z category and OTC companies.

2. To identify the predictors that impact in causing the financial failures of the Z category and OTC companies.
3. To know the financial features of the Z category and OTC companies.
4. To identify whether the characteristics of financially unhealthy companies in the Z category and OTC significantly different from the financially healthy position.

1.5 Scope of the Study

Most of the studies in the international arena were done taking data from failed and non-failed data. The researcher contacted the particular stakeholders of Bangladesh Securities & Exchange Commission (BSEC) and Dhaka Stock Exchanges (DSE) for the data of failed or liquidated companies. But the concerned officers of both the offices do not maintain any data related to delisted companies. Both the authorities keep only data of active companies whose shares are trading on the market i.e., the stock exchange of Bangladesh. Later the researcher asked for the data of Over-The-Counter (OTC) companies because the annual reports are not available on the website of the OTC companies. Finally, the author decided to continue this study using the data of OTC companies because no study was done on the companies in the Over-the-Counter (OTC) trading platform. This study will also include the data of Z-category companies. Although there was a previous study (Chowdhury & Barua, 2009) on Z-category companies, this study will consider the recent data for those companies.

The remaining part of the paper proceeds as follows: The review of the literature is shown in chapter two. The third chapter shows the theoretical framework. The fourth chapter is concerned with the methodology used for the study. The fifth chapter analyses the outcomes and shows the findings. Finally, the conclusion is provided in section six.

CHAPTER TWO
LITERATURE REVIEW

2.1 Definition of Corporate Failure & Financial Distress

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, low profits comparing to forecast, 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. It is essential to define the non-failed and failed companies to reduce potential outliers and in succession type I & II errors (Appiah et al., 2015).Type I Error happens when classifying distressed firms as non-distressed, and Type II Error happens when classifying non-distressed firms as distressed (Balcaen & Ooghe, 2006).

2.2 Importance of Predicting Corporate Failure or Financial Distress

Predicting financial distress is helpful to distinguish between the unhealthy (going to be distressed) and healthy firms. By forecasting the distress situation using a model can help the stakeholders to make appropriate decisions (Alfaro et al. 2008).

Failure of a firm affects various stakeholders which include academics, clients, customers, lenders, suppliers, economic agents, employees, financial institutions, policymakers, auditors, financial managers, investors, depositors, creditors, practitioners (investment analysts, credit analyst), bankers, consultants, the community, the government, lawyers for bankruptcy & reorganization, judges, etc. (Al Manaseer & Al Oshaibat, 2018;Samaraweera, 2018; Laitinen & Suvas, 2013; Fauzias & Chin, 2002; Beynon & Peel, 2001; Dimitras et al., 1996).

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. If the bankruptcy can be detected in the early stage, then protection measures can be taken to lower the risk of distress (Alkhatib & Eqab Al Bzour, 2011). A precise prediction is useful for the stakeholders to prevent huge losses arising from sudden bankruptcies and could serve as a warning to auditors about potential problems concerning going-concern (Boritz et al., 1995). The same view is shown by Mackevicius & Sneidere (2010). The authors opine that if an early prediction can be done, then the management of an entity can take judicious actions to recover from the bad condition by doing an in depth-analysis, investigating the reasons and manipulating elements, implementing efficient decisions, and thus to evade bankruptcy and liquidation. If precautionary measures are not taken in time, then creditors and investors fail to retain their investments, the government loses tax revenue, and subsequently unemployment increases, hurting the economic growth of the country.

By getting an early signal of possible failure, managers can change the strategy and restructure the financial arrangement, or if liquidation is essential, that can be implemented to reduce the period of losses (Frederikslust, 1978).

2.3 Reasons of Corporate Failure or Financial Distress

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. According to Charitou et al. (2004), the main reason that entities fail is their incapacity to pay back their interest as well as debt obligations, which is the result of insufficient cash flows resulting from operating activities. When a firm fails to generate adequate operational cash flows, it becomes incapable of paying the existing obligations. This situation leads to financial failure (Hamid et al., 2016).

The study of Jahur & Quadir (2012) on Small and Medium-Sized Enterprises (SME) shows the causes of financial failure. The most significant causes are the shortage of access to credit, insufficient financing, unavailability of skilled manpower, weak management, weak accounting records, and high-cost structure.

According to Gilbert et al. (1990), there are three key reasons for financial distress. The reasons are the allocation of assets inaptly, unsuitable economic structure, and lack of corporate governance. On the contrary, the study of Sharma & Mahajan (1980) shows that the cause of failures can be classified into two broad categories. First, failures occur due to inefficient management, such as mistakes in the strategic plan and/or its implementation. Second, failures occur due to a lack of adaptability to environmental changes such as unfavorable economic change, customers' shifting behavior

Another finding by Low et al. (2001) opines that sometimes an entity may have enough current assets to cover the obligations for debt still, that company may be distressed if there are many non-cash items in the current assets

According to Mbat & Eyo (2013), the reasons of business failure are public policy (unfavorable interest rate), Economic instability, Socio-cultural factors, Managerial ineffectiveness, and inefficiency (lack of a thriving strategic plan, poor risk evaluation strategy, low productivity, unsuitable costing strategies, high cost in production, inefficient sales force, over-expansion).A firm may also face insolvency due to the prevailing worldwide financial crisis (Camacho-Miñano et al., 2013).

According to Frederikslust (1978), due to a nosedive in sales, a critical situation arises that leads to corporate failure. The reasons for declining sales are inefficient management, unavailability of raw materials, loss of a vital customer, recession, etc.

The study by Islam & Mili (2012) shows the causal factors for which one entity falls into a worse financial position. The causal factors are high cost of production, the susceptibility of environmental risk, an unfavorable policy of the government, fixed mark-up system, restrictions on the patent right, lack of professional distribution house, high level of debt, low sales, sluggish conversion of inventory and receivables into cash, insufficient working capital, inefficient financial management.

2.4 Symptoms of Corporate Failure or Financial Distress

There are different symptoms exposed by a firm when it faces a distressed financial position. Financial patterns of distressed firms are fluctuating compared to non-distressed firms (Martikainen&Ankelo, 1991). The usual symptoms are the disability in paying the financial debts due to not having enough cash flows (Abdullah et al. 2008).

Gyarteng (2019) shows the characteristics of distressed firms that are small profits, illiquidity, and meager asset productivity (due to increased assets without an equivalent increase in Earnings before Interest and Taxes, increase retained earnings, and increase working capital.

Koch (2019) explains the signs which indicate that a company may collapse. The signs are i) Cash hemorrhage (the author opined that if there is a 10% increase in sales, there would be a more or less 10% increase in cash but if it does not occur, something is happening unusually);ii) Accrued income (when receivables grow unreasonably high compared to sales);iii) When the Chief Executive Officer (CEO) engages in an extravagant lifestyle; iv) When the financial reports or annual reports are too complex to understand (the author opines that sometimes the higher authority hides huge debts or hides losses by showing them as the cost of development); v) Rampant acquisitions of failing companies; vi) When a company doesn't get payment from the big customers for a long time which indicates that there is a dispute regarding the payment; vii) The unsubstantiated figure of goodwill shown for the company of acquisition, viii) When the high-ranking management starts to bail in a group by cashing the shares; ix) When the firm fails in adapting to the disruptive technology; and x) Some symptoms in the office like poisonous office morale, secret meetings by the executives with agitated expressions.

According to Fago (2013), the symptoms of a financially distressed firm are excessive overdraw in the bank account, huge accumulated loss, paid-up capital is lower than the accumulated loss, unpaid preferred dividend, taxes due to government, salary and wages due to employees, discontinuation of operation, unable to pay shareholder's dividend, etc. There is no common definition of corporate bankruptcy. The interchangeable terms are financial distress, corporate failure, or corporate bankruptcy

According to Morris (1997), the symptoms of corporate failure are: frequent changes of managers, delayed publication of the annual report, changing in auditors, changing of accounting policies, swelling debt, very much long term investment using short term liabilities, regular losses from basic operations, negative cash flows, reduced dividend payments, declining liquidity, growing loans, dwindling sales at constant prices, shrinking profitability.

Sometimes a new business may fail because new products falter (35 to 80 percent failure rate) to make a profit. It takes eight years on average until a new business becomes successful. Sometimes the old business also fails due to increased competition and lack of growth, misguided diversification, unable to cope up with new technology, interruption of supply of raw materials, over-optimism, believing in quick fixes of the problems, etc. (Mukridakis, 1991).

There is a stimulating finding by Parker et al. (2002) that an entity that replaces its Chief Executive Officer with an outsider is prone to bankruptcy.

2.5 Methods for Predicting Corporate Failure or Financial Distress

From the year 1932 to now, diverse methods or models were applied in predicting corporate failure. 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 followed by Multiple discriminant analyses of Altman (1968) (Abdullah et al. 2008).

Adnan, Aziz & Dar (2006) categorize the prediction models for corporate failure into three general classifications which are Statistical Models, Theoretical Models, and 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, and Cumulative Sums Procedures. The examples of Artificially Intelligent Expert System Models (AIES) are Case-based reasoning models, Recursively partitioned decision trees, Genetic algorithms, Neural networks, Rough sets model. The examples of Theoretical Models are Cash Management Theory, Gambler's ruin theory, Balance sheet decomposition measures, Credit risk theories (including Moody's KMV model, JP Morgan's Credit Metrics, CSFB's Credit Risk+, KcKinsey's Credit Portfolio View).

Appiah et al. (2015) state that most of the methods broadly have four objectives which are i) The ability of prediction by the statistical techniques or variables, ii) Testing the accuracy of prediction of different statistical methods, iii) The prediction capability of the prior models, and iv) Examining the methodological validity. But the authors also recommend that prospective research should emphasize on developing models for corporate failure prediction by including both non-financial and financial information, and variables should not be selected on an ad-hoc basis. And only listed companies should not be considered as a sample because non-listed companies face failure in great numbers.

Among the three broad methods (statistical techniques, Artificially Intelligent Expert System techniques, Theoretical techniques) of predicting corporate failure, the performance level of statistical techniques in the case of predictive and validation accuracy is better compared to the other two models. In the case of assessing type-I error (categorizing distressed firms as non-failed), statistical techniques record lower errors compared to the other two models. On the other hand, classifying type-II error (categorizing non-distressed companies as distressed), the Artificially Intelligent Expert System technique records lower errors compared to the other two models (Appiah et al., 2015).

Prusak (2018) summarizes the available models/tools/techniques/methods used by the authors of former Eastern Bloc countries which are Univariate Analysis, Logit Analysis, Linear Multiple Discriminant Analysis, Artificial Neural Networks, Linear Probability Method, Kohonen Neural Network, Fuzzy Logic Method, Classification Trees, Factor Analysis, DEA Method, Random Forest, Cluster Analysis, ANOVA, ANCOVA, Linear Regression, Genetic Algorithms, Survival Analysis, Cox Regression Model, Takagi-Sugeno Algorithm, Kernel Classifiers, Pyramid of Insolvency Risk, A Naive Bayesian Classifier, The K-Nearest Neighbors Method, Bayesian Networks, Potential Functions, Support Vectors, Combining Classifiers into an Aggregate Model, Survival Analysis By The Cox Model, and others.

According to Samaraweera (2018), the available models/techniques are Univariate model of Beaver (1966), Multivariate Discriminant Analysis of Altman (1968), Artificial Neural Networks (ANN), Logit, Probit, Bayesian models, Genetic Algorithms (GA), Fuzzy models, Support vector machines, Hazard and Hybrid, model, K-nearest neighbor, Decision trees.

The study of García-Gallego et al. (2015) compared the accomplishment of two models under statistical techniques and found that logistic regression achieves better performance than the discriminant analysis model. Sometimes there is an argument that neural network models accomplish better performance than discriminant models or statistical models, and sometimes there is a suggestion to use a neural network as a complementary model in addition to statistical models (Nguyen, H.G., 2005). Among various methods, a hybrid model (combining the best features of best models) can provide increased performance for prediction (Lin & McClean, 2001). According to Taffler (1984), there should be a separate corporate failure prediction model for non-manufacturing and manufacturing companies.

The widely used method is Z-Score model of Altman (1968) based on Multiple Discriminant Analysis (Alaka et al., 2018) but predictive capacity drops significantly for forecasts two and three years prior the failure. Subsequently, the ZETA model of Altman et al. (1977) can categorize insolvent firms up to five years before failure. But Boďa & Úradníček (2016) recommend that the coefficients of Z-score model should be re-assessed while working with financially distressed firms.

2.6 Determinants/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 significantly 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. But variables or predictors should be selected based on bankruptcy theory (Laitinen & Suvas, 2013).

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 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.

The study of Beynon & Peel (2001) is also done using both non-financial and financial factors. The non-financial factors includes LAG (No. of days between the date the financial statements were filed at company registry and account year-end), AGE (No. of years since incorporation date), CHAUD (Status of changing auditor in previous three years), and BIG6 (Whether the company's auditor is a Big6 auditor). The study of Cortés et al. (2006) is also done using non-financial information (legal structure, firm size, activity) in addition to financial information. Dewaelheyns & Van Hulle (2006) used non-financial information for the firm, which is a dummy variable depicting whether there is an affiliation with the parent company or not. The study of Lussier (1995) also used the non-financial information that are staffing and parent, education, and professional advice of failed company are meaningfully different from a successful company.

According to Brabazon et al. (2002), it would be also useful if the models include explanatory variables relating to the entity's share price fluctuation. The study of Acosta-González et al. (2017) used macroeconomic variable which are land price, bank arrears, credit to householders, credit to construction companies, sector's share of Gross Domestic

Product (GDP), inflation, unemployment rate, government debt, country risk premium, volatility of the stock market, interest rate, interest rates term structure (IRTS).

The study of Hsu & Wu (2014) used corporate governance (board structure) as a variable and found the positive relationship between the percentage of independent directors in the boards and the possibility of corporate failure. The appealing finding is that there is less risk of failure if there are a larger percentage of grey directors (non-executive non-independent directors).

Audit quality could be a determinant while selecting variables for the models of corporate failures, because there is an association between fair financial statements and quality audits. Good audit quality is a sign of good governance that prevents corporate failures (Okpala, 2012).

According to Li & Faff (2019), both market-based information and accounting-based information can be used as variables in failure prediction models. Creditors should emphasize (provide more loading or weight) the market-based information as variables while applying the prediction model. On the other hand, bankers should emphasize accounting-based information as variables (accounting ratio) while applying the prediction model. When information asymmetry is high, accounting-based information should be provided with more weight. At the time of the financial crisis (negative economic growth), market-based information should be provided more weight

According to Brabazon et al. (2004), the most used ratios in predicting corporate failure are EBIT / Sales, Inventory /Working Capital, Net Income / Total Assets, Sales / Total Assets, 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 Income / Sales, Return on Equity, Fixed Assets / Total Assets, Cash / Sales, Inventory / Cost of Goods Sold, Total Liabilities / Total Assets, Cash from Operators / Sales, Working Capital / Total Assets, and EBIT / Interest.

Chen (2011) applies factor analysis to choose variables with high prediction ability. Initially, 37 (thirty three financial and four non-financial) variables were chosen. After doing factor analysis three times there were 12 variables with communality value. The selected ratios were Debt/Equity, Current Assets to Total Assets, Gearing Ratio, Inventory to Total Assets Ratio, Acid-Test Ratio, Cash Flow to Total Debt Ratio, Current Ratio, Return on Asset, Cash Flow Ratio, Return on Equity, Earnings per Share, and Debt to Equity Ratio.

According to Abdullah et al. (2008), the widely used variables are total liabilities to total assets, net income to total assets, total liabilities 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, sales to current assets, and cash to current liabilities.

According to Zulkarnain et al. (2001), in the perspective of Malaysia, the significant variables for corporate failures are cash to current liabilities, market value to debts, sales to current assets, total liabilities to total assets. According to Low et al. (2001), the significant elements in predicting financial distress are change in net income, cash and marketable securities to total assets, current assets to current liabilities, sales to current assets. According to Adnan Aziz & Dar (2006), the cash balance is a significant element in predicting corporate failure. There would be a failure of cash management which leads to financial distress if there is an inequity between cash inflows and outflows. According to Almansour (2015) sales to total asset, retained earnings to total asset, the market value of equity to book value of debt, working capital to total assets, a current asset to current liabilities are the important predictors of the possibility of bankruptcy. The selected seven variables by Bhandar & Iyer (2013) are Cash flow coverage of interest, Operating cash flow margin, Operating cash flow divided by current liabilities, Quality of Earnings, Operating cash flow return on total assets, Sales growth of three-year, and Quick ratio. Siciński (2019) finds that exchange rates, export, and expenditures on consumer goods and services influence significantly in predicting corporate failure.

Appiah et al. (2015) compile the most frequently used ratios which are current assets to current liabilities ratio, quick assets to current liabilities ratio, total debt to total assets ratio, net income to total assets ratio, working capital to total assets ratio, EBIT to total assets ratio. The authors suggest that theoretical arguments should be considered while selecting non-financial and financial variables for predicting corporate failure.

Pinches et al. (1973) reduced the extent of all ratios into seven sets, which are receivables intensiveness, inventory intensiveness, cash position, short-term liquidity, financial leverage, capital intensiveness, and profitability. It is found that the volume of free assets (unsecured assets) is a important discriminatory factor in the models of predicting corporate failure. If there are more free assets, there is more possibility to be reorganized as a distressed firm (Sulaiman et al., 2001; Hong, 1984).In the issue of matching non-failed firms with failed firms, there is a use of fiscal year (used in all studies), industry, asset size, sales, number of employees, internal accounting methods (Charitou et al., 2004).

According to Xu & Wang (2009), efficiency could be a sound predictor variable in the failure prediction model because it is commonly known that a prime reason for corporate failure is inadequate management, and that efficiency of business process is a worthy replication of the management of firm. One thing is important that to increase the accuracy of business failure prediction, variables related to falsified financial reporting should be excluded because some big accounting scandals (example: Enron, Worldcom, etc.) were the result of falsified financial reporting (Liou& Yang 2008).

The following table summarizes the various studies focusing on sample size, time-period, methodology, determinants or predictor variables, and short findings. The studies are arranged in chronological order.

Table 2.1: Summary of the Previous Studies on Predicting Corporate Failure

Study	Sample	Time Period	Methodology	Determinants for Prediction	Findings
Beaver (1966)	79 non-failed and failed firms	1954-1964	Univariate analysis	Ratio analysis	Net income /total asset, total debt / total assets, and , cash flow / total debt are significant in estimation
Altman (1968)	33 bankrupt companies and 33 non-bankrupt firms	1946-1964	Multiple Discrepant Analysis	Sales / total assets, Working capital/total assets, Market value of equity/ bookvalue of total debt, Earnings before interest &taxes/total assets, Retained earnings to total assets	Z-Score below 1.81 is bankrupt, Z score above 2.99 is non-bankrupt, and grey zone if Z score between 1.81 & 2.99
Ohlson (1980)	105 bankrupt & 2058 non-bankrupt firms	1970-1976	Logit	Performance, Current liquidity, Firm Size, Total Liabilities/total assets	Dependent variable was binary i.e., distress and non-distressed
Shirata&Shirata (1998)	686 failed& 300 non-failed firms in Japan	1986-1996	Generalizable Bankruptcy Prediction Model Data Mining Method; Stepwise Process; Classification and Regression Tree model	Cumulative E Bankrupt, Expansion of gross capital, Premium for loan, Liquidity,	Generalizable bankruptcy prediction model can predict insolvency accurately about more than 86% irrespective of size and industry.
Low et al. (2001)	26 distressed companies and 42 non-distressed	1996-1998	Logit analysis	Eleven financial variables	The cash situation of a firm indicates a more accurate warning signal of financial deterioration.
Zulkarnain et al. (2001)	24 distressed and non-distressed firms	1980-1996	Stepwise multivariate discriminant analysis	Market value to debts, Total liabilities to total assets; cash to current liabilities, andsales to current assets	Correctness of the market based original model is about 89.7%
Jen Ko et al. (2001)	53 firms (19 distressed and 34	1981-1985	CRIS-Composite Rule Induction System	Cash dividend per share, margin/sales, total liabilities to total assets, quick	To predict financial distress, the logit model underperform

	normal)			assets to current liabilities, and sales to fixed assets	comparing to both neural computing and CRIS model
Barniv et al. 2002	237 firms	1980 - 1992	Logit model	5 non-accounting and 5 accounting variables	Non-financial data improve related information to financial accounting data to predict post insolvency resolution
Neophytou & Molinero (2004)	50 non-failed and 50 failed firms	1988-1999	Ordinal Multidimensional Scaling (MDS)	Non-quantitative information (reasons of failing or not failing)	MDS does not suffer from outliers. Visualization of the reasons for failing and healthiness of firms is possible by MDS.
Charitou et al. (2004)	51 harmonized sets of non-failed & failed firms	1988 - 1997	Neural networks, Logit Analysis	Profitability, Operating cash Flow, Financial leverage,	Profitability, Financial leverage, Operating cash flow produced about 83% accuracy in predicting failure before one year
Brabazon & Keenan (2004)	178 (89 Non-failed and 89 failed) firms in US	1991-2000	Neural Network Model & Genetic Algorithm	Twenty-two financial ratios	Neural Network or Genetic Algorithm can outperform an Linear Discriminant Analysis model
Nguyen (2005)	First 32 companies, then 200 Companies	1988-2002	3 models of Neutral Network:, Logistic Regression, Probabilistic Neural Network; Multi-Layer Neural Network	Financial leverage, solvency, liquidity, and profitability ratios	Logistic regression model does 100% correct prediction; Probabilistic neural network does 93.75% correct prediction
Wu et al. (2006)	32 delisted and 32 active firms	Last year before delisting	Logistic Regression; Na¨ive-Bayes; Neural Network; Decision Tree;	Initially 82 ratios; After reduction (applying Filters & wrappers method), 2 ratios were used: Market price/Book Value, Market Capital over reported Net Income After Tax;	3rd dataset perform well comparing to the other 2 datasets

Hua et al. (2007)	60 failed and 60 non-failed firms	1999 to 2004	Support Vector Machine; Linear Multiple Discriminant; Neural Network,; Logistic Regression	Cash, cash equivalents to current liabilities, Net income to total assets, Gross profit / cost of goods sold, Growth ratio of total assets, Growth ratio of sales, Cash flow ratio, Sales / total assets	Support Vector Machine is superior model compared to other models.
Abdullah et al. 2008	52 distressed and non-distressed firms	1990 to 2000	Logistic Regression, Multiple Discriminant Analysis, and Hazard Model	Growth, Size (total assets employed); Profitability ratios; Cash flow ratios; Leverage ratios	Distressed firm has lower interest coverage, Negative ROA and ROE; Distressed firm is heavily relied on debt; Distressed firm is in negative income growth;
Campbell et al. (2008)	797 bankruptcy firms & 1,614 failure firms	1963-2003	Logit Model	SIGMA, Log of firm's market equity, Total liabilities/book value of total assets (TLTA), Net income/book value of total assets, Log of gross excess return/ value-weighted S&P 500 return	Firms with a highlyfailure risk of be likely to provide unsystematic low average earnings
Appiah, & Abor (2009)	62 firms (31 non-failed and 31 failed)	1994-2004	Z-score using Multiple discriminant analysis	Gross profit margin; Net profit margin	To discriminate non-failed and failed firm, net profit margin perform well comparing to gross profit margin
Min & Jeong (2009)	1271 failed & 1271 non-failed firms	2001 - 2004	Binary Classification	Out of initial 27 variables, 9 variables were taken	The method of Binary classification can work as a capable substitute to the prevailing approaches
Chen (2011)	50 non-failed and 50 failed firms	2000-2007	Decision Tree; Logistic Regression	Initially taken 37 ratios financial and non-financial ratios. After factor analysis, 12 ratios have been selected for the study	Logistic regression approach provides a better approach in the long run compared to the Decision Tree approach.
Premachandra et al. (2011)	50 failed & 901 non-failed companie	1991–2004	Data Envelopment Analysis	9 financial variables	Data Envelopment Analysis method is comparatively weak to predict

	s				corporate failures
Puagwatanaa & Gunawardana (2012	33 companies (12 failed companies)	2001	Logistic Regression	Altman model's four variables: working capital/total assets, retained earnings/total assets, sales/total assets, earnings before interest & taxes/total assets, and another one is net income (loss)/amount of shares	The model has 77.8% prediction accuracy
Lakshan & Wijekoon (2012)	70 non-failed firms & 70 failed firms of Colombo Stock Exchange	2002 to 2008	Logistic Regression	7 corporate governance variables (Outside directors, Audit opinion, CEO duality, Remuneration of directors, Outsider ownership, Board size, Presence of an audit committee)	82.86 percent prediction correctness at one year earlier to failure
Bunyaminu & Issah (2012)	50 distressed and 50 non-distressed firms	2000–2010	Multiple Discriminant Analysis	Used 19 determinants. The best predictors are: Return on total assets, Interest cover, Gearing ratio, & Solvency ratio	Logit model performs well comparing to MDA model
Fago (2013)	24 firms (16 non-failed & 8 failed firms)	1995-2005	Multivariate discriminant analysis	Profitability, Cash flow, Turnover, and Liquidity ratios	MDA can categorize non-failed and failed firms with 79% in 4 years, 91% accuracy in 2 year, and 87.5% accuracy in 1 and 3 year prior to failure of a firm
Bhandar & Iyer (2013)	50 non-failed and 50 failed companies	Data were collected for the previous years of the failed year.	Applied discriminant analysis	Operating cash flow/current liabilities, Operating cash flow margin, Cash flow coverage of interest; Quality of Earning, Sales growth of three-year, Operating cash flow return/total assets, and Quick ratio.	Overall, the DA model accomplished splendidly in forecasting corporate failure.

Pereira (2014)	16 non-failed & 11 failed firms	2003-2007	Hazard Analysis	Initially 28 variables were selected; Finally 3 variables were used which are: Cash-flow/Current liabilities;Current assets/Current liabilities; (Working Capital) / Total liabilities;	Hazard method provides good perspectives for developing a corporate failure prediction model.
Sujeewa (2014)	82 firms	2011-2013	Artificial Neural Network (ANN)	Non-linear relationships of variables	The accuracy of prediction by ANN model is about 86% on average
García-Gallego et al. (2015)	59 failed firms and 396 non-failed firms	41,584 firm year	Logistic regression and Discriminant analysis	15 selected financial ratios	Logistic regression performs better than discriminant analysis model
Nanayakkara & Azeez (2015)	67 failed and 67 non-failed firms	2002-2011	Multivariate Discriminant Analysis	Initially 14 ratios were taken; Finally four variables (firm size, retained earnings to total assets, cash flow from operations to total debts, earnings before interest and taxes) were proved as best predictors	85.8% prediction accuracy were achieved in 1 year before to the financial failure by the Multivariate Discriminant Analysis
Pereira et al. (2016)	401 bankrupt companies & 2032 non-bankrupt companies of hospitality industry	2010-2012	Approaches of Lasso and Ridge regression	Progress of the overall classification for Lasso & Ridge regressions while comparing with stepwise methods of SPSS.	Lasso & Ridge regressions perform not very distinctly from stepwise methods of SPSS.
Waqas et al (2018)	290 firms	2007-2016	Logit regression	Financial ratios (cash flows, profitability, liquidity, and leverage) and market factors (size and particular standard deviation of stock returns of each company.)	There is a consistent performance of the logit model I and II.
Purves & Niblock (2018)	24 firms (12 failed and 12 non-failed)	2004-2008	Exploratory mixed method (considering qualitative and quantitative factors)	Integrated Multi-Measure (IMM) ratio	Managements' participation in managerial strategy and board composition influence on a

					companies failure or success
Haider et al. (2018)	20 failed and 20 non-failed firms	2007-2014	Logit Model	Market, cash flow, activity, profit, liquidity and gearing ratios	Gearing ratio is significant to predict corporate failure
Fredrick & Osazemen (2018)	58 firms registered in the Nigerian stock exchange	2010 to 2016	Method of Panel Corrected Standard Error	Altman Z score, Long term loans to total assets, Fixed asset to total asset ratio, Natural Logarithm of total asset, Growth in revenue, Profit after Tax, Company age from listing year	Capital structure impacts financial distress negatively; Asset tangibility Profitability, company age from listing years impacts financial distress positively
Iqbal et al (2018)	11 Islamic Banks in Indonesia	2010-2016	Comparative descriptive approach	Risk Based Bank Rating, Bankometer and Altman Modification method	3 approaches of assessing the level of financial distress have differences
Casado Yusta et al (2019)	67 failed and 131 non-failed firms	3 years data	Greedy Randomized Adaptive Search Procedure and Logistic Regression	Initially 141 financial ratios and finally 14 financial ratios	GRASP-LOGIT achieves better performance comparing to a simple logistic model by selecting fewer but better predictors
Restaino & Bisogno (2019)	Same number of non-bankrupt and bankrupt firms	2007-2015	Rank transformation	Structure ratios, Operational ratios, Profitability ratios, Per employee ratios	Based on the relevant ratios the procedure can forecast bankruptcy constructing a failure index.
Siciński (2019)	Per year 600-800 reported cases	2000-2017	Econometric cause-effect model; Method of Ordinary Least Squares (OLS)	Macroeconomic Factors: Exchange rates, Export, and Expenditures on consumer goods and services	Exchange rate, Third degree liquidity ratio, and Consumption expenditures assert the important influence on corporate failures
Bolek & Szymańska (2019)	Companies in Warsaw Stock Exchange (4148 observation)	2012-2017	Logit and quadratic functions	Current assets to short term liabilities ratio; Cash conversion cycle; Cash efficiency of FCF / TA; Growth of cash level	Declining value of the current ratio and growing cash efficiency of assets impacts on the good economic situation of company

Yakymova & Kuz (2019)	50 Ukrainian companie s	2014-2017	Ratio analysis & Multiple discriminant analysis using five factor	Current Asset Turnover, Debt to Equity, Return on Equity; Working Capital to Current Assets, and Absolute Liquid Ratios	Average accounts receivable turnover, Current ratio, Equity-assets ratio have maximum discriminatory influence
Adriatico (2019)	45 companie s of Philippine	2015	Descriptive analysis design	Altman Z-Score; Current ratio	On the basis of Z-score of Altman's model, 35 companies appear as distressed; On the basis of current ratio, 12 companies appear as distressed
Gyarteng (2019)	144 firms	2006 to 2016	Used discrete variables according to Altman; Applied paired samples t-test	Altman Z score, liquidity, asset productivity, activity, profitability, solvency ratios	Profitability Solvency, asset productivity, Altman Z score were statistically significant in predicting financial distress. Two of five Altman's ratios (activity ratio and liquidity ratio) are not significant.

Source: Researcher's compilation

2.7 Shortcomings of the Available Models

But the previous models have limitations because those models may not forecast precisely when failures occur due to abrupt environmental incidents. Another problem is that the models can't predict accurately if the managers adopt creative accounting to achieve earnings and conceal the symptoms of distress. Moreover, financial information is produced based on time-lagged (Brabazon et al., 2002). A similar view is found in the study of Du Jardin et al. (2017). The study opines that due to earnings management, the prediction models with the financial variables as predictors will provide distorted results. That is why the level of distortion should be measured for financial information.

Charitou et al. (2004) opines that a good number of prediction models did not include the operating cash flow as a determinant. But the main reason for failure is the incapacity to pay back interest along with debt obligations, and that issue arises due to insufficient cash flows from operating activities.

Under the Multiple Discriminant Analysis (MDA) method, the assumptions of group dispersion and normality have some shortcomings. That is why there may be biases in the estimation of errors and tests of significance (Jones, 1987; Ohlson, 1980; Eisenbeis, 1977; Abdullah et al., 2008). Besides, there is an existence of classification errors in the Multi-

Discriminant Analysis (MDA) models. That is why the models should not be used as a sole means for prediction (Letza et al., 2003).

In the logit model (single period), econometrically two problems arise. Firstly, biasedness in the sample due to the selection of only one and non-random observation of the bankrupt company. Secondly, the model does not include the time-varying changes in reflecting the underlying bankruptcy risk. As a result, there will be a cross-sectional dependence of the data. Consequently, there will be inconsistent, inefficient, and biased coefficient estimates (Hillegeist et al., 2004; Shumway, 2001; Abdullah et al., 2008).

Appiah et al. (2015) summarize the limitations of various models from the perspective of three categories of the models, i.e., theoretical, statistical techniques, and Artificially Intelligent Expert Systems.

The limitations of the statistical techniques are i) Neglecting the multi-dimensional nature of the failure (example: Beaver's (1966) univariate model), ii) Demanding Assumptions of Multivariate normality, Linear separability, & equal and within-group covariance and others (example: Multiple Discriminant Analysis model of Altman (1968)), iii) Results in the model are considered difficult for the general people to explain (example: Meyer & Pifer's (1970) Linear Probability Model and Martin's (1977) Logit model), iv) Some assumptions: Cumulative normal distribution in error term, Dependent variable categorical, and others (example: Zmijewski's (1984) Probit model).

The limitations of the Artificially Intelligent Expert System models are i) Cumulative Sums (CUSUM) method has a 'tiny memory' in the instance of past good accomplishment (example: Kahya & Theodossiou's (1999) Cumulative Sums model), ii) Too narrow (example: Laitinen & Laitinen's (1998) Partial adjustment processes model), iii) Stakeholders concerned in the financial health of organizations not comprised in the main sample must add these (example: Neophytou & Molinero's (2004) Multi-Dimensional Scaling model), iv) Neural Networks methods are considered as 'black boxes' where decision-makers can be unwilling to depend on due to a absence of clarity (example: Khanna's (1990) Neural networks model), v) Assuming that related cases are suitable to predict the result of the new case (example: Kolodner's (1993) Case-Based Reasoning model), vi) The financial year closing date is not certainly a natural beginning point for the failure procedure (example: Lane, Looney & Wansley's (1986) Survival Analysis model), vii) Assuming that the whole space of probable events starts as a single type (example: Quinlan's (1979) Iterative dichotomizer-3 model).

The limitations of the theoretical models are i) Assuming that firms try to keep symmetry in the financial structure (example: Lev's (1973 Balance sheet decomposition measure model), ii) Assuming a net positive possibility that cash flows of a firm will be constantly negative over a run of times (example: Scot's (1981) Gambler's ruin theory), iii) Too simple (example: Aziz, Emanuel, & Lawson's (1988) Cash Management Theory).

Most of the models for predicting corporate failure contain only financial information. Zavgren (1985) opines that the econometric model using financial information only is not perfect in predicting corporate failure. Appiah et al. (2015) compile the limitations of using only financial information in the corporate failure prediction model. Those limitations are i) Small and medium firms will not be included in the sample because generally, those firms do not publish financial accounts or annual reports, ii) Financial information may not be always true and fair due to manipulation using items like consolidation of accounts, expenditure, revenue, inventory, depreciation, etc. iii) Due to extreme values or error and missing values in the ratios, the model will provide contaminated results, iv) All predictors of corporate failure do not exist in financial information. According to Argenti (1985), financial ratios show the symptoms of distress, but the reason for those symptoms can only be known from non-financial information. Beaver (1967b) opines that if all the variables (ratios) for predicting corporate failure are chosen based on the popular ratios of previous studies, then it becomes unreliable because ratios are sometimes prone to be affected by window dressing. The finding of Sharma (2001) shows that using the information of cash flow as a variable does not enhance the value to the accrual failure forecast methods.

There are various studies in which limitations exist in sample selection. Those limitations are i) sample period was chosen arbitrarily, ii) disregard of large size, iii) disregard of corporate failure's the time dimension (Appiah et al. 2015).

Since coefficients of the methods will differ based on the condition of the economy, no distress prediction methods are stable. That is why the latest financial data should be used in the prediction model (Neophytou et al., 2001).

Above all, a prediction model developed for one country is not certainly applicable to another country due to differences in economy, industry, time, accounting standards, socio-economic factors, legal structure, market structure, political structure (Ong et al., 2011).

In conclusion, it can be said that the reasons for corporate failure vary among different firms worldwide. Therefore, detecting the symptoms of failure will be diverse. Consequently, there is no unique method to detect corporate failure. Various methods, along with the application of diverse variables, may be employed to detect corporate failure. Thus, through continuous analysis, we can identify desired findings that can be utilized to predict accurately and, accordingly, take preventive measures.

2.8 Hypotheses

The following hypotheses are developed based on the literature previously stated.

H1: The Z-category and OTC companies are in financially unhealthy positions.

H2: Several factors have an impact on causing financial failures in Z category and OTC companies.

H3: Companies in the Z category and those operating over-the-counter (OTC) exhibit differentiated financial features.

H4: The attributes of financially unhealthy companies classified under the Z category and OTC differ considerably from those in a healthy financial standing.

CHAPTER THREE
THEORETICAL FRAMEWORK

3.1 Relevant Theories

The systematic literature review of Appiah et al. (2015) shows that most of the studies for predicting corporate failure are not based on a theory of economics in selecting the factors for predicting. Existing economic theories could be used such as managerial hegemony theory, legalistic theory, corporate governance theory, resources dependency theory, agency theory, etc to find the real cause of when and why firms fail.

3.1.1 Managerial Hegemony Theory

The managerial hegemony theory denotes the state where professional managers dominate in setting strategic decisions, and the organization's board of governing simply acts as a "rubber stamp". According to managerial hegemony theory, managers can exercise major influence over company strategy, resource allocation, and other key organizational decisions. In the perspective of corporate failure, Managerial Hegemony Theory indicates that the excessive absorption of power in the hands of top managers can contribute to poor decision-making and consequently lead to organizational failure (Cohen et al., 2008).

3.1.2 Legalist Theory

The legalist theory proposes that there should be a rigid legal system to recommend punishments and rewards for particular behaviors. Legalist approaches give emphasis to the importance of sticking to laws, regulations, and internal policies to preserve accountability and integrity within the institution (Brenkert, 2012).In the perspective to corporate failure, legalism can play a role in reducing risks and ensuring compliance. By establishing strong legal and regulatory frameworks, organizations can create a structure that helps avert unethical behavior, fraud, and other forms of delinquency that may lead to corporate failure. In the absence of a strong legal framework to alleviate risks and combat fraudulent activities, the company is vulnerable to probable failure (Rezaee, 2004).

3.1.3 Corporate Governance Theory

Corporate governance is the structure to direct and control a company effectively by setting strategic decisions, leadership, supervising management, and ensuring transparency and accountability through proper reporting. The purpose of corporate governance is to balance the welfare of the related stakeholders.

The purpose of corporate governance is to make sure that a company is controlled in the best interests of its shareholders while taking into account the interests of other stakeholders and complying with legal and regulatory requirements (Mo'taz Amin, 2013).Corporate governance plays a vital role in reducing the risk of corporate failure by promoting transparency, accountability, and effective decision-making within the organization. When corporate governance practices are weak or ineffective, it can increase the likelihood of corporate failure (Fung, 2014).

3.1.4 Resource Dependency Theory

Resource dependency theory indicates that the performance of a company is impacted by strategy, which is further impacted by its control of assets (Wei, 2006). The resource dependence theory views the board as a supplier of resources for the companies. If the board has enough links to the external environment, there is a great scope to access various resources for the company. Resource collection depends on board size, frequency of board meetings, and board attendance (Bhatt & Bhattacharya, 2015).

3.1.5 Agency Theory

Agency theory describes the complications that appear in the companies due to the separation of managers and owners and stresses to decrease this problem. This theory facilitates in employing of various governance approaches to regulate the action of agents in the jointly held companies. In the perspective of corporate failure, agency theory helps us recognize how the misalignment of interests between agents and principals can contribute to the corporate failure (Panda & Leepsa, 2017).

3.2 Models of predicting corporate failure

Most of the models of predicting corporate failure can be categorized broadly into three categories (Appiah et al., 2015; Adnan Aziz & Dar, 2006). They are Theoretical Models, Statistical Models, and Artificially Intelligent Expert System Models. Gyarteng (2019) states that most of the models for predicting corporate failures adopt two approaches: Univariate Analysis and Multiple Discriminant Analysis.

3.2.1 Univariate Analysis

An ideal limit point is projected for each ratio in univariate analysis. Then the firm's value for each ratio and the related ideal cutoff point of that ratio is compared to predict failure (Balcaen&Ooghe, 2006). Characteristics of this analysis are:

- Deals with one variable
- Doesn't concern to show relationships
- Methods to define patterns are mean, median, mode, range, variance, minimum, maximum, quartiles, and standard deviation
- Approaches to express the data are bar charts, pie charts, histograms, frequency distribution tables, frequency polygons, etc.
- Example: Univariate Model by Beaver (1966) to predict bankruptcy based on cash flow to debt ratio.

3.2.2 Multiple Discriminant Analysis

- Deals with multiple variables
- Suitablewhile the Dependent Variable is categorical and Independent Variables are metric
- Good for predicting group membership (E.g., Failed firm vs. Non-failed firms)
- Determine the probability of categorical group membership based on independent variables that are similar to logistic regression.
- Example:
  - i. Multivariate Discriminant Analysis by Altman (1968) to predict bankruptcy before two years of actual bankruptcy. It used 66 companies (33 non-failed and 33 failed)
  - ii. Logistic Regression by Ohlson (1980) using nine variables in the model.
  - iii. Probit Regression by Zmijewski (1984) using three independent variables in the model, etc.

Nonparametric models for corporate failure prediction are genetic algorithms, hybrid models, fuzzy models, hazard models, artificial neural networks, etc.

Models for predicting corporate failure can also be classified as a qualitative model based on internal information and a quantitative model based on financial data (Adriatico, 2019).

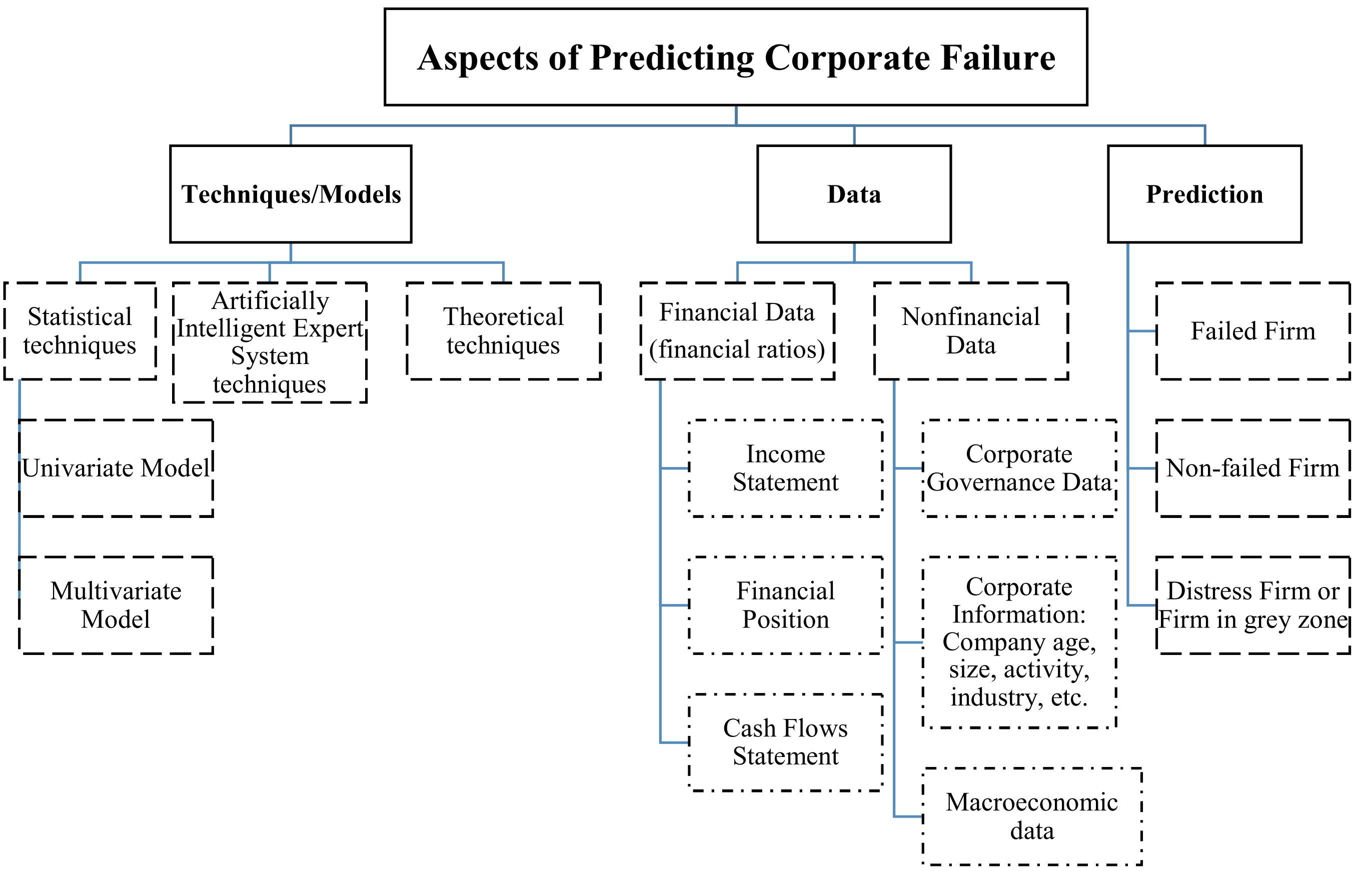


Figure 3.1: Aspects of Predicting Corporate Failure (Researcher's compilation)

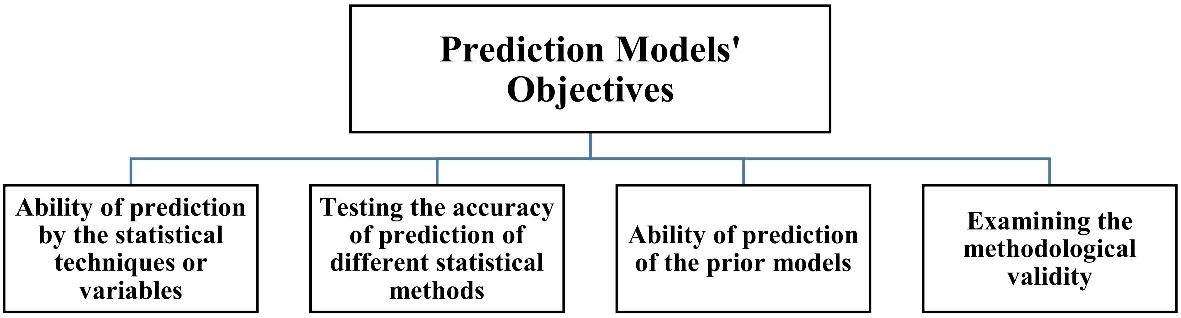


Figure 3.2: Prediction Models' Objectives (Appiah et al., 2015)

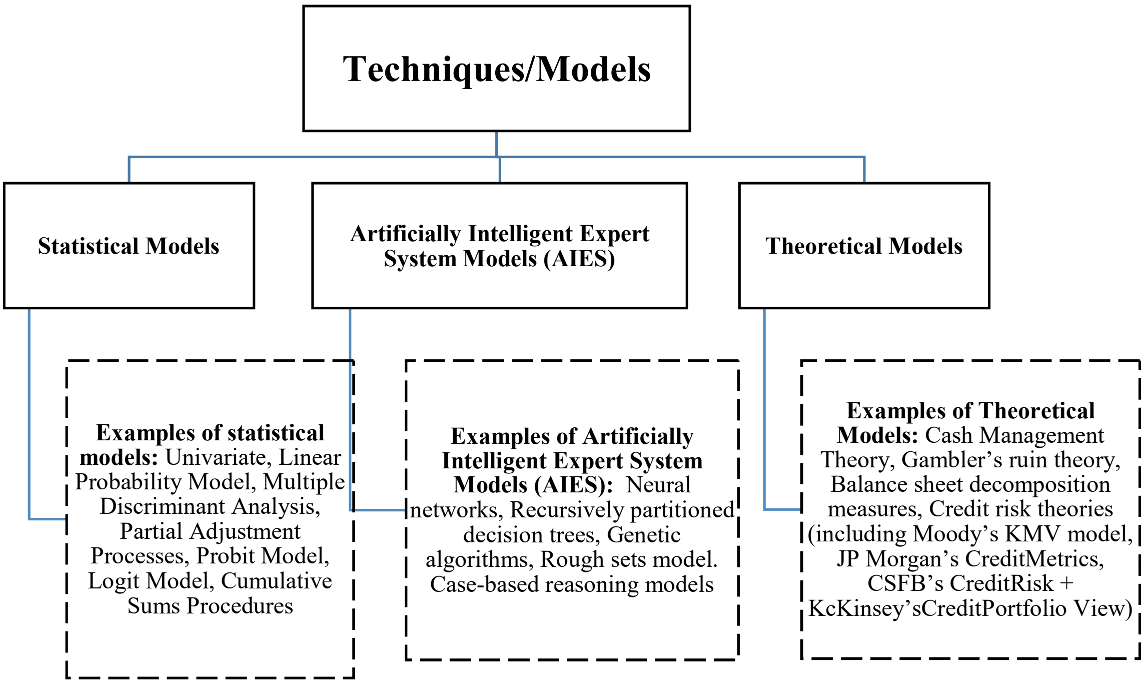


Figure 3.3: Models for Corporate failure prediction (Adnan Aziz & Dar, 2006)

3.3 Logistic Model

For predictive analysis, logistic regression is utilized when there is dichotomous dependent variable (e.g., Yes or No; Presence or Absent; Success or Failure, etc.) Under the model of logistic regression, the dependent variable has a binomial outcome i.e., 0, 1. Generally the dependent variable consists of discrete variable and independent variable can be continuous or discrete. If 1 denotes failed firm and 0 denotes survived firm and if the outcome point is equal to or greater than 0.5, then it will predict failure of the firm (Haider et al., 2018).

The logistic model produces a score after assessing the financial ratios for a firm to classify as failed or non-failed.

The logistic function under the logistic model (Charitou et al., 2004) is as follows:

$P_{jt}(Y=1) = 1/(1 + e^{-z})$

$=1/\{1 + \exp[-(\beta_0 + \beta_1 X_{1,jt} + \beta_2 X_{2,jt} + \ldots + \beta_n X_{n,jt})]\}$

Where,

$P_{jt}(Y=1)$= Failure probability of firm j at the year of t;
exp= exponential function
$\beta_1, \beta_2, \ldots, \beta_n$ = slope coefficients
$X_1, X_2, \ldots, X_n$=independent variable

If the probability is 0.50, then it is a critical value to categorize the companies between non-failed or failed. It indicates that there is an equal possibility of group affiliation.

3.4 Artificial Neural Network

The study of Odom and Sharda (1990) is the first effort in using the Artificial Neural Network (ANN) for predicting corporate failure. It works based on biological neural networks. It can be used as data mining methods to categorize failed and non-failed firms. ANN has the ability to learn as well as generalize from experience and data (Salehi et al., 2016).

Neural Network is a computer approach that acts like a brain. In solving particular problems or determining specific forms in the data, the neural network can be trained. There are 3 layers in the neural network: input layer, concealed layer, & output layer. Hidden layers include the hidden neurons, and output layers include the single neuron (Neophytou et al., 2001).

Artificial Neural Network (ANN) can provide more accurate prediction compared to traditional models, but there are no fixed guidelines in ANN in the case of parameter values or structure. That is why choosing the appropriate topology of ANN is a challenging task. Before determining a standard model, various ANN topologies need to be constructed with diverse parameters and structures. This experimental process is tiresome, but this provides a good prediction model. Nevertheless, a perpetual solution does not exist. But ANN performs very well compared to the traditional methods in predicting corporate failure (Nasir et al., 2000).

In the ordinary Artificial Neural Network model, there is a multilayer perception, and the process is known as back propagation. But the ordinary ANN has a problem in dealing with the vast amount of predictors. That is why a hybrid (combining statistical methods with ANNs) model can perform better than the ordinary ANN models. In the hybrid model, the risk of over fitting is reduced by preselecting the variables. It also lessens the time taken to choose the model (Yim& Mitchell, 2005).

3.5 Multiple Discriminant Analysis by Altman

The widely used multivariate model is Altman's (1968) Multiple Discriminant Analysis. In the Altman (1968) model, 33 failed firms and 33 non-failed firms (chosen based on a stratified random considering industry and size) were included initially for the study of the Z-Score. Data for both bankrupt & non-bankrupt firms have been collected from the same year. Among the twenty-two variables (ratios), five variables have been selected due to the best performance in predicting corporate failure (Altman, 1968).

The discriminant function of Altman's Z-Score (1968) was as follows:

$$Z = 0.012X1 + 0.014X2 + 0.033X3 + 0.006X4 + 0.999X5$$

Where, Z = Overall Index

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

X2 = Retained Earnings/Total assets

X3 = Earnings before interest and taxes/Total assets

X4= Market value equity/Book value of total debt

X5 = Sales/Total assets

A company will fall into the "non-bankrupt" sector if the Z score is higher than 2.99. If the Z score of a firm is below 1.81, then it will be considered as "bankrupt". If the score falls between1.81-2.99, then it is the "gray area" or "zone of ignorance" which indicates the uncertainty of predicting. The prediction model does accurate prediction up to two years before the real failure (Altman, 1968).

Absolute percentage values should be taken for the variables X1 to X4, i.e., if the calculated value is 10%, then it should be included as 10, not as 0.10. The value for the variable X5 should be in the form of the number of times, i.e., if S/Ta is 200%, then it should be written as 2. But over the years, the model is now in the following form:

$$Z = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 1.0X5$$

In the case of the above formula, we should use percentage form (i.e., write 0.10 instead of 10%) for the variables of X1 to X4. For variable X5, we need to use the form of "number of times" (Altman, 2000).

Z-Score model predicts corporate failure correctly up to 2 years before distress. When the lead time increases, the prediction accuracy reduces significantly. But the recent ZETA® model has shown greater accuracy for prediction over an extended period (up to 5 years before failure) of time (Altman, 2000).

If data is taken from a private firm, then it is necessary to substitute the book values of equity for the Market Value for the variable X4, and the model would be as follows:

$$Z' = 0.717(X1) + 0.847(X2) + 3.107(X3) + 0.420(X4) + 0.998(X5)$$

In the above model, Z-score below 1.21 indicates a insolvent firm, Z-score above 2.90 indicates a non-failed firm, and Z-Score between 1.23 to 2.90 implies a grey area (Altman, 2000).

If we take data from a non-manufacturing firm, then the variable X5 (Sales/Total Assets) needs to be omitted. Then the revised Z"-Score model (Altman, 1993) would be as follows:

Z" = 6.56 (X1)+ 3.26 (X2) + 6.72 (X3) + 1.05 (X4)

Where,

Z = Overall Score

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

X2= Retained Earnings/Total Assets

X3= Earnings Before Interest and Taxes /Total Assets

X4= Book Value of Equity/Total Liabilities.

For the above mentioned formula, if the Z"-Scores is lower than 1.10, then it indicates a failed firm. If the Z"-Score is higher than 2.60, then it indicates a non-failed firm. The Z"-Score of 1.10 to 2.60 implies a grey zone (Altman, 1993; Abdulkareem, 2015).

In conclusion, it can be said that while there are theories associated to corporate failure, most studies predicting corporate failure do not rely on an economic theory when selecting factors for prediction. Nevertheless, existing theories can be employed to identify the actual causes of when and why firms fail. Nowadays, the use of artificial neural network models is increasing, but statistical methods continue to be widely utilized.

CHAPTER FOUR
METHODOLOGY

4.1 Research Approach

The author contacted the particular stakeholders of Bangladesh Securities and Exchange Commission (BSEC) and Dhaka Stock Exchanges (DSE) for the data of failed or liquidated companies. But the concerned officers of both the offices do not maintain any data related to those companies. Both the authorities keep only data of active companies whose shares are trading on the market i.e., the stock exchange of Bangladesh. Later the author asked for the data of Over-The-Counter (OTC) companies because the annual reports are not available on the website of the OTC companies. Finally, the author decided to continue this study using the data of OTC companies because no study was done on the companies in the Over-the-Counter (OTC) trading platform. This study will also include the data of Z-category companies. Although there was a previous study (Chowdhury & Barua, 2009) on Z-category companies, this study will consider the recent data for those companies.

Although the firms are declared as Z category by the regulator, there is no effect on the trading because there is no reflection in the stock prices. Rather there is an increasing trend in the price of some securities (Barman, 2020) that are detrimental for some of the general shareholders when there will be a price correction. According to Mahmud (2019), the share of junk companies in the OTC or the share of Z category companies has shown abnormal rising in price even though there is no price sensitive information or earning growth. As a result, the capital market can fall into instability situations. That means declaring a firm as the Z category or OTC is not the solution. In some cases, stockholders lose their full investment as a whole that is harmful to the general investors as well as undesirable to the regulators. In some cases, the regulator could not trace companies in the OTC market. (Habib, 2018).

In considering the above-mentioned perspective regarding the companies of the Z category & OTC market, the regulator can use models of prediction to forecast the financial health of the companies under both category companies and take alternative measures to protect the interest of various stakeholders, especially the general investors.

Descriptive statistics are calculated to know the financial features of the Z category and OTC companies. After that Altman's (1968) model in calculating the Z score has been applied to find out whether there is any failed, grey, and non-failed position in the Z category and OTC companies. Then One Way ANOVA and Independent Samples T-Test have been applied to identify whether the mean values of the predictors of financial position are considerably different between or among failed, grey, and non-failed status. Finally, Binary Logistic Regression has been applied to find out the predictors or factors that impact in causing the financial failures of the Z category and OTC companies.

4.2 Population of the Study

Companies in Z-categories and OTC firms listed in the Dhaka Stock Exchange are the population of the study.

A total of 46 firms were found in the Z-Category company list of Dhaka Stock Exchange in November 2017, and the author collected a hardcopy of 13 OTC companies provided by the concerned officer of DSE.

4.3 Sample of the Study

Out of 46 Z-category companies, 35 companies' data were collected based on the obtainability of annual reports on the websites of those companies. Data from 2007-2019 were collected based on availability. Data of 13 companies of the OTC market were collected based on available hardcopy from Dhaka Stock Exchange.

A total of 217 firm years' data 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). The details of the available annual report are as follows:

Table 4.1: List of the Z category Companies used in this study as sample

Z-Category Company	Years	No. of Years
AB Bank	2010-2018	9
AlhajTex	2012-2018	7
AllTex Industries	2017-2019	3
AppllolIspat	2013-2018	5
Aramit Cement	2017-2019	3
BD Services	2018-2019	2
BD Thai	2009-2019	10*
BD Welding Electronics	2016-2017	2
Beach Hatchery Ltd	2011-2017	6*
Beximco Synthetics Limited	2014-2019	6
Bangladesh Industrial Finance Co	2015-2018	4
Dacca Dyeing & Manu. Co	2013-2014	2
Delta Spinners Limited	2016-2017	2
Dulamia Cotton Spinning Mills	2013-2019	7
Emerald Oil Industries Ltd	2013-2016	4
Family Tax BD Ltd	2016-2019	4
Fareast Finance & Investment Ltd	2015-2016	2
First Finance Limited	2011-2017	7
Golden Son Limited	2013-2019	6*
ICB Islamic Bank	2008-2018	11
Imam Button Industries	2013-2019	7

Intech Limited	2017-2019	3
Key Cosmetics Ltd	2016-2018	3
Khan Brothers PPW Bag	2013-2019	6*
Libra Infusions Ltd	2011-2017	7
Meghna Condensed Milk	2018-2019	2
Meghna Pet Industries	2018-2019	2
PLFS	2011-2017	7
PFIL	2009-2018	10
RN Spinning Mills	2008-2019	12
Salvo Chemical Industries	2012-2019	7*
Shinepukur Ceramics Ltd	2007-2019	13
United Air	2012-2015	4
Usmania Glass Sheet Factory	2018-2019	2
ZahinTex Industries	2015-2019	5
Total 35 Z-category companies		Total 191 Firm Years

* Data for the year 2014 or 2015 was not found due to a change in the financial year by the regulator. Instead of that year, the companies prepared annual reports for 18 months.

Table 4.2: List of the OTC Companies used in this study as sample

OTC Company	Years	No. of Years
Monospool	2018-2019	2
GachihataAgri	2018-2019	2
Rangamati Food	2018-2019	2
Yusuf Flour	2018-2019	2
MAQ paper	2018-2019	2
MAQ Enterprise	2018-2019	2
Padma Printers	2018-2019	2
Tamijuddin Textiles	2018-2019	2
Monno Fabrics	2018-2019	2
Jessore Cement	2018-2019	2
Al-Amin Chemical	2018-2019	2
Paper Processing and packaging	2018-2019	2
TheEngineersLtd	2018-2019	2
Total 13 OTC companies		Total 26 Firm Years

4.4 Data Collection

4.4.1 Data Sources

The data of Z categories companies were collected from the annual reports available on the website of particular firms. The data of the OTC companies were collected from the Dhaka Stock Exchange in the form of a Hard Copy of Annual Reports.

4.4.2 Time Period of the Study

The author took a snapshot of the company name in the Z categories in November 2017 and found 46 companies in the Z category on the website of Dhaka Stock Exchange. The data of insurance companies have been excluded because the nature of financial information is different compared to other companies. The annual reports of 35 Z-category companies have been found available on the respective website of those companies. The rest of the companies in the Z category did not maintain any annual reports on their website or there is no website. Data from 2008-2019 were collected based on the obtainability of annual reports on the websites of those companies.

4.4.3 Data Processing

Considering the Altman variables for the Altman Z score, data were collected from the Income Statement and Financial Position of the annual reports on the following issues: Current assets, Total assets, Current liabilities, Earnings before Interest and Taxes, Retained Earnings, Book Value Equity (Market Value of Equity were not found based on firms years), Book value of total debt or Liability, and Sales. Initially, data were input into MS Excel Sheet. After that data was exported to the Statistical Package for the Social Sciences (SPSS) for calculating the required variables for Altman Model as well as for other analysis purposes.

4.5 Dependent and Independent Variables

The analysis was done in two stages. In the first stage, Altman Z score was calculated where the dependent variable is Z Score and the independent variables are Earnings before Interest and Taxes/Total Assets, Net Working Capital /Total Assets, Book Value Equity/Book Value of Total Debt or Liability, Retained Earnings/Total Assets, and Sales/Total assets. 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 dependent variable is dichotomous (Failed and Non-Failed) and independent variables are the same as mentioned in the first stage.

4.6 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=Earnings before interest and taxes/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" sector if the Z score is above 2.99. If the Z score of a firm is below 1.81, then it will be considered as "bankrupt". If the score falls between 1.81-2.99, then it is the "gray area" or "zone of ignorance" 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/Total Assets

X3=EBIT/Total Assets

X4 =Book Value of Equity/Total Liabilities

For the above mentioned formula, if the Z"-Scores is lower than 1.10, then it indicates a failed firm. 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 zone.

4.7 Forward 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 OTC companies) but the independent variables and financial information of Z category bank and non-bank financial institutions are not same with the other two categories. That is why logistic regression has been applied excluding the firm years of Z category bank and non-bank financial institutions. Thus, the firm-years for the Forward Logistic Regression is 168.

Table 4.3: Variables and Method used for Forward 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/Total assets	
	X3=Earnings before interest and taxes/Total assets	
	X4 Book value equity/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 next model, the system adds the independent variable that has more impact on the dependent variable. This way it goes on step after step. 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	168 cases (firm years)	

CHAPTER FIVE
ANALYSIS & FINDINGS

5.1 Introduction

The analysis section will focus to scrutinize the data in order to derive findings that are linked to the research questions of this study. Altman's (1968) Z-score model has been employed to achieve the first objective of determining if there are any financially unhealthy firms in the Z category and OTC companies. Binary Logistic Regression has been employed to fulfill the second objective of this study by identifying the predictors that impact the occurrence of financial failures in Z category and OTC companies. Descriptive statistics are computed to fulfill the third objective of the study, aiming to understand the financial characteristics of Z category and OTC companies. Independent Samples T-Test and One-Way ANOVA have been applied to determine whether the characteristics of financially unhealthy companies in the Z category and OTC significantly differ from those in a financially healthy position. These statistical tests will identify whether the mean values of the predictors of financial position are significantly different among failed, grey, and non-failed statuses.

5.2 Multicollinearity Test

Multicollinearity is a state when the independent variables are very correlated with each other. A multicollinearity test is done to check whether there is any unnecessary independent variable in the model that may provide unstable regression coefficient estimates. The outcome of the multicollinearity test for the independent variables applied in this study is shown below:

Table 5.1: Correlations Coefficient between Independent Variables

		X1	X2	X3	X4	X5
X1	Pearson Correlation	1	.691**	.593**	.359**	-.331**
	Sig. (2-tailed)		.000	.000	.000	.000
X2	Pearson Correlation	.691**	1	.512**	.283**	-.354**
	Sig. (2-tailed)	.000		.000	.000	.000
X3	Pearson Correlation	.593**	.512**	1	.194*	.027
	Sig. (2-tailed)	.000	.000		.012	.732
X4	Pearson Correlation	.359**	.283**	.194*	1	-.043
	Sig. (2-tailed)	.000	.000	.012		.576
X5	Pearson Correlation	-.331**	-.354**	.027	-.043	1

	Sig. (2-tailed)	.000	.000	.732	.576	
**. Correlation is significant at the 0.01 level (2-tailed).						
*. Correlation is significant at the 0.05 level (2-tailed).						

Here, N=168

Multicollinearity is a problem when the correlation coefficient is 0.80 or above between any two independent variables (Gujarati, 2010). The above table shows that there is no multicollinearity issue between the independent variables.

5.3 Descriptive Statistics

Table 5.2: Descriptive Statistics of the Z Category (Manufacturing and Service Providing) Companies based on Gross Financial Data

Elements	N*	Minimum	Maximum	Mean	Std. Deviation
Current Assets	142	14160155	26734676230	1991956634	3617865302
Current Liabilities	142	7711470	9142107520	1097897191	1363112711
Total Assets	142	80246191	31949984097	4144180941	4830604653
Retained Earnings	142	**-4052046972**	3210883312	240264015	827979603
Earnings Before Interest and Taxes	142	**-322205002**	2675804821	210905911	438905038
Book Value of Equity	142	**-830054700**	14045442370	2305937726	2608484883
Total Liabilities	142	7711470	17904541727	1838243215	2663007948
Sales	142	0	10576038751	1356771879	1887520422

Here, N=Number of Firm Years; Source: Author's Calculation

The descriptive statistics of the Z category (manufacturing and service providing) companies based on gross financial data shows that the minimum balance of Retained Earnings, Earnings before Interest and Taxes, and Book Value of Equity are in a negative position.

Table 5.3: Descriptive Statistics of the Z Category (Manufacturing and Service Providing) Companies based on Ratios

Ratios	N	Minimum	Maximum	Mean	Std. Deviation
(Current assets - Current liabilities) /Total assets	142	-2.29	.63	.0901	.48095
Retained Earnings/Total assets	142	-2.70	.43	**-.1303**	.61229
Earnings before interest and taxes/Total assets	142	-.20	.22	.0314	.07006
Book value equity/Book value of total debt or Liability	142	-.67	37.27	3.0269	5.40182
Sales/Total assets	142	.00	1.65	.4020	.34180

Here, N=Number of Firm Years; Source: Author's Calculation

The descriptive statistics of the Z category (manufacturing and service providing) companies based on ratios shows that the mean value of the Retained Earnings to Total assets ratio is in negative figure (-0.1303).

Table 5.4: Descriptive Statistics of the Z Category (Bank and Non-Bank Financial Institution) Companies based on Gross Financial Data					
Elements	N	Minimum	Maximum	Mean	Std. Deviation
Current Assets	49	467302728	220533818418	31747649555.67	65069661075.205
Current Liabilities	49	1387140742	218769451479	37653500059.22	62822501784.748
Total Assets	49	3278064756	322525971619	56301045262.82	93300443369.198
Retained Earnings	49	**-18230405451**	6830946921	**-2576934207.12**	7570977786.510
Earnings Before Interest and Taxes	49	**-829379836**	6078778140	856884981.29	1413705062.185
Book Value of Equity	49	**-10950620568**	23114460182	3097823579.92	9247215258.413
Total Liabilities	49	2403497385	299875489746	54067643096.51	85349279130.303

Here, N=Number of Firm Years; Source: Author's Calculation

The descriptive statistics of the Z category (Bank and Non-Bank Financial Institution) companies based on gross financial data shows that the minimum balance of Retained Earnings, Book Value of Equity, & Earnings before Interest and Taxes are in a negative position. The mean value of Retained Earnings is also a negative figure.

Table 5.5: Descriptive Statistics of the Z Category (Bank and Non-Bank Financial Institution) Companies on the Ratios					
	N	Minimum	Maximum	Mean	Std. Deviation
(Current assets - Current liabilities)/Total Assets	49	-1.496	.030	**-.39263**	.339858
Retained Earnings/Total Assets	49	-1.595	.133	**-.26458**	.509194
EBIT/Total Assets	49	-.077	.175	.02096	.039444
Book Value of Equity/Total Liabilities.	49	-.489	.468	.06176	.282997

Here, N=Number of Firm Years; Source: Author's Calculation

The descriptive statistics of the Z category (Bank and Non-Bank Financial Institution) companies based on ratios shows that the net working capital ratio & retained earnings to total assets ratio are in a negative figure.

Table 5.6.: Descriptive Statistics of the OTC Companies on the Gross Financial Data					
	N	Minimum	Maximum	Mean	Std. Deviation
Current Assets	26	7183467	2412997003	403980103.77	631635848.316
Current Liabilities	26	14957885	2368024229	489981417.88	639927902.175
Total Assets	26	10573272	6918831550	1564720984.19	2393123891.081
Retained Earnings	26	**-2471848722**	312260707	**-266505917.81**	721088626.854
Earnings Before Interest and Taxes	26	**-16447787**	188778110	28179350.19	52361738.024
Book Value of Equity	26	**-951272886**	4539172087	612387280.92	1334318563.781
Total Liabilities	26	14957885	3853632212	953433378.92	1312328842.221
Sales	26	0	2413583451	374505158.35	641284746.944

Here, N=Number of Firm Years; Source: Author's Calculation

The descriptive Statistics of the OTC companies based on gross financial data shows that the minimum balance of Retained Earnings, Book Value of Equity, &Earnings Before Interest and Taxes are in a negative position. The mean value of Retained Earnings is also a negative figure. The findings are similar to the Z category (Bank and Non-Bank Financial Institution) companies.

Table 5.7: Descriptive Statistics of the OTC Companies on the Ratios

	N	Minimum	Maximum	Mean	Std. Deviation
(Current assets - Current liabilities) /Total assets	26	-.88	.32	**-.2467**	.41106
Retained Earnings/Total assets	26	-2.58	.19	**-.6791**	.92917
Earnings before interest and taxes/Total assets	26	-.09	.17	.0192	.06688
Book value equity/Book value of total debt or Liability	26	-.37	2.15	.2387	.58900
Sales/Total assets	26	.00	1.41	.4017	.35244

Here, N=Number of Firm Years; Source: Author's Calculation

The descriptive statistics of the OTC companies based on ratios shows that the net working capital ratio & retained earnings to total assets ratio are in a negative figure. The findings are similar to the Z category (Bank and Non-Bank Financial Institution) companies.

5.4 Summary of Failed, Grey, and Non-failed Firm Years

After applying the model of the Altman Z score on the Z category and OCT companies, the following summary table has been prepared. The detailed findings have been shown in Appendix A, B, and C.

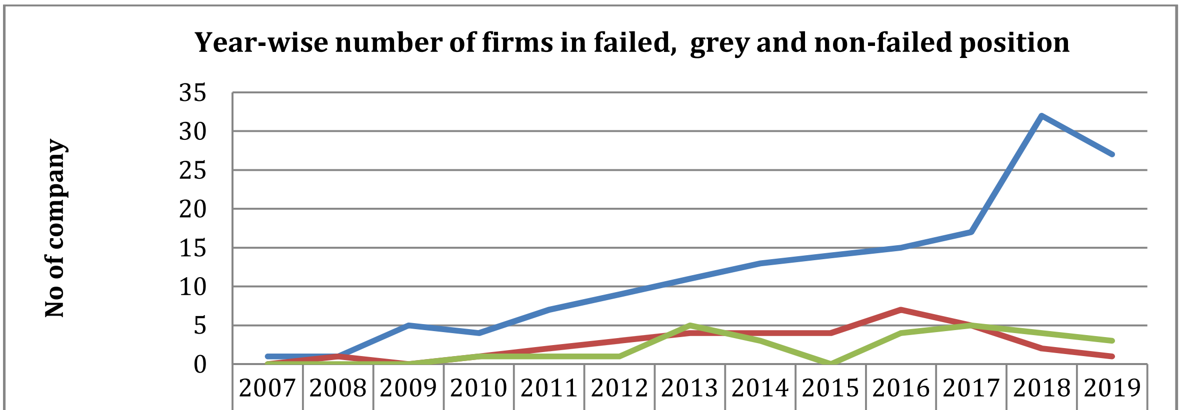
Table 5.8: Summary of Failed, Grey, and Non-failed Firm Years of Z Category and OTC Companies

Category according to DSE	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 Z Score

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 finds that overall percentage of failure is 72% in the Z category companies. This finding is alike to the findings of the study by Chowdhury & Barua (2009), where 77% companies are in failed position. In specific scenario, 98% Bank and Non-Bank Financial Institutions in Z category are in failed position. This finding is alike to other finding of the study of Hamid et al. (2016), where 93% companies are in failed position.



	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Failed	1	1	5	4	7	9	11	13	14	15	17	32	27
Grey	0	1	0	1	2	3	4	4	4	7	5	2	1
Nonfailed	0	0	0	1	1	1	5	3	0	4	5	4	3

Figure 5.1: Trend of Distressed Firms over the years

According to Figure 5.1, there is a apparent trend of a progressive rise in the number of failed firms. However, it is important to note that this study does not incorporate balanced panel data, rendering this figure insufficient to accurately portray the genuine scenario.

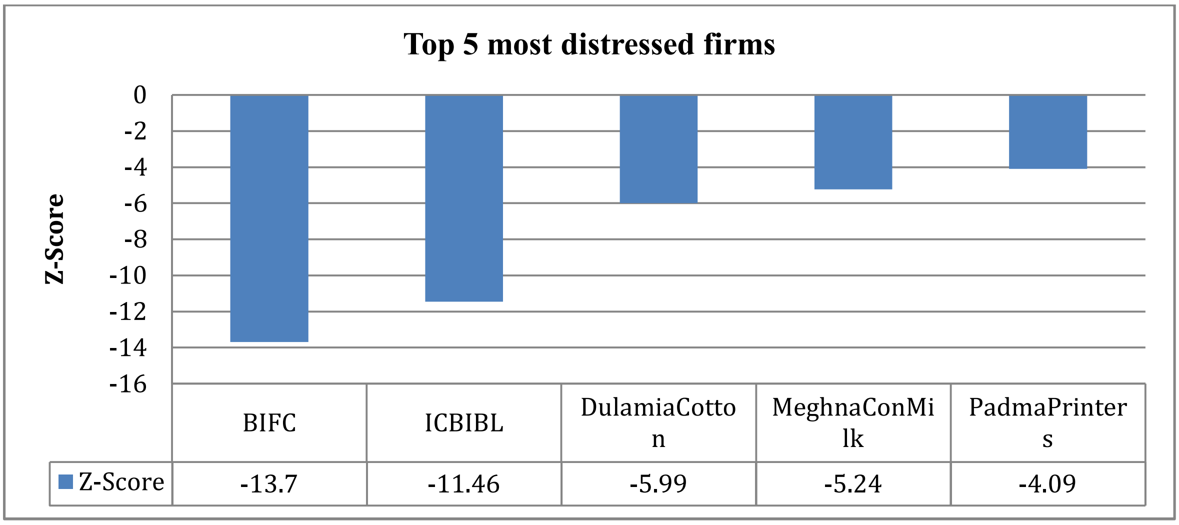


Figure 5.2: Top 5 Most Distressed Firms over the years

Figure 5.2 indicates that the top five most distressed firms are Bangladesh Industrial Finance Company Limited (BIFC), ICB Islamic Bank Limited (ICBIBL), Dulamia Cotton Spinning Mills Limited (Dulamia Cotton), Meghna Condensed Milk Industries Ltd. (Meghna Condensed Milk), and Padma Printers & Colour Ltd (Padma Printers). These findings are based on the Z Score, and the number of firms in the sample is 48.

5.5 One Way ANOVA Analysis

One-way analysis of variance (ANOVA) is applied to discover whether there are any significant variances statistically between the means of more than two sets of the experimental variables. Three (Failed, Non-Failed, and Grey) categories were found after applying Altman Z-Score in Z category Manufacturing and Servicing Companies. The result of the One-way analysis of variance is as follows:

Table 5.9: One Way ANOVA analysis based on Financial Status of Z category Manufacturing and Servicing Companies

Variable	Financial Status	N	Mean	F-Value	P-Value
X1=(Current assets - Current liabilities) /Total assets	Failed	84	**-.0773**	16.014	**.000****
	Non-Failed	27	**.4152**		
	Grey	31	**.2605**		
	Total	142	.0901		
X2=Retained Earnings/Total assets	Failed	84	**-.3204**	11.554	**.000****
	Non-Failed	27	**.1915**		
	Grey	31	**.1043**		
	Total	142	-.1303		
X3=Earnings before interest and taxes/Total assets	Failed	84	**.0008**	26.938	**.000****
	Non-Failed	27	**.0725**		
	Grey	31	**.0786**		
	Total	142	.0314		

X4=Book value equity/Book value of total debt or Liability	Failed	84	**.9879**	74.409	**.000****
	Non-Failed	27	**10.9985**		
	Grey	31	**1.6087**		
	Total	142	3.0269		
X5=Sales/Total assets	Failed	84	.3492	2.704	.070
	Non-Failed	27	.4492		
	Grey	31	.5040		
	Total	142	.4020		

Note: * variable is significant at the 0.05 level;** variable is at the 0.01 level (2 tailed).

The above table on the one-way analysis of variance (ANOVA) shows that the mean value of X1 of the Failed, Non-Failed, and Grey firm years are -0.0773, 0.4152, and 0.2605 respectively, and the finding is statistically significant ($\alpha = 0.000$). Thus it can be deduced that the mean value of the net working capital ratio of a failed firm tends to be negative.

The mean value of X2 of the Failed, Non-Failed, and Grey firm years are -0.3204, 0.1915, and 0.1043 respectively, and the finding is statistically significant ($\alpha = 0.000$). Thus it can be deduced that the mean value of the Retained Earnings/Total assets ratio of a failed firm tends to be negative. Negative retained earnings indicate that the company is facing recurring losses. When the profitability of a company continuously declines, negative retained earnings emerge. To increase profitability, the management should take the prudent decision in allocating the available resources. Utilization of resources is the key issue to increase profitability (Dillon, 2003).

The mean value of X3 of the Failed, Non-Failed, and Grey firm years are 0.0008, 0.0725, and 0.0786 respectively, and the finding is statistically significant ($\alpha = 0.000$). Thus it can be deduced that the mean value of the Earnings before interest and taxes to Total Assets ratio of a failed firm tends to be very low compared to non-failed firms.

The mean value of X4 of the Failed, Non-Failed, and Grey firm years are 0.9879, 10.9985, and 1.6087 respectively, and the finding is statistically significant ($\alpha = 0.000$). Thus it can be deduced that the mean value of the Book value equity to Book value of total debt or Liability ratio of a failed firm tends to be very low compared to a non-failed firm.

On the other hand, there are no substantial differences in the mean value of X5 (Sales/Total assets) for the failed, non-failed, and grey firms because the finding is not statistically significant ($\alpha = 0.070$).

5.6 Independent Sample T-Test

After applying the Altman Z score on the OTC companies, two groups (failed and grey) were found and no non-failed firm years were found. In comparing the means of two groups, Independent Samples T-Test is applied. To compare whether there are any significant differences between the failed and grey firm years regarding the independent variables, Independent Samples T-Test is done. The following table is the Independent Sample T-Test between Failed and Grey Firm Years of OTC companies.

Table 5.10: **Independent Sample T-Test** based on Failure Status of OTC Companies					
	Status (Group)	N	Mean	t-value	p-value
(Current assets - Current liabilities) /Total assets	Failed	24	-.2838	-1.646	.113
	Grey	2	.1980		
Retained Earnings/Total assets	Failed	24	-.7491	-1.353	.189
	Grey	2	.1609		
EBIT/Total assets	**Failed**	24	**.0081**	-3.548	**.002**
	Grey	2	**.1524**		
Book value equity/Book value of total debt or TL	Failed	24	.2142	-.728	.474
	Grey	2	.5327		
Sales/Total assets	Failed	24	.3893	-.618	.543
	Grey	2	.5515		

According to the above table, only one ratio i.e., EBIT/Total assets has significant (p-value: 0.002) differences in the comparison of "failed" and "grey" firms. It should be mentioned that no firm-year is found as "non-failed" in the OTC companies.

After applying the Altman Z score on the Z category Bank and NBFI companies, two groups (failed and grey) were found and no non-failed firm years were found. In comparing the means of two groups, Independent Samples T-Test is applied. The following table is the Independent Sample T-Test between Failed and Grey Firm Years of Z category Bank and NBFI companies.

Table 5.11: **Independent Sample T-Test** based on Failure Status of Z category Bank and NBFI Companies					
	Status (Group)	N	Mean	t-value	p-value
(Current assets - Current liabilities)/Total Assets	Failed	48	-.39939	-.963	.340
	Grey	1	-.06833		
Retained Earnings/Total Assets	Failed	48	-.27286	-.785	.436
	Grey	1	.13288		
EBIT/Total Assets	**Failed**	48	**.01774**	-4.771	**.000**
	Grey	1	**.17545**		
Book Value of Equity/Total Liabilities.	Failed	48	.05405	-1.332	.189
	Grey	1	.43174		

According to the above table, only one ratio i.e., EBIT/Total assets has significant (p-value: 0.000) differences in the comparison of "failed" and "grey" firms. It should be mentioned that no firm-year is found as "non-failed" in the Z category Bank and NBFI companies.

5.7 Forward Logistic Regression

There were three outcomes from the Altman Z Score i.e., failed, non-failed, and grey. The author turned the outcomes into two categories that are: failed and non-failed. The non-failed category includes 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.

Table 5.12: Encoding of Dependent Variable	
Original Value	Internal Value
Non-Failed (all grey and non-failed firm year are shown as non-failed)	**0**
Failed	**1**

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 OTC companies) but the independent variables and financial information of Z category bank and non-bank financial institutions are not same with the other two categories. That is why logistic regression has been applied excluding the firm years of Z category bank and non-bank financial institutions. Thus, the firm-years for the logistic regression is 168.

Table 5.13: Overall Classification[a,b] in Logistic Regression					
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. The cut value is .500					

From the above table on the overall classification, there is an indication that the overall correct prediction is 64.3% because the overall classification regarding the non-failed firms is not accurate resulting from the logistic regression.

In this study, the Forward Logistic Regression method is applied. Under the Forward Logistic Regression, the system will create different models. The first model will not have any independent variable. In the next model, the system adds the independent variable which has more impact on the dependent variable. This way it goes on step after step. This method of adding an independent variable in the model step by step in each model is called Forward Logistic Regression.

Table 5.14: Model Summary of Logistic Regression

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. Estimation ended at iteration number 6 because parameter estimates changed by less than .001.

b. Estimation finished at iteration number 7 because parameter estimates changed by less than .001.

c. Estimation finished at iteration number 10 because parameter estimates changed by less than .001.

d. Estimation finished at iteration number 11 because parameter estimates changed by less than .001.

e. Estimation finished at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Here, the Nagelkerke R Square measures the variability in the dependent variable that is explained by the independent variable in this logistic regression model. The more the Nagelkerke R Square, the better the variation explained. Generally, the values exist between 0 to 1. The model in step one is showing 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. The Nagelkerke R Square value in model five is indicating that the model explained the variation in the dependent variable fully but it is statistically insignificant. That is why model four is the best model with statistical significance. The significance level can be found in Table 5.17.

Hosmer and Lemeshow Test is a goodness-of-fit test that shows how far the model is fit.

Table 5.15: Hosmer and Lemeshow Test			
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: Output of Forward Logistic Regression done by the Researcher

Under the Hosmer and Lemeshow test, the null hypothesis says that the model adequately fits the data. In this Hosmer and Lemeshow Test, if the significant value is less than 0.05, we reject the null hypothesis. In the above table, the significance is greater than 0.05 in all steps. So, we accept the null hypothesis i.e., all the models adequately fit the data.

The classification plot explains the hit ratio in Table 5.16.

Table 5.16: Classification of Failed and Non-Failed in different models[a]					
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. The cut value is .500					

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 dependent variable. Notably, the X2 variable has not been automatically used in any model. That means X2 has not any adequate impact on the data. Model five in step 5 is not significant because the variables in this model are showing statistically insignificant. The statistical significance of each variable used in those models is shown below. Based on statistical significance, model 4 is the best to explain the variation in the dependent variable in this logistic regression.

Table 5.17: Variables in the Equation based on Forward Logistic Regression

		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**	1729944302.5

							68
Step 5e	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) taken on step 1: X3.

b. Variable(s) taken on step 2: X1.

c. Variable(s) taken on step 3: X4.

d. Variable(s) taken on step 4: X5.

e. Variable(s) taken on step 5: X2.

The above table is showing that among the five variables, the X3 (Earnings before interest and taxes to total assets) is the best variable in explaining the financial distress level because individually it can explain 78.0% variation in the dependent variable. According to model four (95.8% prediction accuracy with the Nagelkerke R Square of 0.903), it can be also construed that the logistic prediction model could be as follows:

Probability of Failure = 21.271 - 14.223X1 - 62.507 X3 - 7.194 X4 - 10.006 X5

In the end, it can be said that the probability of failure can be better predicted by X1([Current assets - Current liabilities[/Total assets), X3 (Earnings before interest and taxes to Total assets), X4 (Book value equity to Book value of total debt or Liability), X5 (Sales to Total Assets). It is also found that X2 (Retained Earnings to Total assets) is not a good predictor in predicting corporate failure.

CHAPTER SIX
CONCLUSION AND IMPLICATIONS

6.1 Summary of Empirical Analysis

The first aim of this study is to find out whether there are any financially unhealthy firms in the Z category and OTC companies. Altman's (1968) model in calculating Z score has been applied for this purpose. The summary of the Z score 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.

The second objective of this study is to identify the predictors that impact in causing the financial failures of the Z category and OTC companies. Binary Logistic Regression has been applied for this purpose. In considering the single impact, the ratio of Earnings before Interest and Taxes/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 dependent variable. Thus, it can be said that the probability of failure can be better predicted by X1([Current assets - Current liabilities]/Total assets), X3 (Earnings before interest and taxes to Total assets), X4 (Book value equity to Book value of total debt or Liability), X5 (Sales to Total Assets). It is also found that X2 (Retained Earnings to Total assets) is not a good predictor in predicting corporate failure.

The third objective of the study is to know the financial characteristics of the Z category and OTC companies. Descriptive statistics are calculated for this purpose. The descriptive statistics of the Z category companies based on gross financial data show that the minimum balance of Earnings Before Interest and Taxes, Retained Earnings, and Book Value of Equity are in a negative position. The mean value of Retained Earnings is also a negative figure. On the other hand, the descriptive statistics of the Z category companies based on ratios show that the mean value of the net working capital ratio and Retained Earnings/Total assets ratio is in a negative figure. The findings of the descriptive statistics of the OTC companies are similar to the Z category companies.

The fourth objective of the study is to identify whether the mean values of the predictors of financial position are substantially different between or among failed, grey, & non-failed status.

Independent Samples T-Test & One Way ANOVA have been applied to identify whether the characteristics of financially unhealthy companies in the Z category and OTC significantly different from the financially healthy position. After applying the Altman Z score on the Z category Bank and NBFI companies and OTC companies, only two outcome groups (failed and grey) were found and no non-failed firm years were found. In comparing the means of two groups, Independent Samples T-Test is applied. According to the findings of Independent Samples T-Test, only one ratio i.e., EBIT/Total assets has significant differences in the comparison of “failed” and “grey” firms.

On the other hand, three (Failed, Non-Failed, and Grey) categories were found after applying Altman Z-Score on Z category Manufacturing and Servicing Companies. The findings of the one-way analysis of variance (ANOVA) show that the mean value of X1 of the Failed, Non-Failed, and Grey firm years are -0.0773, 0.4152, and 0.2605 respectively, and the finding is statistically significant ($\alpha = 0.000$). Thus it can be deduced that the mean value of the net working capital ratio of a failed firm tends to be negative. The mean value of X2 of the Failed, Non-Failed, and Grey firm years are -0.3204, 0.1915, and 0.1043 respectively, and the finding is statistically significant ($\alpha = 0.000$). Thus it can be deduced that the mean value of the Retained Earnings/Total assets ratio of a failed firm tends to be negative. The mean value of X3 of the Failed, Non-Failed, and Grey firm years are 0.0008, 0.0725, and 0.0786 respectively, and the finding is statistically significant ($\alpha = 0.000$). Thus it can be deduced that the mean value of the Earnings before interest and taxes to Total Assets ratio of a failed firm tends to be very low compared to a non-failed firm. The mean value of X4 of the Failed, Non-Failed, and Grey firm years are 0.9879, 10.9985, and 1.6087 respectively, and the finding is statistically significant ($\alpha = 0.000$). Thus it can be deduced that the mean value of the Book value equity to Book value of total debt or Liability ratio of a failed firm tends to be very low compared to a non-failed firm. On the other hand, there are no substantial differences in the mean value of X5 (Sales/Total assets) for the failed, non-failed, and grey firms because the finding is not statistically significant ($\alpha = 0.070$). According to the above table, only one ratio i.e., EBIT/Total assets has significant (p-value: 0.002) differences in the comparison of “failed” and “grey” firms. It should be mentioned that no firm-year is found as “non-failed” in the OTC companies.

6.2 Implications of the Study

The study implies that simply declaring some firms as the Z category or OTC category is not enough. Because the general investors are not aware of the real financial health from the BSEC’s declared reasons for transferring a company to Z category or OTC. Although the firms are declared as Z category by the regulator, there is no effect on the trading because there is no reflection in the stock prices. Rather there is an increasing tendency in the prices of some junk securities that are detrimental for the general investors when there will be a price correction. As a result, the capital market can fall into instability situations. There were instances that sometimes the regulator could not trace a few companies in the OTC which is harmful to the general investors. According to the findings of this study, there is a failure level up to 98% and 92% in the firms of Z category and OTC category respectively. That is why the failure prediction model could be used for distressed firms and effective actions should be taken to protect the interest of the general investors. Although recently there was a directive from the Bangladesh Securities and Exchange

Commission which permits that a delisted firm or the firm in the OTC or ATB can apply for an exit plan for selling the securities if there is any available offeror who could apply for buying the securities under the exit plan. But these measures will not be fruitful if there is no available offeror. According to Grigaraviˇcius (2003), when a firm reaches the distressed level in which it is essential to be declared insolvent, there should be effective infrastructure for bankruptcy so that filing could be done immediately to reduce losses associated with the restructuring procedures or bankruptcy procedure. If there is a delay in the bankruptcy or restructuring procedure, it creates three impacts. First, it increases direct and indirect spending related to bankruptcy; Second, it decreases the recovery potentials of the indebted firms; Third, it reduces the reimbursements of obligations to creditors. That is why it is essential to file an appeal for bankruptcy for the distressed firm in the initial stage of their indebtedness; otherwise, problems will be aggravated. To avoid failure, the Chief Executive Officer should comprehend the nature of the failure and the aspects that contributed to it. Then there should be corrective measures to prevent the failure. Mistakes should be recognized and there should be precautious actions to protect the organization from future mistakes (Mukridakis, 1991).

6.3 Limitations of the Study

Most of the studies in the international arena were done taking data from non-failed and failed data. But due to the unavailability of the data of failed firms, the author decided to continue his research using the data of OTC companies and Z-categories companies registered under the Dhaka Stock Exchange.

In recent cases, most of the studies on predicting corporate failure are done using an Artificial Neural Network, but the author of this thesis doesn't have any training or knowledge on it. That's why there is a use of the Altman model and Logistic regression. And no non-financial information, especially data on corporate governance has been used due to the complexity of collecting such data.

The author could not access some of the annual reports of Z category companies because some companies don't have any website and some companies don't maintain annual reports on their website. On the other hand, no OTC Company has any online data. That is why authors could not collect all the annual reports in hard copy because OTC companies are irregular to produce or provide hardcopy of annual reports.

6.4 Future Research

Future research could be done using failed firm data, if available. Besides, non-financial information could be included along with financial information to make better inferences about the prediction of corporate failure. A rigorous study could be done by collecting all the annual reports of OTC companies. A hybrid approach (using Artificial Neural Network along with statistical models) could be used to get a deep understanding of the corporate failure in the Bangladeshi perspective.

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APPENDIX

A) Distress Level or Position of the Z Category Selected (Manufacturing and Serving Providing) Companies

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
AlhajTex	2018	0.48	0.04	0	0.76	0.45	1.53	Failed
	2017	0.53	0.07	0.04	0.83	0.53	1.9	Grey
	2016	0.5	0.06	0.04	0.78	0.72	2	Grey
	2015	0.48	0.05	0.03	0.72	0.54	1.7	Failed
	2014	0.42	0.06	0.04	0.63	0.6	1.7	Failed
	2013	0.43	0.08	0.1	0.79	0.88	2.31	Grey
	2012	0.34	0.05	0.04	0.72	0.98	2.01	Grey

Here, X1=(Current assets - Current liabilities) /Total assets; X2=Retained Earnings/Total assets; X3=Earnings before interest and taxes/Total assets; X4=Book value equity/Book value of total debt or Liability; X5=Sales/Total assets

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
AllTex	2019	-0.04	-0.25	-0.05	0.25	0.07	-0.35	Failed
	2018	-0.31	-0.14	-0.08	0.38	0.11	-0.5	Failed
	2017	-0.1	-0.02	0.02	0.57	0.31	0.57	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
ApplloIspat	2018	0.28	0.13	0.04	1.52	0.3	1.86	Grey
	2017	0.32	0.16	0.08	1.66	0.46	2.32	Grey
	2016	0.35	0.17	0.09	1.91	0.47	2.57	Grey
	2015	0.37	0.16	0.09	1.74	0.47	2.49	Grey
	2014	0.42	0.15	0.09	1.79	0.5	2.58	Grey
	2013	0.25	0.14	0.12	0.88	0.63	2.06	Grey

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
AramitCem	2019	-0.14	-0.09	0.04	0.01	0.39	0.24	Failed
	2018	-0.03	-0.06	0.04	0.05	0.42	0.45	Failed
	2017	-0.02	-0.03	0.05	0.12	0.47	0.65	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
BdServices	2019	-0.1	-0.13	-0.03	-0.02	0.07	-0.33	Failed
	2018	-0.1	-0.12	-0.04	0.02	0.03	-0.37	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
BdThai	2019	0.23	0.06	0.02	1.51	0.21	1.54	Failed
	2018	0.23	0.06	0.03	1.52	0.29	1.66	Failed
	2017	0.25	0.05	0.02	1.61	0.2	1.6	Failed
	2016	0.23	0.06	0.04	1.51	0.23	1.62	Failed
	2014	0.28	0.03	0.03	1.56	0.17	1.56	Failed
	2013	0.49	0	0	1.53	0.17	1.68	Failed
	2012	0.26	-0.07	0.01	1.85	0.18	1.52	Failed
	2011	0.25	-0.08	0	1.89	0.17	1.5	Failed
	2010	0.25	-0.09	0.03	2.18	0.15	1.72	Failed
	2009	0.04	-0.03	0.04	1.22	0.13	0.99	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
BdWelding	2017	0.29	0.03	-0.06	0.87	0.04	0.77	Failed
	2016	0.12	-0.14	0.07	1.11	0.09	0.93	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
BeachHatch	2017	0.47	0.04	-0.02	7.07	0	4.78	Non-Failed
	2016	0.48	0.07	-0.03	8.06	0.05	5.47	Non-Failed
	2014	0.49	0.14	0.05	9.37	0.24	6.83	Non-Failed
	2013	0.47	0.21	0.09	9.8	0.28	7.31	Non-Failed
	2012	0.45	0.15	0.09	10.22	0.26	7.45	Non-Failed
	2011	0.42	0.15	0.15	9.6	0.37	7.34	Non-Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
BexSyn	2019	0.29	-0.32	-0.05	0.69	0.04	0.18	Failed
	2018	0.42	-0.2	-0.02	0.85	0.37	1.03	Failed
	2017	0.22	-0.12	-0.03	1.24	0.13	0.88	Failed

	2016	0.3	-0.05	0.01	1.5	0.12	1.32	Failed
	2015	0.31	-0.04	0.02	1.61	0.29	1.64	Failed
	2014	0.35	-0.02	0.03	1.79	0.36	1.92	Grey

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
DaccaDyeing	2014	0.03	0.02	0.02	1.03	0.25	1.02	Failed
	2013	0.09	0.02	0.02	1.1	0.25	1.13	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
DeltaSpin	2017	0.21	0.08	0.04	1.51	0.3	1.69	Failed
	2016	0.26	0.1	0.03	1.51	0.3	1.78	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
DulamiaCotton	2019	-2.29	-2.64	-0.13	-0.67	1.28	-5.99	Failed
	2018	-1.94	-2.24	-0.2	-0.63	1.65	-4.86	Failed
	2017	-1.6	-1.84	-0.17	-0.58	1.56	-3.85	Failed
	2016	-0.16	-1.54	-0.13	0.1	1.26	-1.44	Failed
	2015	-1.69	-1.94	-0.1	-0.59	1.33	-4.09	Failed
	2014	-1.79	-1.83	-0.17	-0.6	1.27	-4.36	Failed
	2013	-1.64	-1.54	-0.07	-0.58	1.56	-3.13	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
EmeraldOil	2016	0.36	0.17	0.16	0.65	0.78	2.36	Grey
	2015	0.38	0.15	0.16	0.64	0.86	2.44	Grey
	2014	0.19	0.12	0.13	0.69	0.81	2.07	Grey
	2013	0.16	0.1	0.16	0.47	1.05	2.17	Grey

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
FamilyTax	2019	0.61	0.13	0	13.72	0.22	9.38	Non-Failed
	2018	0.6	0.18	0	19.73	0.25	13.07	Non-Failed
	2017	0.59	0.22	0.01	27.1	0.3	17.6	Non-Failed
	2016	0.58	0.26	0.05	34.14	0.51	22.22	Non-Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
GoldenSon	2019	0.2	0.06	0	1.03	0.1	1.05	Failed
	2018	0.16	0.08	-0.01	1.17	0.09	1.07	Failed
	2017	0.07	0.11	-0.01	1.53	0.13	1.23	Failed
	2016	0.16	0.15	0.01	2.05	0.16	1.83	Grey
	2014	0.27	0.18	0.06	3.01	0.26	2.84	Grey
	2013	0.37	0.21	0.09	4.68	0.36	4.19	Non-Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
ImamButton	2019	-0.17	-0.5	-0.05	1.04	0.54	0.09	Failed
	2018	-0.18	-0.41	-0.03	1.05	0.55	0.28	Failed
	2017	-0.18	-0.35	-0.03	1.03	0.56	0.37	Failed
	2016	-0.07	-0.32	-0.08	1.2	0.47	0.38	Failed
	2015	0	-0.09	-0.12	2.29	0.35	1.2	Failed
	2014	-0.15	-0.2	-0.12	1.03	0.36	0.12	Failed
	2013	-0.38	-0.35	-0.09	0.36	0.36	-0.66	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
IntechLtd	2019	0.53	0.06	0.03	6.29	0.31	4.91	Non-Failed
	2018	0.52	0.11	0.09	8.98	0.38	6.86	Non-Failed
	2017	0.43	0.1	0.1	37.27	0.43	23.78	Non-Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
KeyCosmetic	2018	0.55	0.04	0.08	0.78	0.33	1.79	Failed
	2017	0.62	0.06	0.09	0.81	0.36	1.98	Grey
	2016	0.63	0.05	0.08	0.84	0.38	1.99	Grey

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
KhanBroBag	2019	0.51	0.12	0.03	8.9	0.42	6.64	Non-Failed
	2018	0.48	0.11	0.06	6.44	0.52	5.32	Non-Failed
	2017	0.47	0.13	0.08	8.3	0.6	6.59	Non-Failed
	2016	0.42	0.15	0.11	7.43	0.93	6.49	Non-Failed
	2014	0.4	0.2	0.14	7.61	1.31	7.1	Non-Failed
	2013	0.44	0.15	0.14	7.18	1.26	6.76	Non-Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
LibraInfusion	2017	-0.03	0.01	0.01	0.76	0.05	0.52	Failed
	2016	-0.03	0.01	0.01	0.76	0.05	0.52	Failed
	2015	-0.03	0.01	0.01	0.76	0.06	0.54	Failed
	2014	-0.02	0.02	0.02	1.98	0.1	1.35	Failed
	2013	-0.05	0.02	0.02	2.47	0.08	1.58	Failed
	2012	-0.02	0.02	0.01	2.73	0.09	1.78	Failed
	2011	0.02	0.02	0.02	3.72	0.14	2.47	Grey

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
MeghnaConMilk	2019	-0.98	-2.62	-0.05	-0.66	0.15	-5.24	Failed
	2018	-0.76	-2.45	-0.06	-0.64	0.16	-4.76	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
MeghnaPet	2019	0.25	-1.59	-0.03	-0.29	0	-2.2	Failed

	2018	0.24	-1.51	0.04	-0.26	0	-1.86	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
RN Spin	2019	0.09	-2.7	0.08	0.46	1.29	-1.85	Failed
	2018	0.21	0.32	0.04	6.95	0.29	5.27	Non-Failed
	2017	0.14	0.36	0.05	5.06	0.43	4.29	Non-Failed
	2016	0.28	0.41	0.02	8.91	0.33	6.65	Non-Failed
	2014	0.29	0.43	0.06	9.21	0.41	7.09	Non-Failed
	2013	0.25	0.38	0.18	5.72	0.52	5.37	Non-Failed
	2012	0.17	0.18	0	1.34	0.32	1.59	Failed
	2011	-0.02	0.25	0	1.59	0.57	1.86	Grey
	2010	0.33	0.26	0.22	5.61	0.82	5.66	Non-Failed
	2009	0.06	0.03	0.03	0.28	0.16	0.52	Failed
	2008	0.08	0.05	0.07	1.64	0.54	1.91	Grey

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
Salvo Chem	2019	-0.1	0.09	0.06	0.98	0.29	1.09	Failed
	2018	-0.06	0.09	0.07	1.1	0.22	1.15	Failed
	2017	-0.06	0.11	0.09	2.53	0.27	2.16	Grey
	2016	-0.02	0.11	0.1	3.42	0.32	2.82	Grey
	2015	-0.04	0.08	0.04	2.59	0.11	1.87	Grey
	2013	0	0.11	0.12	3.61	0.33	3.04	Non-Failed
	2012	-0.03	0.08	0.09	3.24	0.27	2.57	Grey

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
Shinepukur	2019	-0.08	-0.01	0.03	1.81	0.23	1.32	Failed
	2018	-0.1	-0.02	0.04	1.83	0.23	1.31	Failed
	2017	-0.11	-0.03	0.03	1.81	0.22	1.25	Failed
	2016	-0.11	-0.03	0.05	1.75	0.32	1.35	Failed

	2015	-0.08	-0.01	0.04	1.75	0.21	1.27	Failed
	2014	-0.11	-0.01	0.04	1.76	0.25	1.29	Failed
	2013	-0.01	0.02	0.05	1.88	0.25	1.57	Failed
	2012	0	0.05	0.08	1.76	0.27	1.67	Failed
	2011	0	0.06	0.07	1.7	0.27	1.61	Failed
	2010	0.03	0.08	0.11	1.14	0.38	1.58	Failed
	2009	-0.04	0.06	0.1	1.14	0.37	1.42	Failed
	2008	-0.03	0.07	0.09	1.15	0.34	1.4	Failed
	2007	0.04	0.06	0.12	0.51	0.45	1.3	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
United Air	2015	0.12	0.05	0.04	1.25	0.27	1.36	Failed
	2014	0.06	0.06	0.11	1.11	0.51	1.68	Failed
	2013	0.07	0.04	0.11	1.3	0.61	1.88	Grey
	2012	0.07	0.08	0.08	1.7	0.49	1.97	Grey

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
Usmania Glass	2019	0.03	-0.14	-0.05	2.3	0.1	1.16	Failed
	2018	0.08	-0.08	-0.01	2.48	0.08	1.5	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
Zahin Tex	2019	0.32	0.03	0.01	1.04	0.1	1.19	Failed
	2018	0.39	0.08	0.05	1.15	0.21	1.64	Failed
	2017	0.39	0.09	0.07	1.39	0.36	2.01	Grey
	2016	0.37	0.1	0.08	1.63	0.52	2.35	Grey
	2015	0.35	0.09	0.08	1.56	0.5	2.26	Grey

Appendix B. Distress Level or Position of the Z Category Selected (Bank and NBFI) Companies

Company	Year	X1	X2	X3	X4	Z-Score	Position
AB Bank	2018	0.005	0.018	0.006	0.076	0.21	Failed
	2017	0.007	0.019	0.008	0.078	0.25	Failed
	2016	0.027	0.022	0.009	0.079	0.39	Failed
	2015	0.03	0.024	0.015	0.087	0.47	Failed
	2014	0.014	0.027	0.024	0.077	0.42	Failed
	2013	0.002	0.024	0.018	0.089	0.31	Failed
	2012	-0.173	0.03	0.018	0.102	-0.81	Failed
	2011	-0.133	0.035	0.016	0.108	-0.54	Failed
	2010	-0.069	0.036	0.026	0.116	-0.04	Failed

Here, X1= (Current assets - Current liabilities)/Total Assets; X2=Retained Earnings/Total Assets; X3= EBIT/Total Assets; X4= Book Value of Equity/Total Liabilities

N.B: X5 is not applicable for Bank and NBFI

Company	Year	X1	X2	X3	X4	Z-Score	Position
BIFC	2018	-0.597	-0.048	-0.063	0.09	-4.4	Failed
	2017	-0.645	-0.123	-0.077	0.032	-5.12	Failed
	2016	-1.378	-0.855	-0.058	-0.409	-12.64	Failed
	2015	-1.496	-0.991	-0.026	-0.454	-13.7	Failed

BIFC =Bangladesh Industrial Finance Co.

Company	Year	X1	X2	X3	X4	Z-Score	Position
FFIL	2016	-0.343	0.007	0.011	0.063	-2.08	Failed
	2015	-0.43	0.007	0.032	0.065	-2.52	Failed

FFIL =Fareast Finance & Investment Ltd

Company	Year	X1	X2	X3	X4	Z-Score	Position
FFL	2017	-0.56	-0.021	0.007	0.119	-3.57	Failed
	2016	-0.625	0.006	0.032	0.179	-3.68	Failed
	2015	-0.61	0.002	0.036	0.164	-3.58	Failed
	2014	-0.484	0.007	0.036	0.181	-2.73	Failed
	2013	-0.462	0.016	0.055	0.248	-2.35	Failed
	2012	-0.15	0.032	0.064	0.271	-0.17	Failed
	2011	-0.281	0.036	0.061	0.364	-0.93	Failed

FFL=First Finance Limited

Company	Year	X1	X2	X3	X4	Z-Score	Position
ICBIBL	2018	-0.873	-1.595	-0.002	-0.489	-11.46	Failed

	2017	-0.823	-1.505	0.006	-0.47	-10.76	Failed
	2016	-0.815	-1.413	0.013	-0.45	-10.34	Failed
	2015	-0.738	-1.337	0.019	-0.434	-9.53	Failed
	2014	-0.632	-1.206	0.023	-0.407	-8.35	Failed
	2013	-0.644	-1.162	0.023	-0.395	-8.27	Failed
	2012	-0.636	-1.054	0.043	-0.364	-7.7	Failed
	2011	-0.648	-0.826	0.031	-0.297	-7.04	Failed
	2010	-0.49	-0.702	0.027	-0.237	-5.57	Failed
	2009	-0.397	-0.617	0.021	-0.189	-4.67	Failed

ICBIBL= ICB Islamic Bank

Company	Year	X1	X2	X3	X4	Z-Score	Position
PLFS	2017	-0.074	-0.043	0.004	0.105	-0.49	Failed
	2016	-0.069	-0.048	-0.01	0.119	-0.56	Failed
	2015	-0.262	-0.032	-0.029	0.142	-1.87	Failed
	2014	-0.547	0.013	0.024	0.254	-3.12	Failed
	2013	-0.58	0.019	0.025	0.299	-3.26	Failed
	2012	-0.527	0.027	0.042	0.334	-2.74	Failed
	2011	-0.459	0.03	0.057	0.333	-2.18	Failed

PLFS=People's Leasing And Financial Services Limited

Company	Year	X1	X2	X3	X4	Z-Score	Position
PFIL	2018	-0.231	-0.107	0.01	0.295	-1.48	Failed
	2017	-0.244	-0.09	-0.006	0.223	-1.7	Failed
	2016	-0.246	-0.058	-0.024	0.234	-1.72	Failed
	2015	-0.164	-0.007	0.006	0.298	-0.75	Failed
	2014	-0.14	0.033	0.044	0.404	-0.08	Failed
	2013	-0.155	0.039	0.045	0.434	-0.13	Failed
	2012	-0.14	0.068	0.04	0.468	0.06	Failed
	2011	-0.077	0.103	0.082	0.449	0.85	Failed
	2010	-0.068	0.133	0.175	0.432	1.62	Grey
	2009	-0.208	0.063	0.087	0.214	-0.35	Failed

PFIL=Prime Finance & Investment Ltd.

Appendix C. Distress Level or Position of the OTC's Selected Companies

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
Monospool	2019	0.05	0.12	0.16	0.43	0.53	1.54	Failed
Monospool	2018	0.04	0.07	0.14	0.39	0.48	1.3	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
GachihataAgri	2019	-0.22	-0.26	0	1.5	0	0.28	Failed
GachihataAgri	2018	-0.16	-0.04	0	2.15	0	1.04	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
RangamatiFood	2019	-0.8	-0.99	-0.03	0.13	0	-2.37	Failed
Rangamati Food	2018	-0.77	-0.94	-0.08	0.11	0	-2.46	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
YusufFlour	2019	-0.03	0.02	0.03	0.03	0.71	0.81	Failed
YusufFlour	2018	-0.06	0.02	0.03	0.03	0.75	0.82	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
MAQpaper	2019	-0.43	-0.57	0.01	-0.1	0.44	-0.89	Failed
MAQpaper	2018	-0.46	-0.6	0.06	-0.11	0.4	-0.87	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
MAQEnterprise	2019	0.32	-2.41	0.01	-0.3	0.61	-2.53	Failed
MAQEnterprise	2018	0.24	-1.8	0.01	-0.25	0.66	-1.68	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
PadmaPrinters	2019	-0.71	-2.58	-0.02	-0.29	0.98	-3.72	Failed
PadmaPrinters	2018	-0.73	-2.58	-0.03	-0.29	0.68	-4.09	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
TamijuddinTex	2019	-0.02	0.05	0.01	0.69	0.41	0.92	Failed
TamijuddinTex	2018	0.01	0.05	0	0.64	0.39	0.87	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
MonnoFabrics	2019	0.01	-0.36	0.01	0.82	0.14	0.19	Failed
MonnoFabrics	2018	0.07	-0.85	0.01	-0.25	0.21	-1.03	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
JessoreCem	2019	-0.83	-0.2	-0.09	0.06	0	-1.52	Failed
JessoreCem	2018	-0.74	-0.15	-0.08	0.15	0	-1.28	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
Al-AminChem	2019	-0.88	-1.98	0.02	-0.37	0.23	-3.76	Failed
Al-AminChem	2018	-0.88	-1.92	0.01	-0.36	0.3	-3.64	Failed

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
PaperProcPack	2019	0.18	0.19	0.14	0.58	0.56	1.85	Grey
PaperProcPack	2018	0.21	0.13	0.17	0.48	0.55	1.83	Grey

Company	Year	X1	X2	X3	X4	X5	Z-Score	Position
TheEnggLtd	2019	0.11	-0.05	0.05	0.22	1.41	1.76	Failed
TheEnggLtd	2018	0.06	-0.03	-0.02	0.11	0	0.03	Failed