

Assessing the Determinants of Business Failure of Companies Listed on the Ghana Stock Exchange

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This study aims at assessing the determinants of business failure of companies listed on Ghana Stock Exchange using financial ratios as indicators of failure. Using 15 corporate determinants, a collective sample of 25 companies were split into 30% hold out sample, 70% estimation sample and the overall prediction for a cumulative five-year data set. To obtain the significant ratios that bring about business failure, factor Analysis and logit model were respectively employed to reduce the number of correlated variables into smaller uncorrelated variables and to predict the accuracy of the ratios that are significant indicators of failure. From the analysis, the corporate determinants that are consistent indicator of financial distress are profitability ratio, specifically the Return on total asset and Leverage ratio. The study therefore recommends that the regulatory authorities such as the Ghana Stock Exchange and the Securities and Exchange Commission should monitor and assess the financial health of listed firms based on the two significant financial variables (profitability ratio and Leverage ratio).

Keywords: Profitability Ratio, Logit Model, Factor Analysis, Business Failure.

BACKGROUND OF THE STUDY

The Ghana Stock Exchange is a private sector initiative that is limited by guarantee which has over the years assisted companies listed on it to raise equity capital and aided the trading of listed securities. It was established in July 1989 to serve as a public market for the trading of securities between institutions and licensed dealing members. It currently lists 42 equities from 37 companies and 2 corporate bonds (Ghana Stock Exchange, 2018). Companies listed on the Ghana Stock Exchange are grouped based on their industry. The categorized industries are banking and finance, distribution, food and beverage, mining and oil, insurance and manufacturing (GSE Fact Book, 2008). The essence of the Stock Exchange is to enable its listed companies to boost their domestic savings and increase the quantity and quality of investments through the floating of shares and bonds on the market for the growth and expansion of their

operations. It also gives investors the opportunity to increase their portfolio and liquidate some of their shares for cash.

Despite the enormous benefits available to companies listed on the Ghana Stock Exchange, it would be unprincipled to discuss business success without exploring and understanding business distress or failure which is an inevitable phenomenon in the business cycle (Arista, 2011). This phenomenon cuts across every discipline and there is no specific body of science to which failure exclusively belongs (Pretorius, 2009 cited in Arasti, 2011). Business discontinuation is an important feature of dynamic economies, and entries and exits of businesses are closely linked (Bosma et al., 2009). This phenomenon affects businesses (public and private) of all sizes but unlike small and medium scale enterprises (SMEs), the meltdown of a listed company will definitely catch the attention of the media. The health of any competitive firm is measured by its profitability and liquidity rates and once a firm faces challenges in making profit and settling debt, its development falls until it completely fails.

Business Failure, simply known as going out of business refers to a company ceasing its operations following its inability to make profit or enough revenue to cover its operational cost (Jimmy, 2009 cited in Yeboah, 2009). Business distress or failure occurs when a company becomes insolvent and cannot continue its operations.

Over the years, there have been many stories of business failure across the world. There has been the exit of establishments such as Enron Corp, WorldCom, Xerox, Lehman Brothers, AIG, and Freddie. Ghana has recorded incidents of business failure. Ghana has seen the collapse of Tano Agya Rural Bank, Meridian BIAO Bank, Plant Pool Limited (a subsidiary of Social Security), Bank for Credit Commerce International and recently, National Insurance Trust, Nova Fishing complex, State Construction Corporation, Ghana Airways Limited (Yeboah, 2009), Gateway Broadcasting Services, Ghana Co-operative Bank, Bank for Housing and Construction, National Savings, Credit Bank, Juapong Textiles Limited, Bonte Gold Mines and Divine Sea Foods Limited (Appiah, 2011).

Business distress and failure may be caused by poor leadership and supervision, inadequate financing for projects, fraudulent activities and poor marketing strategy. Business failure has ripple effects on stakeholders like investors, bankers, government and regulatory bodies, auditors, creditors and employees. However, if a number of listed firms simultaneously face financial failure, it can have wide-ranging effect on the national economy and possibly on other countries. An example is the financial crisis that occurred in Thailand in 1997 that affected most of the Asia-Pacific countries. It is then necessary to develop theoretical corporate failure prediction models to protect the market from unnecessary losses. Using these, government are able to develop policies in time to maintain industrial cohesion and minimize the damage caused to the economy as a whole.

There is a vast literature on why and how business failure occurs in various disciplines. Many research conducted are in the context of developed economies but little studies have been done in developing countries such as Ghana. Therefore, this study is relevant and adds up to literature because it seeks to assess the determinants of business failure of companies listed on the Ghana Stock Exchange.

REVIEW OF LITERATURE

The type one of business failure mostly occurs to newly established firms or small companies. Failure of these indicates that their performance never arose above poor before it sank. These companies mostly collapse within five years of its establishment. The company is mostly characterized by lack of managerial expertise since it may have only one manager. It may have limited financial system such as budget, cost system to carefully examine revenue, and make financial reports. This deficiency could make the owner overestimate the revenue or underestimate cost leading to more financial distress. They may as a result of insufficient funds obtain loans or launch big projects with the intention of raising funds but mostly they begin life with serious defects (Mofokeng, 2012).

The type two of corporate failure occurs to young companies that have survived longer than the type one companies. This type of companies' performances shoot upwards till it reaches its apex or maximum then dwindles. These firms face a similar managerial handicap as the type one companies but they

diversify their operations thereby increasing their sales. As the sales increase, it brings about new capital resources which are readily available for trading. Since the company is known and in the public eye, the company will attempt various strategies that will help them succeed. The company therefore sells more (mostly on credit) and borrow more to fund their operations. Their sales grow rapidly but with no profit to matchup. This deters banks from giving further credit to the business for its operations. This will have a negative impact on the companies hence halting their operations. The collapse of these companies occur swiftly and no creative accounting could save the company from collapse (Mofokeng, 2012).

The type three of failure affects companies that are mature and have been in existence for years. These businesses before failure experienced a slow start, rapid buildup, then an indefinite period of stable 'good to excellent' performance (S-curve). They have high turnovers, good profit margins and low gearing rates. These companies have much more complex operations. This failure is about 20%-30% of all business failures.

They may have experienced defects in their management structure in the form of a non-participating management board and defects in their accounting information system which might not have been quickly resolved (Mofokeng, 2012).

Empirical Literature Review

Beaver (1966), one of the pioneers of quantitative model studied corporate failure using financial ratios. He explored 79 failed and 79 non-failed companies between 1954 and 1964. He based his prediction using 30 ratios and these ratios were applied five years prior to failure. He concluded that the significant ratio for predicting failure was cash flow to total debt ratio with a definite success precision of 78%.

Altman (1968) developed the multivariate discriminant model with the aim of solving some of the deficiencies of the univariate system. In this investigation, he matched 33 failed and non-failed companies with the years of 1946 and 1965, using a combination of ratios into one score to determine the financial stability of the firm. He concluded using that a higher z-score meant a higher or better financial health and a lower z-score indicated poor financial health (Altman, 1968).

Neophytou and Molinero (2004) applied the multidimensional scaling to predict corporate failure. The technique has a link with factor analysis (component analysis). This technique is superior to others because it is easy to understand. Its robust nature makes it less convincing, they concluded their research that the MDS results produced show that failed and non-failed firms fail in some clearly distinct areas.

Andreica (2009) in her study applied the CHAID model, the logit and hazard model and the ANN model in predicting the probability of bankruptcy of a set of distressed and non-distressed firms from 2006 to 2008. She concluded that the profitability ratios were the best predictors of bankruptcy. The second set of her three-year cumulative data highlighted solvency ratio as an indicator of bankruptcy with a precision of 96.7%.

Appiah (2011) examined business failure in a developing economy. He examined business failure on listed companies on the Ghana Stock Exchange. He applied the Altman Z-score model on a sample of 15 failed and non-failed companies from the year 2004 to 2005. He presented that corporate failure cannot be predicted using the Altman model due to the high type II errors.

Mohammed (2013) in her study using the Altman's (1993) Z-score showed that current ratio, retained earnings to total asset, earnings before interest, taxes to total assets and book value of equity to total liabilities can be used to successfully predict failures.

According to Orabi (2014) tested the effectiveness of financial failure prediction models on forecasting the failure of public shareholding companies. He tested and compared the Altman model and the Sherrod model to ten shareholding companies listed on the ASE. He concludes in his study that the Altman is a better reflector to screen out successful companies from failing ones.

Bunyaminu and Bashiru (2014) examined a combination of quantitative and qualitative models to predict business failure with an appreciable degree of accuracy and precision. They asserted that failed firms face inability to settle debts, have weak finance directors and possess low profitability.

Bunyaminu (2015) explored business prediction models. He made an empirical study of business failure using survival analysis and generalized linear modeling (GLM). He matched companies from all the industry sector categories from 1994 to 2011. He concluded in the study that financial ratios and non-financial factors (managerial factors) have significant predictive ability for detecting failure of Ghana's public listed companies.

Muntari (2015) assessed the financial distress of listed companies to understand their sources, signs, detection and elimination. He applied the Altman Z-score on the financial statements from 2007 to 2013 of ten listed companies on the Ghana Stock Exchange. He found that six companies were financially sound, two were in financial distress and the remaining two were experiencing financial deterioration.

METHODOLOGY AND DATA

Sample Size and Sampling

Both distressed and non-distressed were drawn from the six industry sector categories on the Ghana Stock Exchange. The data set sampled consisted of twelve companies, that is, six were distressed and six were non-distressed companies to ensure that there are equal sets of distressed and non-distressed companies for matching. The six matched-pairs of distressed and non-distressed companies were matched based on their industry, asset turnover and size.

TABLE 1
CAYEGORIES OF COMPANIES

Categories	Sector
1	Banking & Finance
2	Distribution
3	Food & Beverage
4	Insurance
5	Manufacturing
6	Mining & Oil

Source: GSE Fact Book (2018)

Data Collection

The data and information used in the research was secondary data from secondary sources. The secondary data employed were the published financial annual statements of both distressed and non-distressed companies obtained from the Ghana Stock Exchange and its Fact Books. Financial ratios were computed from the available financial reports and this is shown in table 2 below. There were nineteen (19) financial ratios calculated and these ratios fell broadly under five main ratio categories namely: Profitability, Leverage, Asset Utilization, Growth Ability and Size.

TABLE 2
FINANCIAL RATIOS

Category	Code	Financial Ratios	Definition
Profitability/ Employee efficiency	X ₁	Return on shareholders' funds (%)	Net profit or loss / Equity *100
	X ₂	Return on capital employed (%)	(Net profit or loss / Total assets-Current liabilities) *100
	X ₃	Return on total assets (%)	(Net profit or loss / Total assets) *100
	X ₄	Profit margin (%)	(Net profit or loss / Turnover)*100
	X ₅	Profit per employee (unit)	Net profit or loss / Number of employees
	X ₆	Turnover per employee (unit)	Operating revenue / Number of employees
Leverage/ Liquidity	X ₇	Current ratio (x)	Current assets / Current liabilities
	X ₈	Liquidity ratio (x)	Current assets-Stocks / Current liabilities
	X ₉	Solvency ratio (%)	(Equity/ Total assets) *100
	X ₁₀	Gearing (%)	Long-term debts + Normal overdraft / Equity *100
	X ₁₁	Interest cover (x)	Earnings before interest and taxes(EBIT)/ Interest expense
Asset Utilisation	X ₁₂	Working capital per employee (unit)	Working capital / Number of employees
	X ₁₃	Total assets per employee (unit)	Total assets / Number employees
	X ₁₄	Net assets turnover (x)	Turnover/ Net assets
	X ₁₅	Fixed assets turnover (x)	Turnover/ Fixed assets
Growth Ability	X ₁₆	Turnover growth	(Turnover 1- Turnover 0) / Turnover 0
	X ₁₇	Growth rate on net profit	(Net P/ L 1 - Net P/L 0) / Net P/L 0
	X ₁₈	Growth rate on total assets	(Total assets 1 – Total assets 0) / Total assets 0
Size	X ₁₉	Total assets	Total assets

In many previous researches, missing values of financial ratios were simply deleted from the analysis and those missing value trimmed by ratios with extreme values at certain percentiles and replacing the missing values by mean or random values (Tucker, 1996). By this principle, this research instead of deleting missing variables replaced them with the mean values of the financial ratios using the SPSS software package.

Data Analysis

Factor Analysis Technique

The study initially used nineteen ratios which got reduced to 15 due to inability to find data for certain ratios. The Factor Analysis was then used to reduce the dimensionality of the data from 15 ratios to 9 financial ratios. The Factor Analysis is a mathematical, statistical and chronological technique that aided to reduce the dimensionality of the financial data. This helps to sample out significant ratios that clearly identify whether a firm is distressed or non-distressed and to almost accurately predict corporate failure.

Misra and Vikram (2008) (as cited in Bunyaminu & Bashiru, 2014) explained Factor Analysis model as a mathematical model that attempts to reduce a large number of inter-correlated variables to a smaller number of uncorrelated factors. Factor Analysis involves a mathematical procedure that reduces the dimensionality of the initial data space by transforming a number of possibly correlated variables into a smaller number of uncorrelated variables called Factors. These factors are synthetic variables of maximum variance, computed as a linear combination of the original variables (Andreica et al., 2009). The Factor Analysis procedure employed in this research was adopted from Bunyaminu and Issah (2012) but with some minor adjustment.

Regression Analysis (Logit) Model

The logistic model, according to Shumway (2001), is a single-period classification model which uses maximum likelihood estimation to provide the conditional probability of a firm belonging to a certain category given the values of the independent variables for that firm. It explains the relationship between a dichotomous variable (Y) which takes the values 1 or 0 for distress and non-distress companies respectively and their explanatory variables (X_i) representing its financial ratios. The Logit model was employed in this research by combining several characteristics into a probability score for each company, which identified the 'vulnerability to failure' or the 'failure probability'. The model was adopted from Ohlson (1980); Tucker (1996); Abdullah et al. (2008, p. 205) and Bunyaminu and Issah (2012).

$$Z_i = \beta'x_i + u_i \quad (1)$$

where: Z_i is a Discriminant score for company i

β' is the weight (coefficient) of variables

x_i is company's financial ratios

u_i is an error term

Z_i ranges from $-\infty$ to $+\infty$

The probability and likelihood function for the non-failed company can be defined as follows:

$$P_i = E(Y = 2 | X_i) = \frac{1}{1 + e^{-(\beta'x_i + u_i)}} \quad (2)$$

For ease of exposition, it is written as

$$P_i = \frac{1}{1 + e^{-z_i}}$$

where $Z_i = \beta'x_i + u_i$

Equation (2) represents what is known as the (cumulative) logistic distribution function.

For the application of the logit prediction model, the weights of each financial ratio was estimated in equation (1) using the financial ratios of listed companies. If P_i represents the probability of non-failed company which is given in equation (2), then $(1 - P_i)$ would be the probability of failed. For a failed firm, it would take the form:

$$1 - P_i = 1 - \frac{1}{1 + e^{-z_i}} \quad (3)$$

In applying this model, a cut-off probability must be estimated. The estimated probability from the logit model is then compared to the pre-determined cut-off score to classify an observation into one of the groups, whether distressed or non-distressed. The cut-off point for the study was set at 0.5 as frequently used in most previous research though others have used multiple cut-offs to test their results. If the probability estimated falls below the cut-off, the firm is said to be non-distressed but if it is above the cut-off probability score, the observation is considered distressed. However, the approach for determining the cut-off probability is still indecisive and depends on the context and payoff functions.

DATA ANALYSIS AND RESULTS

Factor Analysis

A sample of 25 companies for the cumulative five years was split into a 30% holdout sample and a 70% estimation sample. The Factor Analysis method was used and the results are indicated in table 3.

TABLE 3
TOTAL VARIANCE

Total Variance Explained

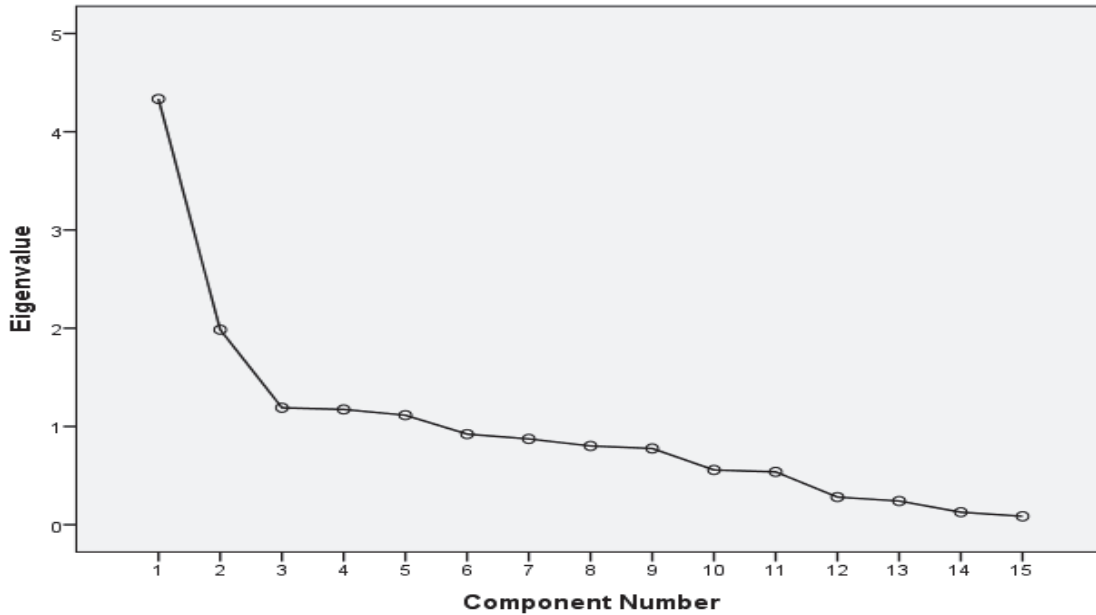
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.334	28.891	28.891	4.334	28.891	28.891	3.015	20.097	20.097
2	1.985	13.233	42.124	1.985	13.233	42.124	2.135	14.236	34.333
3	1.190	7.936	50.060	1.190	7.936	50.060	1.968	13.120	47.453
4	1.173	7.821	57.881	1.173	7.821	57.881	1.500	9.999	57.452
5	1.115	7.431	65.312	1.115	7.431	65.312	1.179	7.860	65.312
6	0.922	6.149	71.461						
7	0.874	5.824	77.286						
8	0.801	5.343	82.629						
9	0.776	5.174	87.803						
10	0.557	3.714	91.517						
11	0.538	3.584	95.101						
12	0.281	1.875	96.976						
13	0.241	1.606	98.582						
14	0.127	0.850	99.432						
15	0.085	0.568	100.000						

Extraction Method: Principal Component Analysis.

The Table 3 shows the Total Variance Explained for the eigenvalues. From the table there are five eigenvalues greater than 1. The first five values arranged in descending order are: $\lambda_1=4.334$, $\lambda_2=1.985$, $\lambda_3=1.190$, $\lambda_4=1.173$ and $\lambda_5=1.115$. The first factor contributes the highest of about 28.89% of the total gain of recovered information, followed by the second and third factors contributing 13.23% and 7.94% respectively. The fourth and fifth factors add 7.82% and 7.43% respectively to the cumulative total variance explained. These five factors constitute about 65.31% significance to the variance. This proves that many ratios have been presented and accounted for.

The Scree plot below, Figure 1 displays the eigenvalues of the factors used. Using Cattell’s criteria, the plot inculcates just three factors for representing the data. It would hence be suitable to use the three sufficient components.

**FIGURE 1
THE SCREE PLOT**



The Rotated Factor Matrix

Table 4 shows the partial correlation between the rotated factor and the financial ratios. The financial ratio above 0.5 for each factor is chosen. The rotation had effect of associating the Current ratio (87.2%), Liquidity ratio (81%), Fixed Asset turnover (61.4%), Growth rate on net profit (93.4%) more with the first factor; Return on total assets (65.5%), Profit margin (69.1%) with the second factor; Net asset turnover (86.2%), Fixed asset turnover (66.6%) with the third factor; Return on capital employed (64.4%) with the fourth factor and Turnover growth (57.1%) with the fifth factor.

TABLE 4
ROTATED FACTOR MATRIX

	Factor				
	1	2	3	4	5
Return on shareholders' funds (%)	0.051	0.217	0.035	0.075	0.012
Return on capital employed (%)	0.076	0.492	0.153	.644	0.036
Return on total assets (%)	0.363	0.655	0.238	-0.185	0.121
Profit margin (%)	0.055	0.691	-0.032	0.353	0.019
Current ratio (x)	0.872	0.117	0.090	0.036	0.333
Liquidity ratio (x)	0.810	0.145	0.133	0.067	0.354
Solvency ratio (%)	0.038	0.412	0.078	0.070	-0.025
Gearing (%)	00.065	0.302	0.092	0.393	-0.024
Interest cover (x)	0.025	0.471	0.075	-0.108	0.216
Net assets turnover (x)	0.166	0.230	0.862	-0.056	0.146
Fixed assets turnover (x)	0.614	0.200	0.666	-0.075	-0.213
Turnover growth	0.213	0.081	0.028	0.001	0.571
Growth rate on net profit	0.934	0.118	0.139	0.018	-0.037
Growth rate on total assets	0.010	0.008	-0.012	0.059	0.011
Total assets	-0.068	-0.048	-0.034	0.185	-0.057

Extraction Method: Principal Axis Factoring.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 7 iterations.

TABLE 5
SUMMARIZED FACTOR ANALYSIS RESULT

Data Set	Initial Set of Variables	Variables Excluded	Factors Retained	% of Gained Information
Cumulative Five-Year Data Sets	X ₁ , X ₂ , X ₃ , X ₄ , X ₇ , X ₈ , X ₉ , X ₁₀ , X ₁₁ , X ₁₄ , X ₁₅ , X ₁₆ , X ₁₇ , X ₁₈ , X ₁₉	X ₁ , X ₉ , X ₁₀ , X ₁₁ , X ₁₈ , X ₁₉	X ₂ , X ₃ , X ₄ , X ₇ , X ₈ , X ₁₄ , X ₁₅ , X ₁₆ , X ₁₇	65.31%%

The Table 5 highlights the factors retained after employing the factor analysis. The variables retained are return on capital employed, return on total assets, profit margin, current ratio, liquidity ratio, net assets turnover, fixed assets turnover, turnover growth and growth rate on net profit.

The Stepwise Regression Analysis

Estimation Sample

The Stepwise method was used in developing the regression model for the descriptive variables. This technique is suitable since it combines all the explanatory variables into the model chronologically. In this research, the model employs variables with the highest correlation with the predicted variables. If a

variable is insignificantly contributing to a predicted variable, the variable can be exempted. This method is thereby helpful if the independent variables are large and of great significance to the model. The research considered models 1, 2, and 3 on the Stepwise Regression Model in the table below (Table 6) as the best models.

TABLE 6
COEFFICIENTS OF THE VARIABLES FROM ESTIMATION SAMPLE (70% DATA)

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients		95.0% Confidence Interval for B		
		B	Std. Error	Beta	T	Sig.	Lower Bound	Upper Bound
1	(Constant)	1.910	0.078		24.399	0.000	1.752	2.069
	Return on total assets (%)	-0.032	0.004	-0.768	-7.298	0.000	-0.040	-0.023
2	(Constant)	2.029	0.069		29.412	0.000	1.889	2.169
	Return on total assets (%)	-0.022	0.004	-0.526	-5.199	0.000	-0.030	-0.013
	Return on capital employed (%)	-0.015	0.003	-0.452	-4.468	0.000	-0.022	-0.008
3	(Constant)	2.046	0.064		32.154	0.000	1.917	2.175
	Return on total assets (%)	-0.017	0.004	-0.420	-4.182	0.000	-0.026	-0.009
	Return on capital employed (%)	-0.014	0.003	-0.419	-4.466	0.000	-0.020	-0.008
	Liquidity ratio (x)	-0.013	0.005	-0.253	-2.776	0.009	-0.022	-0.003

a. Dependent Variable: Type of company

Justification for Selecting Models 1, 2 and 3 as the Best Models

The SPSS package selects explanatory variables that are highly significant in influencing the dependent variable. The model identified Return on total assets variable being the highest contributor to the dependent variable (Distressed and Non-Distressed Companies). It then identified Return on capital employed ratio (%) as having the second highest partial correlation with the dependent variable, so it is added to the second model, model 2. Liquidity ratio (%) contributed the third highest and it is added to the model 3 (with reference Table 6).

Mathematically the final and best model for the estimation sample is: $Y = 2.046 - 0.017X_2 - 0.014X_3 - 0.013X_8$

TABLE 7
MODEL SUMMARY FOR ESTIMATION SAMPLE (70% DATA)

Model Summary^d

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.768 ^a	0.590	0.579	0.32856
2	0.858 ^b	0.736	0.722	0.26715
3	0.885 ^c	0.784	0.765	0.24528

The estimation sample using the Stepwise model produced an overall accuracy of 76.5% as in Table 7. The variables considered to be significant are profitability ratios (return on total assets, return on capital employed) and leverage ratios (liquidity ratio).

This means that financially distressed companies have low return on total assets, return on capital employed and liquidity. A non-distressed firm may however, have a high return on total assets, return on capital employed and liquidity.

Hold-out Sample

TABLE 8
RESULT OF HOLD-OUT SAMPLE (30% DATA)

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients		Sig.
		B	Std. Error	Beta	t	
1	(Constant)	1.558	0.072		21.718	0.000
	Return on capital employed (%)	-0.015	0.003	-0.646	-4.708	0.000

a. Dependent Variable: Type of company

For the hold-out sample (shown in Table 8), only one model was generated. It then identified Return on capital employed ratio (%) as having the highest partial correlation with the dependent variable. Mathematically the final and best model for the hold-out sample is: $Y = 1.558 - 0.015X_2$

TABLE 9
MODEL SUMMARY FROM THE HOLD-OUT SAMPLE

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.646 ^a	0.417	0.398	0.39231

a. Predictors: (Constant), Return on capital employed (%)

Construction and Testing of Prediction Model

With regards to Table 9, showed that for the hold-out sample using the logit model has produced an overall accuracy of 39.8% for the cumulative five-year data set. The variable considered to be significant is Profitability ratio (return on capital employed).

Overall Logit Model (Overall Five Years)

The overall prediction using the logit model can be obtained from the tables below, consisting of the coefficients for the logit model, excluded variables and the model summary of the logit model.

The STEPWISE model produces four models. The SPSS package then selects explanatory variables that are highly significant to the dependent variable. The model identified profit margin ratio as being the highest contributor to the dependent variable (distressed and non-distressed companies). It then identified return on capital employed ratio (%) as having the second highest partial correlation with dependent variable, so it is added to the second model, model 2. Return on total assets ratio contributed the third highest and it is added to the model 3. Model 4 included all the previous variables with liquidity ratio which is the fourth highest contributor to the dependent variable (in Table 10).

Mathematically the final and best model for the overall logit model is: $Y = 1.805 - 0.005X_2 - 0.007X_3 - 0.013X_4 - 0.012X_8$.

TABLE 10
COEFFICIENTS FOR THE OVERALL LOGIT MODEL

		Coefficients ^a						
		Unstandardized Coefficients		Standardized Coefficients		95.0% Confidence Interval for B		
Model		B	Std. Error	Beta	T	Sig.	Lower Bound	Upper Bound
1	(Constant)	1.636	0.043		38.426	0.000	1.551	1.720
	Profit margin (%)	-0.010	0.001	-0.638	-8.966	0.000	-0.012	-0.008
2	(Constant)	1.673	0.040		41.534	0.000	1.593	1.753
	Profit margin (%)	-0.006	0.001	-0.419	-5.121	0.000	-0.009	-0.004
	Return on capital employed (%)	-0.008	0.002	-0.370	-4.515	0.000	-0.011	-0.004
3	(Constant)	1.790	0.047		37.778	0.000	1.697	1.884
	Profit margin (%)	-0.004	0.001	-0.274	-3.248	0.002	-0.007	-0.002
	Return on capital employed (%)	-0.008	0.002	-0.384	-4.996	0.000	-0.011	-0.005
	Return on total assets (%)	-0.018	0.004	-0.288	-4.107	0.000	-0.027	-0.009
4	(Constant)	1.805	0.047		38.341	0.000	1.712	1.898
	Profit margin (%)	-0.005	0.001	-0.305	-3.625	0.000	-0.007	-0.002
	Return on capital employed (%)	-0.007	0.002	-0.353	-4.586	0.000	-0.010	-0.004
	Return on total assets (%)	-0.013	0.005	-0.213	-2.772	0.007	-0.023	-0.004
	Liquidity ratio (x)	-0.012	0.006	-0.153	-2.213	0.029	-0.023	-0.001

a. Dependent Variable: Type of company

**TABLE 11
MODEL SUMMARY FOR THE LOGIT MODEL**

Model Summary^e

Model R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.638 ^a	0.407	0.38325
2	0.704 ^b	0.496	0.35497
3	0.749 ^c	0.560	0.33293
4	0.761 ^d	0.578	0.32742

a. Predictors: (Constant), Profit margin (%)

b. Predictors: (Constant), Profit margin (%), Return on capital employed (%)

c. Predictors: (Constant), Profit margin (%), Return on capital employed (%), Return on total assets (%)

d. Predictors: (Constant), Profit margin (%), Return on capital employed (%), Return on total assets (%), Liquidity ratio

e. Dependent Variable: Type of company

Construction and Testing of Prediction Model

The study showed that the logit model has produced an overall accuracy of 57.8% for the cumulative five-year data set. The variables (shown 11) considered to be significant are Profitability ratio (profit margin, return on capital employed, return on total assets) and leverage model (liquidity ratio). For a non-distressed companies, they may have high returns on the significant variables while the distressed firms may suffer low returns on the significant variables.

**TABLE 12
SUMMARIZED PREDICTION RESULTS**

Logit Model					
Data Set	Estimation Sample	Hold Out Sample	Overall Prediction	Significant Variable	
Cumulative Five-Year Data Sets	88.5%	64.6%	76.1%	Return	on total assets

From the table 12 above, for the five-year cumulative data sets, the estimation sample yielded 88.5% and the hold-out sample resulted in an accuracy of 64.6%. Comparing the 70% estimation sample and the 30% holdout sample, the estimation sample yielded a higher accuracy level as compared to that of the hold-out sample.

The overall prediction accuracy for the Logit model is 76.1%. This is above that of the hold out sample. The study identified return on total assets to be the most significant variable for predicting corporate failure. This ratio cuts across the estimation sample, hold-out sample and the logit model.

KEY CONTRIBUTIONS OF THE PAPER

The significant ratios that have shown to be consistent indicators of both companies are profitability ratio (profit margin, return on capital employed, return on total assets) and leverage ratio (liquidity ratio). This study affirmed that distressed firms experience low profitability and high level of debt. This is consistent to the results reported by Charitou et al. (2004); Abdullah et al. (2008); Neophytou et al. (2000) and Ciampi and Gordini (2008).

This study clearly shows that there are no surprises in firms folding up. Companies in Ghana on the brink of failure will post low profits made worse by high debt regime, which should send alarm bells for stakeholders to figure out a bail out before the situation takes a turn for the worse resulting in abject failure with dire consequences.

CONCLUSION

The descriptive statistics concluded that distressed companies had a remarkably low gearing ratio and non-distressed companies had high gearing ratios, where that of the distressed companies is pegged at -1.84% and 99.69% for the non-distressed, an indication that the non-distressed type rely more on debt financing. It was also found that the Interest Cover of the distressed and the non-distressed companies could not be compared because the value for the distressed was 2.51%, while the non-distressed, valued 119.8%.

The mean value of Profit Margin for the failed companies is negative with a value of -2.13, while there were no negative values for non-distressed companies. Return on Capital Employed happened to be the best predictor of failure as identified with the logit model.

The justification for selecting the logit model was principally because recent reports suggested that where the dependent variables (distressed or non-distressed) are binary, it gave a more accurate results. But however, this model still holds on to some few drawbacks with respect to its underlying assumptions.

The predictor variables used in the construction of the model was selected using Factor Analysis and the conclusions reached are purely based on the cumulative five-year data sets. The Factor Analysis concluded that nine (9) factors are significant- Return on Capital Employed, Return on Total Assets, Profit Margin and Current Ratio, Liquidity Ratio, Net Asset Turnover, Fixed Assets Turnover, Turnover Growth and Growth Rate on Net Profit with total information gained of 65.31%.

The Logit Model constructed was evaluated in terms of estimation sample, hold out sample and overall prediction point of view. The estimation sample by far produced a strong prediction accuracy rate of 88.5% for the cumulative five-year data set. The significant variables that have appeared as a constant indicator of financially distressed companies in the Logit Model were Profitability Ratios (Return on Total Assets, Return on Capital Employed and Profit Margin) and Leverage model (Liquidity Ratio).

The only recognised variable for the hold-out Sample concluded by the Logit Model was Return on Capital Employed as the only good predictor of failure while the other variables such as Current Ratio, Liquidity Ratio, Fixed Assets Turnover, Growth Rate on Net Profit, Return on Total Assets, Profit Margin Net Assets Turnover and Turnover Growth were excluded from the determinants, resulting in a lower accuracy rate of 64.60%.

The logit model employed for the study showed overall prediction strength of 76.10%. The effect was eminent as it reflected in only four factors being significant- Profit Margin, Return on Capital Employed, Return on Total Assets and Liquidity Ratio.

DISCLAIMER

Authors declare that they do not have any contending financial, professional, or personal interests from other parties.

REFERENCES

- Abdullah, N.A.H., Halim A., Ahmad, H., & Rus R.Md. (2008). Predicting corporate failure of Malaysia's listed companies: Comparing multiple discriminant analysis, logistic regression and the hazard model. *International research journal of finance and economics*, 15, 201-217.
- Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, 23(4), 589-609.
- Andreica, M.E (2009). *Predicting Romanian financial distressed companies*. MSc Dissertation. Doctoral School of Banking and Finance, Bucharest.
- Arasti, Z. (2011). An empirical study on the causes of business failure in Iranian context. *African journal of business Management*, 17(5), 7488-7498.
- Bahson, P., & Bartley, J. (1992). The sensitivity of failure prediction model to alternative definitions of failure. *Advances in accounting*, 10, 255-278.
- Balcaen, S., & Ooghe, H. (2004). *35 years of studies on business failure: an overview of the classical statistical methodologies and related problems*. Dissertation, Ghent University.
- Beaver, W. H. (1966), Financial ratios and predictors of failure, *Empirical Research in Accounting: Selected Studies, Supplement of Accounting Research*, 71-111. Institute of Professional Accounting, Chicago, IL.
- Bunyaminu, A., & Bashiru, S. (2014). Corporate failure prediction: A fresh technique for dealing effectively with normality based on quantitative and qualitative approach. *International journal of financial economics*, 2(1), 1-12.
- Bunyaminu, A., & Issah, M. (2012). Predicting corporate failure of UK's listed companies: Comparing multiple discriminant analysis and logistic Regression. *International research journal of finance and economics*, 94, 1450-2887.
- Bunyaminu, A. (2015). Business failure prediction: An empirical study based on survival analysis and generalized linear modeling (GLM) Techniques. *International journal of financial economics*, 4(3), 135-149.
- Business Failure. P5 Advanced performance management. (n.d.). Retrieved May 9, 2019, from www.accaglobal.com/zm/en/student/exam-support-resources/professional-exams-study
- Charitou, A., Neophytou, E., & Charalambous, C. (2004). Predicting corporate failure: Empirical evidence from the UK. *European accounting review*, 13(3), 465-497.
- Ciampi, F., & Gordini, N. (2008). *Using economic-financial ratios for small enterprise default prediction modelling: An empirical analysis*. Oxford business & economics conference program. ISBN : 978-0-9742114-7-3
- Donkor, S. (2011). *Determinants of business failure: The perspective of SMEs building contractors in the Ghanaian construction industry*. Thesis, Kwame Nkrumah University of science and technology.
- Ghana Stock Exchange (n.d.). *Overview of Ghana Stock Exchange*. Retrieved May 29, 2019, from <https://gse.com.gh/about/overview>
- Ihab, A. I. (2014). *Financial cash flow determinants of company failure in the construction industry*. Doctorial dissertation, University of Michigan.
- Mahama, M. (2015). Assessing the state of financial distress in listed companies in Ghana: Signs, sources, detection and elimination – A test of Altman's Z-Score. *European Journal of Business and Management*, 7(3), 1-10.
- Mofokeng, T. G. (2012). *Assessment of the causes of failure among small and medium sized construction companies in the free state province*. Dissertation, University of Johannesburg.
- Mohammed S. (2013). Bankruptcy prediction of firms listed at the Nairobi securities exchange. Dissertation, University of Nairobi.
- Narayanan P., & Altman, E. (1997). Business failure classification models: An International survey. *Financial markets. Institutions and instruments*, 6(2), 1-57.
- Neophytou, E., & Mar-Molinero, C. (2001). *Predicting Corporate Failure in UK; A Multidimensional Scaling Approach*. Working Paper. School of Management, University of Southampton, pp. 1-23.

- Ohlson, J. (1980). Financial Ratios and their Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, 1, Spring, 109-131.
- Pogue, M. (2008). *Business failure: Prediction and prevention*. ACCA Student Accountant (June-July). Retrieved March 13, 2019, from http://www.accaglobal.com/content/dam/acca/global/PDFstudents/2012/sa_jj08_mpogue.pdf
- Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *Journal of business*, 74(1), 101-124.
- Yeboah, A. (2009). *Business failure in Ghana: A case of Ghana airways limited*. Thesis, Kwame Nkrumah University of Science and Technology.