COULD THE ALTMAN Z-SCORE MODEL DETECT THE FINANCIAL DISTRESS IN GHANA? MULTIVARIATE DISCRIMINANT ANALYSIS

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Abstract

The purpose of this paper is to assess the effectiveness of the Altman Z-score model to discriminate between financially distressed and non-financially distressed manufacturing firms listed on the Ghana Stock Exchange. Eleven firms consisting of two financially distressed and nine non-financially distressed manufacturing firms were analysed. Independent descriptive statistics, independent sample t-test, and multivariate discriminant analysis were the analytical tools used to analyse the hypotheses of this study. The study revealed that working capital/total assets and sales/total assets were the major discriminators of financially distressed firms on the Ghana Stock Exchange. Multivariate discriminant analysis revealed an accuracy rate of 79.9% to detect financially distressed firms in Ghana.

Keywords: Altman Z-score, Financially Distressed, Non-financially Distressed, Discriminant Analysis

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1. INTRODUCTION

Accurately predicting corporate distress is very important for any investor, bank, company, regulatory authority, and other stakeholders before entering into bankruptcy (Andreica, 2009). Early detection of financially distressed firms provides a signal needed to avoid the high costs associated with bankruptcy. Bankruptcy is a legal process through which a financially troubled debtor or firm declared as insolvent will have its assets liquidated and distributed to creditors according to the bankruptcy law of the country (Pangkey, Saerang, & Maramis, 2018). Bankruptcy costs include direct costs and indirect costs to investors and other stakeholders (Maksimovic & Philips, 1998; Butler, 2016). Direct costs to bankruptcy include litigation fees, management fees, and auditors' fees. Indirect costs occur when there is a fall in the market value of assets and inefficient sale of assets. Direct costs are pay-outs to the debt holders when bankruptcy occurs. These costs are very important in order to determine the total direct cost of bankruptcy.

To minimize the risk and other costs associated with bankruptcy, stakeholders should independently and periodically, use the Altman Z-score model to assess the financial health of their investments before the firm goes into bankruptcy. Although institutions such as the Security and Exchange Commissions and professional firms such as external auditors are responsible for credible information to investors and stakeholders, the past few years have seen that some "watchdog" institutions have connived with the management of some listed firms to provide inadequate information to their stakeholders (Verschoor, 2011). This does not adequately protect the interest of stakeholders, hence, the need to periodically analyse their investments or firms' financial statements with appropriate forensic tools and models. Sometimes, the protection to investors from the "watchdog" institutions comes a little too late when "so much water is gone under the bridge". For instance, it was alleged that auditors of Lehman Brothers Holdings Incorporated, Ernst & Young, had signed financial statements that invested in the bank appear better than it was (Verschoor, 2011). It was also reported that Enron Corporation paid $2.1 million to Washington lobbying firms (Bratton, 2002) for the manipulation of their financial data. The author stated that "Enron spent $10.2 million to influence Washington between 1997 and 2000" (Bratton, 2002, p. 4). Quite recently in Ghana, it was reported in the September 4, 2019 issue of the Daily Graphic that four audit firms (Deloitte and Touche, Parnell Kerr Foster (PKF), J. Mills Lamptey & Co., and Morrison & Associates) were sanctioned for various infractions committed while exercising due diligence on the financial position of the five collapsed banks. The five banks are Royal Bank Limited, Beige Bank Limited, UniBank Ghana Limited, Sovereign Bank Limited, and Construction Bank Limited have their banking licenses revoked by the Bank of Ghana. The four audit firms were fined a total of GH¢ 2.2 million for non-compliance with auditing standards. These collapse banks have brought so much hardship to the creditors, depositors, shareholders, and other stakeholders of these firms. Again, the Ghana Stock Exchange (GSE) has compulsorily delisted Pioneer Kitchenware Limited (PKL), African Champion Industries (ACI), Transaction Solutions Limited (TSL), and Golden Web from the main equity market of the exchange, a move was seen by financial analysts as protection of shareholders. Even though the action of the GSE as a regulator is laudable, it happened when "so much water is gone under the bridge" and stakeholders lost a substantial amount of their investment. A move that was in-line with the Bank of Ghana on the revocation of some banking licenses in Ghana to protect and secure the financial sector in Ghana.

Hence, relying solely on the works of regulatory institutions and professional accountants could be disastrous to investors and creditors. Therefore, having a tool or model that can predict financial distress will help both investors and creditors to make timely and informed decisions on their investments to protect themselves from financially unhealthy firms. When a condition of financial distress is detected early by the investor and creditor, it will enable the investor and the creditor to divest from financially distressed firms and invest in profitable ventures or non-financially distressed firms. Also, the managers of distressed firms will take preventive actions that will save the firm from going into bankruptcy. Many businesses fail not only because of a lack of profits but also because of cash flow problems (Lartey, 2012) as financial distress occurs when a firm is unable to settle its day to day financial obligations to creditors. Knowledge of the Altman Z-score model may empower shareholders to predict independently and quickly, the financial distress status of their firms. This has become necessary because, often, management fails to disclose the going-concern status of their firms or they provide inadequate information until the firms end in bankruptcy.

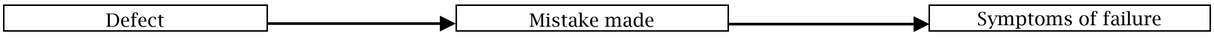
To protect the interests of investors, creditors, and other stakeholders (both current and potential), accounting standards require that management disclose the going-concern status of their firms in financial statements. The going-concern status provides guidelines to the auditors to examine whether the entity has used the going-concern inappropriately. BPP Learning Media (2009) postulated that the auditor's role with regards to the going-concern status is to obtain adequate and appropriate evidence towards management going-concern assumption and to conclude whether there exist material uncertainties to cast any significant doubt on the company's ability towards this assumption. This implies that management has to state the going-concern status of their firms while auditors are to assess whether the going-concern assumption provided by management is appropriate or not when assessing their financial statements. There were many instances were these disclosure requirements were ignored. In the recent case cited involving the role of the four audit firms, the Institute of Chartered Accountants in Ghana (ICAG) announced sanctions that they have meted out to four audit firms for shortfalls in their professional duties to comply with the required International Auditing Standards for their roles in the distressed financial institutions in Ghana (Frimpong, 2019). This implies that investors and creditors can independently assess the financial distress of firms in addition to the role played by external auditors. The rest of the paper is structured as follows. Section 2 reviews relevant literature and develops hypotheses. Section 3 analyses the methodology that has been used to conduct empirical research on the Altman Z-score model. Section 4 presents and discusses the empirical results. Section 5 concludes the paper, emphasizing its main implications to the paper.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1. Qualitative models

The qualitative models and other predictive tools are used by financial analysts and researchers to detect unhealthy firms. Qualitative models are not widespread in use because of their subjective nature compared to the quantitative models. The qualitative models are based on the premise that financial ratios taken from manipulated audited financial statements cannot be an effective measure for the performance of an organization as they cannot explain the causes of the failure. For this reason, opponents of the quantitative models have advocated for qualitative models that are based on non-accounting variables rather than accounting variables. These models are largely used for internal assessment of firms.

Figure 1. Failure process based on the qualitative model



The qualitative model focuses on the identification of causes of corporate failure rather than the predictive indicators of the failure. This model is shown in Figure 1. One of the notable qualitative models is the A-score model attributed to Argenti (1976) which suggests that the failure process of a company follows a predictive sequence: defects, mistakes made, and symptoms of failure (Pogue, 2005). The process of defects can be divided into management deficiencies and accounting deficiencies. Management deficiencies include the following: autocratic chief executive, failure to separate role of chairman and chief executive, passive board of directors, lack of balance of skills in management team (finance, legal, marketing, etc.), weak finance director, lack of 'management in-depth' and response to change. Accounting deficiencies include no budgetary control, no cash flow plans, and no costing system. Any of the management deficiencies and accounting deficiencies is given a mark as shown in Table 18 and enclosed in the Appendix. The total mark for defects (i.e., management and accounting deficiencies) should be 43. According to Argenti (1976), a mark is assigned based on the level of deficiencies and total of 10 or less indicates absence of management and accounting deficiencies. When a company's management and accounting are deficient it will inevitably make mistakes, which may not become evident immediately but will take a long time possibly five or more years.

The process of mistakes starts after the company's management and accounting deficiencies. Argenti (1976) identified three main mistakes that are likely to occur at this stage: high gearing, overtrading, and engagement in big projects whose failure would bring the company down. A suggested mark for mistake is a maximum score of 15 for each, making a total of 45. The past mark for the mistake is 15. High gearing occurs when a company allows gearing to raise to such a level that one unfortunate event can have disastrous consequences on the company. Overtrading occurs when a company expands faster than its financing facility can support. A big project is a mistake when a project has gone wrong from the intended purpose and has created an obligation that the company will not be able to settle. This is referred to as project failure, which would bring the company down. Argenti (1976) suggests that if there are defects in a company's management then it is inevitable that mistakes will be made, but the evidence in the symptoms will not show immediately but rather take some time to show. Symptoms are the final stage of the corporate failure process and when it happens, failure becomes visible for all to see. There are three symptoms of corporate failure according to Argenti (1976) as financial signs, creative accounting, non-financial signs, and terminal signs. The first sign of corporate failure is shown by financial difficulties and it is a sign that the firm is heading to failure. The second sign of corporate failure is when the firm adopts creative accounting practices to conceal financial weaknesses from the public. The final sign of corporate failure is when the firm shows non-financial problems like unclean or untidy offices, high staff turnover in the company, low morale and rumours. The overall pass mark is 25 and any company scoring above the 25 mark, indicates that it has many of the signs preceding failure and should therefore cause concern.

2.2. Quantitative models (involving the use of the Altman Z-score model)

One of the well-known quantitative models for detecting corporate financial distress is the Altman Z-score model. A quantitative model is based on information gathered from published financial statements. According to Poque (2005), quantitative models identify financial ratios that will discriminate between financially distressed and non-financially distressed firms. The quantitative model is used to identify firms that exhibit the challenging financial features of failure. The most commonly accepted financial features of failure include low profitability, low equity returns, poor liquidity, high gearing and high variability of income. Altman Z-score model is based on multivariate discriminant analysis (MDA). A model is an analytical tool that combines ratios in a multivariate discriminant context to predict corporate failure for listed firms in the USA and it has since been referred to as the Altman Z-score model (Andreica, 2009). Altman used the model to discriminate between failed firms and non-failed firms listed on the USA stock exchange.

Table 1. Altman Z-score model

Altman Z-score	*Meaning of the cut-off points*
Z > 2.90	Non-distress zones
1.23 < Z < 2.90	Grey zones
Z < 1.23	Distress zones

Source: Adapted from MacCarthy (2017).

Table 1 shows the cut-off points of the Altman Z-score model. The model is made up of several predictors (i.e., independent) variables and predictive discriminatory (i.e., dependent) variables in the form of:

$$Z = \alpha + \beta_1 X_1 + \beta_2 X_2 + \dots \beta_n X_n \quad (1)$$

where, Z is the predictive discriminatory variable or Z-score for firms; a is the intercept; β_1, β_2, and β_n are the discriminant weight for the selected variables; X_1, X_2, and X_n are the predictor (i.e., independent) variables.

The results of the Altman Z-score model revealed that bankruptcy could be predicted up to 95% for the first year when it happened, 72% for the second year when it happened, 48% for the third year when it happened, and 36% for the fourth year when it happened. Despite the worldwide acceptance of the Altman Z-score model, it has faced several criticisms from Slowinski and Zopounisdis (1995) that the model lacks qualitative variables and is unable to integrate with modern techniques. Another weakness of Altman Z-score is based on the assumption of MDA that data should be normality distributed and have group dispersion around the mean. It advocates that there should be two dispersions from the mean, those that are distressed and those that are non-distressed. These assumptions are often violated and this creates a bias in the test of significance and the estimation of error rates. To enhance the use of MDA as a quantitative analytical technique, care must be taken to ensure data are normally distributed before progressing with the analysis. To overcome the challenges of the quantitative model involving MDA, other quantitative models were developed mainly Logit Analysis and Artificial Intelligence Expert Model to detect and predict the financial distress of firms. These quantitative models were developed with the hope of finding improvements to MDA and thus, overcome its weaknesses identified. These models used conditional probability to observe some of the independent variables of the model (Neophytou & Mac-Molinero, 2001). However, these other quantitative models were not able to bring the desired improvement to the Altman Z-score model that was based on MDA. Therefore, Logit Analysis and Artificial Intelligence Expert Model required further refinements to get wider acceptance and usage in businesses.

2.3. Empirical review on the Altman Z-score model and detection of financial distress

Several quantitative models were developed to improve the predictive ability of firms in financial distress although these models have remained inconclusive. Many studies conducted on the Altman Z-score model agree that the model provides a convincing association between the financial ratios selected from audited accounts to predict financial health and business failure (Abdullah, Abd Halim, Abd Halim Hamilton, & Rohani, 2008; Sori, Hamid, Nassir, & Mohamad, 2001). Altman (2000) found the model to be extremely accurate in classifying 95.4% of the firms studied as bankrupt a year prior to failure and 78.8% of the firms two years prior to the actual failure. Calandro (2007) concluded in his research that the Altman Z-score model is used as a strategic assessment and performance management tool in credit risk analysis, distressed investing, merger and acquisition targeting analysis, and financial turnaround in management of firms. Odipo and Sitati (2010) also concluded that the Altman Z-score based on MDA offers an excellent measure in evaluating the financial health of a company and that it can measure explicitly the company's relative liquidity, longevity, operating profitability, leverage, solvency, and productivity. He stated further that the Altman Z-score, devoid of any biases, can predict accurately corporate failure and also provide reliable recommendations when needed. Dandago and Baba (2014) opined that Altman Z-score is the most extensively used and applied model for predicting financial distress. Currently, financial analysts and researchers still consider the Altman Z-score model as an effective and suitable indicator of a firm's ability to avoid bankruptcy. Additionally, most financial and credit agencies still rely on the model to mitigate risk and debt portfolios of firms. The Altman Z-score model has gained worldwide acceptance by a variety of stakeholders such as investors, financial analysts, consultants, bankers, auditors, and management accountants (Sulphey & Nisa, 2013).

2.4. Hypotheses development

The following two hypotheses were developed so that inference can be made for this study.

2.4.1. Altman Z-score model can discriminate between financially distressed and non-financially distressed firms

According to Poque (2005), the Altman Z-score model based on the quantitative model is able is to discriminate between financially distressed and non-financially distressed firms. It means the variables in financial distress firms exhibit low profitability; low equity returns; poor liquidity; high gearing and high variability of income as compared to non-financially distress firms. This leads us to the following hypothesis:

Hypothesis 1 (H1): There is no significant difference between the means of financially distressed manufacturing firms and non-financially distressed manufacturing firms' variables determined by the Altman Z-score model.

2.4.2. Firms classified as financially distressed as two years prior to actual failure (i.e., to become bankrupt)

According to Altman (2000), the model is extremely accurate in classifying firms classified as bankrupt two years prior to the actual failure. This leads to hypothesise that the Altman Z-score model can detect that the two manufacturing firms were financially distressed and the ten manufacturing firms were not financially distressed two years ago on the GSE.

Hypothesis 2 (H2): Altman Z-score model cannot discriminate between financially distressed manufacturing firms and non-financially distressed manufacturing firms listed on the GSE.

3. RESEARCH METHODOLOGY

This study is a quantitative research design involving exploratory data analysis. The analytical tools employed in the study are correlation matrix, independent sample t-test, and multivariate discriminant analysis (MDA) to either accept or reject the null hypothesis of the study. The analysis is done using the Statistical Package for the Social Sciences (SPSS).

3.1. Sample and data research methods

The sample consists of two firms delisted by the Ghana Stock Exchange and is classified as "financially distressed firms" and ten firms still listed on the Ghana Stock Exchange and are classified as non-financially distressed firms". The study assumed that the firms delisted from the GSE are bankrupt. Secondary data is collected from annual financial statements from 2011 to 2015 to test the research hypotheses under consideration. This period was chosen to allow 2-3 years prior to the delisting of the two manufacturing firms from the GSE in the middle of 2017. This gives 60 observations from 12 manufacturing firms over a five-year period. Observation of 60 is sufficient to provide an accurate conclusion for the study (Dowen & Mann, 2004).

3.2. Research variables

The study employed two types of variables namely a predictive discriminatory variable and five predictors (i.e., independent) variables. The five different variables are used to calculate the overall index of the dependent variable (i.e., Z-score). The criteria used to select the predictor variables for the analysis were based on financial ratios taken from the firms' audited financial statements similar to previous researchers' work (Altman, 1968; Thai, Goh, The, Wong, & Ong, 2014).

3.2.1. Predictive discriminatory variable (i.e., dependent variable)

The predictive discriminatory variable is a categorical (non-metric) form and represented by Z. The Z is the discriminant score calculated from the weighted combination of the predictor (i.e., independent) variables. Two cut-off values are assigned for financially distressed and non-financially distressed for this analysis.

3.2.2. Predictor variables (i.e., independent variables)

There are five predictor variables used in this analysis which are in the metric form. These variables are X_1, X_2, X_3, X_4, and X_5. Each variable is used as a separate predictor of predictive discriminatory variables in this study.

Table 2. Predictor variables

Variables	*Ratios*
X_1	Working capital/Total assets (WC/TA)
X_2	Retained earnings/Total assets (RE/TA)
X_3	EBIT/Total assets (EBIT/TA)
X_4	Market capitalization/Book value of total liabilities (MC/TL)
X_5	Sales/Total assets (S/TA)

Source: Adapted from MacCarthy (2017).

3.3. Model specification

Since the main objective of this study is to assess the financial health of firms, a model similar to the Altman Z-score model was used to examine the hypotheses of this study. The model is made up of several predictors (i.e., independent) variables and dependent variables that discriminate between failed firms from non-failed firms.

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + .999X_5 \quad (2)$$

where, Z is the known predictive discriminatory variable and it is the overall score calculated from X_1 to X_5. X_1 to X_5 are the predictor (i.e., independent) variables. A higher Z-score indicates that the company is safer or the company is not financially distressed and has a higher chance to avoid bankruptcy.

3.4. Testing the research assumptions of the model

The secondary data taken from audited financial statements were organised into suitable variables for the analysis. For the variables to be in a form suitable for the analysis it must satisfy some basis underlining discriminant analysis assumptions. Hence, to ensure that the variables do not violate the assumptions of discriminant analysis, the study tested the following assumptions of the discriminant analysis: linearity, normality, multicollinearity, homogeneity of variances, and the difference between the groups. The study employed these diagnostic tools: Scatterplot, Shapiro-Wilk or Kolmogorov-Smirnov test, Variance Inflator Factor (VIF), and log determinants. The outcome of testing these assumptions showed that the assumptions were not violated, hence, the reliability of the discriminant analysis. The study used scatterplot to plot each predictor variable (i.e., X_1, X_2, X_3, X_4, and X_5) against the predictive discriminatory variable. The results showed a positive linear relationship between the predictor variables and predictive discriminatory variable. The Shapiro-Wilk or Kolmogorov-Smirnov test was the second test used to check whether the variables used for the analysis were normally distributed. This assumption is tested at a 5% significance level. When data is normally distributed, it means the outcome from the discriminant analysis will provide a valid conclusion for the relationship between the independent variables and predictive discriminatory variables in this study. When the p-value is greater than 5% (i.e., $p > 0.05$), then the assumption that secondary data used for the analysis is statistically and significantly different from a normal distribution is not rejected. Table 3 shows that the p-value is greater than 5% (i.e., $p > 0.05$), and it implies that the data used for the analysis is normally distributed, hence, is not rejected.

Table 3. Shapiro-Wilk's test of normality distribution

	Kolmogorov-Smirnov[a]			*Shapiro-Wilk*		
	Statistic	*df*	*Sig.*	*Statistic*	*Df*	*Sig.*
Z-score	0.91	55	0.200	0.969	55	0.097

Source: Researcher's SPSS version 21 computation.

Multicollinearity is used to check correlations between the predictive discriminatory variables used for this study. Table 4 shows the test of VIF of the independent variables used for the predictive discriminatory variables. The VIF method is used to test the presence of multicollinearity. The existence of multicollinearity would not affect the way in which the regression is performed but rather affect the interpretation of the result (Anderson, Sweeney, & Williams, 2009).

Table 4. Test of multicollinearity

Variables	*Tolerance*	*VIF*
X_1	0.603	1.659
X_2	0.560	1.787
X_3	0.699	1.430
X_4	0.785	1.274
X_5	0.845	1.183

Source: Researcher's SPSS version 21 computation.

The tolerance levels (TL) and the VIF are used to measure the presence of correlation between the independent and control variables. A tolerance level should not be lower than 0.10 while the VIF should not be greater than 10. All the variables have tolerance levels above 0.10 and the VIF lower than 10.

Table 5. Tests of equality of group means

Variables	*Wilk's Lambda*	*F*	*df1*	*df2*	*Sig.*
X_1	0.388	83.475	1	53	.000
X_2	0.753	17.415	1	53	.000
X_3	0.758	16.932	1	53	.000
X_4	0.828	11.002	1	53	.002
X_5	0.580	38.390	1	53	000

Source: Researcher's SPSS version 21 computation.

The highest VIF was X_2 with a VIF of 1.787, indicating that there were no multicollinearity problems within the independent variables used for the analyses. Table 5 provides the statistical evidence needed to show that there is a significant difference between the means of financially distressed manufacturing firms and non-financially distressed manufacturing firms. Each of these variables should have a p-value of less than 5% for the result to be accepted.

There is a significant difference between the two groups since the p-value for each predictor variable is 0.000. The equality of group means assumption is not violated when the p-value is less than 5% significant level (i.e., $p < 0.05$). This means the tests of equality of group means is statistically significant for all the five predictor variables since all the predictor variables have p-values less than 0.05 (i.e., $p < 0.05$). The smaller the Wilk's Lambda in the result, the greater the importance of predictor variable in the discrimination model or function. This implies that X_1 is the best discriminator of the two groups followed by X_5 since X_1 and X_5 have the smallest Wilk's Lambda of 0.388 and 0.580 respectively.

Table 6. Log determinants

Status	*Rank*	*Log determinant*
Financially distressed manufacturing firms	5	-10.562
Non-financially distressed manufacturing firms	5	-7.889
Pooled within-groups	5	-5.206

Source: Researcher's SPSS version 21 computation.

The Log determinants and the Box's M are diagnostic tools used to verify whether the covariance matrices of the groups formed by the predictor variables and the groups are the same or equivalent. This assumption is referred to as the homogeneity of variances. The Box's M must be interpreted in conjunction with the inspection of the Log determinants. For this assumption to hold, the Log determinant should be larger while the p-value of Box's M should be smaller than the 5% significant level. Table 6 shows that the Log determinants are quite close to each other and the values very large while the result of Box's M in Table 7 is 166.30 with an F value of 8.66 and a significant value of 0.000.

Table 7. Box's M test results

Box's M		166.30
F	*Approx.*	8.66
	df1	15
	df2	1024.95
	Sig.	0.000

Source: Researcher's SPSS version 21 computation.

Since the p-value of the Box's M test is lesser than 0.05 and is consistent with the result obtained for the Log determinants, then the assumption of homogeneity of variances (i.e., equality of variance-covariance) is satisfied and accepted.

4. EMPIRICAL RESULTS

The results from the independent descriptive statistics, correlation matrix, independent sample t-test analysis, and discriminant analysis are presented to aid discussion in this study.

4.1. Descriptive statistics

The study used descriptive statistics to present the central tendency of the variables used in this analysis. Table 8 depicts the mean, standard deviation and standard error means for the financially distressed and non-financially distressed firms used. The second column shows the mean of negative 0.935 and positive 6.401 for financially distressed manufacturing firms and non-financially distressed manufacturing firms respectively. The standard deviations are 1.038 and 2.970 for financially distressed firms and non-financially distressed firms respectively. Therefore, the outcome provides persuasive evidence that there is a significant difference between the variables in the financially distressed and non-financially distressed firms, but not the conclusive evidence needed for this study. It is also important to note that, the difference in the mean is an indicator that the variables are good discriminator for the analysis to precede but provided inconclusive evidence at the moment.

Table 8. Independent descriptive statistics

Status	*Observation*	*Mean*	*St. Dev.*	*Std. Error*
Financially distressed	10	-0.935	1.038	0.328
Non-financially distressed	45	6.401	2.970	0.443
Total	55			

Source: Researcher's SPSS version 21 computation.

4.2. Correlation matrix

Pooled within-groups matrices were used to determine whether there was a significant relationship between predictor variables and the predictive discriminatory variable to buttress the evidence obtained in the independent descriptive statistics for the discriminant analysis to be carried out.

Table 9. Pooled within-groups matrices

Variables	X_1	X_2	X_3	X_4	X_5	*Z-score*
X_1	1					
X_2	0.260	1				
X_3	0.081	0.423	1			
X_4	0.250	0.058	0.077	1		
X_5	-0.381	0.075	0.016	-0.064	1	
Z-score	0.241	0.235	0.248	0.912	0.281	1

Source: Researcher's SPSS version 21 computation.

Table 9 shows that the result from the Pooled Within-Groups Matrices shows that all the five predictor variables have a significant positive effect on the Z-score variable. Again, the result shows that the predictive variables or independent variables are not correlated. A tolerable level between predictor variables should be below 0.50, when the coefficient between two predictor variables is between 0.50, it is referred to as the absence of multicollinearity.

4.3. Independent sample t-test

Once satisfactory results were obtained from testing basic assumptions of the model, and a positive relation between the five predictor variables and predictive discriminatory variable, the study proceeded to test two hypotheses of the study.

Table 10. Independent samples t-test

		Levene's test for equality of variances		*t-test for equality of means*						
		F	*Sig.*	*t*	*df*	*p-value*	*Mean difference*	*St. error difference*	*95% confidence interval of the difference*	
									Lower	*Upper*
Z-score	Equal variances assumed	6.212	0.02	-7.66	53.00	0.000	- 7.336	0.958	-9.257	-5.415
	Equal variances not assumed			- 13.31	42.65	0.000	-7.336	0.552	-8.447	-6.224

Source: Researcher's SPSS version 21 computation.

The first hypothesis (*H1*) is tested at 95% confidence level (i.e., 5% significance level) using independent sample t-test as an analytical tool to determine whether there is a significant difference among the categorization (i.e., financial and non-financially distress firms) based on the Altman Z-score model. Table 10 shows that there is a significant difference among the categorization (i.e., financially and non-financially distressed firms) based on the Altman Z-score model. The F-test in the independent sample t-test is 0.02 and is less than a 5% level of a significant level. Therefore, the values associated with "equal variances not assumed" which occurs at the mean score of t = -13.31 and the p-value is 0.02 is used.

4.4. Multivariate discriminant analysis

The second hypothesis (*H2*) is tested at 95% confidence level (i.e., 5% significance level) using multivariate discriminant analysis (MDA). MDA is a higher regression analysis that optimises between-group variance and minimises the within-group variance. The study used the MDA to estimate the association between a predictive discriminatory variable and five sets of predictor variables. The eigenvalue and canonical correlation values of the test results are used to determine the predictive powers of the multivariate discriminant analysis. The eigenvalue provides the ratio between the explained and unexplained variation in the model. For a good model to be accepted for the analysis, the eigenvalue must be greater than one. The bigger the eigenvalue, the stronger the discriminating power of the model. However, the canonical correlation measures the association between the groups in the predictive discriminatory (i.e., dependent) variable and the discriminant model. A higher value of canonical correlation implies a higher level of association between the two groupings and vice-versa. Table 11 shows that the canonical correlation is 0.894 and it explains that the model can predict 79.9% of the variation of the dependent variable. It is calculated as the squared of the canonical correlation value. Therefore, the model can explain about 79.9% that the selected firms are either financially distressed or not.

Table 11. Eigenvalues

Function	*Eigenvalue*	*% of variance*	*Cumulative %*	*Canonical correlation*
1	3.987[a]	100.0	100.0	0.894

Note: [a] First 1 canonical discriminant functions were used in the analysis.

The Wilk's Lambda confirms statistically the overall validity of the MDA function. Smaller the value of Wilk's Lambda, then the greater the discriminatory ability of the model. The Wilk's Lambda shows a proportion of the variation that cannot be explained by the model in the grouping variables (i.e., it is converse of the squared of canonical correlation value). Table 12 shows that the model failed to explain about 20.1% of the variation in the grouping variable. The Wilks' Lambda is used to test the significance of the discriminant functions of the value. It ranges from 0 to 1 and it is significant when the function is small. Generally, the model is significant because it can explain about 79.9% of the variation.

Table 12. Wilk's Lambda

Test of function	*Wilks' Lambda*	*Chi-square*	*Df*	*Sign.*
1	0.201	81.144	5	.000

Source: Researcher's SPSS version 21 computation.

The standardized canonical discriminant function coefficient table provides an index of the importance of each predictor and a sign indicating the direction of the relationship. The coefficients with large absolute values correspond to values with greater discriminating ability.

Table 13. Standardized canonical discriminant function coefficient table

Variables	*Function*
	1
X_1	0.915
X_2	-0.052
X_3	0.267
X_4	0.079
X_5	0.812

Source: Researcher's SPSS version 21 computation.

Table 13 shows that X_1 and X_5 were the strongest predictors of financially distressed firms with values of 0.915 and 0.815 respectively. These two predictor variables have the largest coefficients which indicate that they are significant predictors between financially and non-financially distressed firms. However, X_2 has a negative relationship with the financially distressed firms while X_3 and X_4 have positive lower significant predictor variables of financially distressed with values of 0.267 and 0.079 respectively. The structure matrix correlations show the correlations of each predictor variable to the predictive discriminatory variable. Table 14 shows the structure matrix correlations which are considered more accurate than the standardized canonical discriminant function coefficients. However, we do not interpret loadings in the structure matrix unless the values are 0.30 or higher. Based on the structure matrix correlation, the predictor variables that have a strong association with discriminatory variables are X_1 and X_5 with values of 0.629 and 0.426 respectively.

Table 14. Structure matrix correlations

Variables	*Function*
	1
X_1	.629
X_5	.426
X_2	.287
X_3	.283
X_4	.228

Source: Researcher's SPSS version 21 computation.

Table 15 is used to assess each predictor variable's unique contribution to the predictive discriminatory function of the study. It shows that the predictive discriminatory function has a positive relationship between X_1, X_3, X_4, and X_5.

Table 15. Canonical discriminant function coefficients

Variables	*Function*
	1
X_1	2.412
X_2	-0.229
X_3	0.661
X_4	0.032
X_5	0.763
(Constant)	-1.675

Source: Researcher's SPSS version 21 computation.

The function shows that X_1, X_5, and X_3 are the strongest predictor variables that can discriminate between financially and non-financially distressed firms in descending order of significance, while X_2 has a negative relationship with financially distressed firms. Therefore, Table 13 provides the discriminatory predictor function written as follows:

$$Z = 1.675 + 2.412X1 - 0.229X2 + 0.661X3 + 0.032X4 + 0.763X5 \tag{3}$$

The centroids express the averages of the independent variables for each group. It is an additional way of interpreting the discriminant analysis results.

Table 16. Functions at group centroids

Distressed status	*Function*
	1
Financially distressed firms	-1.342
Non-financially distressed firms	4.026

Note: Unstandardized canonical discriminant functions evaluated at group means.

Consequently, centroids are used to identify each of two categories or a group to which a firm belongs that is either into a "financially distressed firm" or a "non-financially distressed firm" in terms of the function. The centroid table is used to establish the cutting point for the discriminating cases. If the two groups are of equal size, the best cutting point is halfway between the values of the functions at group centroids, but if the groups are unequal, the optimal cutting point is the weighted average of the two values. We can determine the group to which a firm belongs by calculating a cut score halfway between the two centroids: Cut score = (4.026 -1.342)/2 = .342. This implies that if a firm discriminant score function (i.e., Z) is above 1.342 then it is probably going to be considered as non-financially distressed. However, a firm whose discriminant score is below 1.342 will be considered as financially distressed. A firm's discriminant score predicts which group it will belong to.

Table 17. Classification of results[a,c]

		Status	*Predicted group membership*		*Total*
			Financially distressed	*Non-financially distressed*	
Original	Count	Financially distressed	10	0	10
		Non-financially distressed	1	44	45
	%	Financially distressed	100.0	0	100.0
		Non-financially distressed	2.2	97.8	100.0
Cross-validated	Count	Financially distressed	9	1	10
		Non-financially distressed	1	44	45
	%	Financially distressed	90.0	10.0	100.0
		Non-financially distressed	2.2	97.8	100.0

Note: (a) 97.8% of original grouped cases correctly classified; (b) cross-validation is done only for those cases in the analysis. In cross-validation, each case is classified by the functions derived from all cases other than that case; (c) 96.4% of cross-validated grouped cases correctly classified.

Table 17 shows that the original function can generate an average prediction power of 97.8% for financially distressed firms and non-financially distressed firms respectively and the cross-validation association showed that an overall 96.4% was correctly classified. The cross-validated group is a more reliable presentation of the power of the analysis than the original grouped cases (Ayogu, Madukwe, Yekinni, 2015). The cross-validated group is often referred to as a 'Jack Knife' classification. Therefore, Table 17 implies that the MDA can predict on average 96.4% on cross-validated grouped cases correctly for the financially distressed firms and non-financially distressed firms determined by the Altman Z-score model. This outcome is consistent with Apoorva, Curpod, and Namratha (2019) and Thai et al. (2014) who argued that MDA based on quantitative models can discriminate between financially distressed and non-financially distressed firms.

4.5. Discussions of results

The two hypotheses (i.e., *H1* and *H2*) were espoused to address the purpose of this study. The result in Table 10 shows that the independent sample t-test has revealed a significant difference between the means of financially distressed firms and non-financially distressed firms' variables at confidence level two years to the demise of the financially distressed firms on the GSE. This implies that the Altman Z-score model has effectively categorised the 12 manufacturing firms into financially distressed manufacturing firms and non-financially distressed manufacturing firms'. The five predictive variables in the financially distressed firms' exhibit low profitability, low equity returns, poor liquidity, high gearing and high variability of income as compared to non-financially distress firms. In view of the result obtained from the independent sample t-test, the null hypothesis (*H1*) is rejected. This outcome is consistent with previous studies on the Altman Z-score model (Altman, 2000; Hasamain & Shah, 2012) that concluded that the model can discriminate effectively between financially distressed and non-financially distressed firms. Additionally, the results obtained from the Altman Z-score calculation for the two delisted manufactured firms (i.e., ACI and PKL) shown the firms were financially distressed in 2011, 2012, 2013, 2014, and 2015, two years to delisting on the GSE. This outcome is attached as Table 19 and Table 20 respectively in the Appendix in this study. Even though, the five predictor variables from X_1 to X_5 are collectively responsible for discriminating firms into financially and non-financially distressed firms. However, X_1 and X_5 are the major discriminators of financially distressed in this study. In view of the result obtained from MDA, the null hypothesis (*H2*) is rejected. The study revealed that the model can predict at least 96.4% for the cross-validation association of the study. Generally, an acceptable classification of at least 50% is accepted. This means that the 14 firms selected for this study, were effectively classified into financially distressed manufacturing firms and non-financially distressed manufacturing firms based on the model. This result is consistent with the conclusion drawn by Altman Z-score model that, the model can predict at least 72% for the second year, 48% for the third year when it happened, and 36% for the fourth year when it happened (Altman, 2000; Appoorva et al., 2019).

5. CONCLUSION

The study found significant differences in five predictor variables (i.e., X_1, X_2, X_3, X_4, and X_5) used to discriminate between the financially distressed manufacturing firms and non-financially distressed manufacturing firms used in this study. The study concludes that the variables of financially distressed manufacturing firms exhibit "unhealthy" financial characteristics which resulted in their delisting from the GSE in the middle of 2017. The Log determinants were quite close to each other and with a significant value of 0.000, this result confirms that the assumptions of equality of covariance matrices as well as other assumptions were not violated before the analysis was carried out. Again, the study concludes based on the results from Table 13 and Table 14 that X_1 and X_5 are the two strongest predictor variables among the five predictive variables used in this study. These predictive variables X_1 and X_5 are represented by Working capital/Total assets (WC/TA) and Sales/Total assets (S/TA) respectively. The values of X_1 and X_5 are 0.629 and 0.429 respectively in Table 14 and imply there are the major discriminators to financially distressed firms. This outcome of X_1 and X_5 being the major discriminators of financially distressed is consistent with Thai et al.'s (2014) conclusion. Therefore, running a firm with inadequate working capital to total assets will create difficulties for the firm as the firm would not be able to source inventory at the right discount and time that will eventually affect efficient operations of the firm, and that will also worsen the cash-flow possible of the firm. The study recommends to management as well as other stakeholders to pay attention to X_1 and X_5 being the two strongest discriminators of financially distressed on the GSE. The management and other stakeholders can put in corrective steps early enough to prevent bankruptcy from happening when X_1 and X_5 variables are closely monitored to enhance the efficiency of the firm. Finally, the study assumes that the variables taken from the financial statements were not manipulated prior to bankruptcy. Manipulated financial statements will affect the predictive power of MDA in this study.

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APPENDIX

Table 18. A-score model (qualitative model for failure prediction)

Process of failure predictive	***Marks***	***Total***	***This score***
Defect: Management deficiencies			
Autocratic CEO	8		
Failure to separate role of chairman & CEO	4		
Passive Board of directors	2		
Lack of balance of skills in management team	4		
Weak finance director	2		
Lack of ‘management in depth’	1		
Poor response to change	15		
Total of management deficiencies	34	34	
Defect: Accounting deficiencies			
No budgetary control	3		
No cash flow plans	3		
No costing system	3		
Total accounting deficiencies	9	9	
Total of management and accounting deficiencies	43		
High leverage	15		
Overtrading	15		
The big project-internal/external that can bring the company down	15		
Total score for mistakes	45	45	
Symptoms of failure			
Financial signs	4		
Creative accounting	4		
Any non-financial signs of problems	4		
Total symptoms of failure	12	12	
Total A-score	100	100	

Table 19. African Champion Industries (ACI)

Variables	***2011***	***2012***	***2013***	***2014***	***2015***
X_1	(4.68)	(5.91)	(1.43)	(1.51)	(1.35)
X_2	(6.50)	(2.65)	(0.15)	(0.14)	0.56
X_3	0.75	(2.04)	0.17	0.04	1.04
X_4	0.25	0.06	0.05	0.02	0.05
X_5	0.35	1.18	0.25	0.19	0.23
Z-score	(9.84)	(9.35)	(1.12)	(1.39)	(0.52)

Table 20. Pioneer Kitchenware Limited (PKL)

Variables	***2011***	***2012***	***2013***	***2014***	***2015***
X_1	(1.99)	(4.53)	(0.19)	(0.25)	(0.28)
X_2	(0.89)	(1.77)	(0.06)	(0.07)	(0.04)
X_3	(0.72)	(1.97)	(0.07)	(0.01)	(0.02)
X_4	0.89	0.88	0.55	0.39	0.37
X_5	1.00	1.05	0.02	0.04	0.01
Z-score	(1.71)	(6.35)	0.37	0.09	0.04