Business Failure Prediction: A Tri-dimensional Approach

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Investigations of corporate failure prediction research usually implement binary classification into one of the distinguished groups – Distress or non-Distress companies. This study looks at a tri-dimensional approach which cluster firms into three (3) distinct dimensions namely - non-distress, semi-distressed and distressed. The study used secondary data from 2011 to 2015 obtained from the Ghana Stock Exchange (GSE) spanning across six industries, namely, Banking & Finance, Distribution, Food & Beverage, Insurance, Manufacturing and Mining & Oil. The study initially adopted the Altman (1968) Z score bankruptcy model to classify companies into non-distress, semi-distressed and distressed. Further analysis was conducted using the Hierarchical agglomerative cluster analysis to cluster companies into non-distress, semi-distressed and distressed. A comparison was then made between the Hierarchical agglomerative clustering against the Altman (1968) Z score bankruptcy classification to obtain higher classification. The outcome of the analysis revealed that the Hierarchical agglomerative cluster analysis and the Altman (1968) Z score bankruptcy model can both be used to classify companies into non-distress, semi-distressed and distressed based on the tri-dimensional approach instead of the binary classification (distressed and non-distressed). The study recommends that future research can explore other clustering methods for bankruptcy prediction to achieve higher and better classification.

INTRODUCTION

Investigations of corporate failure prediction research usually implement binary classification of companies into one of two distinct groups – distress or non-distress companies (Altman 1983; Ballantine, Cleveland & Koeller, 1992; D'Aveni, 1989; Dugan & Zavgren, 1989; Koh & Killough, 1990; Pech & Alistair 1993; Shumway, 2001; Chava & Jarrow, 2004; Bunyaminu & Issah, 2012; Bunyaminu & Bashiru, 2014; Bunyaminu, 2015; Gavurova, Packova, Misankova & Smrcka, 2017). Using this dichotomous approach (Taffler, 1983; Storey et al., 1987; Neophytou et al., 2000), there is a possibility of misclassification. Different from the previous studies, this study adopts a tri-dimensional approach to cluster firms into three (3) distinct groups, namely - non-distress, semi-distressed and distressed.

Using various statistical techniques, business failure prediction models attempt to estimate the bankruptcy probability of a firm using a set of covariates such as financial ratios, market-related variables, or non-financial variables. Some of the researchers in this field point out that the causes for distress are mostly external (exogenous), rather than internal (endogenous, or caused by mismanagement) and others argue that various industries could exhibit characteristics involving high grades of failure.

DEVELOPMENT OF FAILURE PREDICTION MODELS AND SUBSEQUENT REFINEMENTS

Prior to the development of business failure prediction models or techniques, agencies such as Dun and Bradstreet were established to supply a qualitative type of information assessing the credit-worthiness of particular merchants (Altman, 1968). However, business failure prediction became a subject of formal quantitative analysis since 1932 when Fitzpatrick (1932) compared ratios of successful industrial enterprises with those of failed firms and these were matched according to date, size and industry. Consequently, the development of corporate failure models started with univariate analysis, pioneered by Beaver (1966).

Beaver (1966) applied financial ratios and each ratio was classified separately. A percentage of misclassification (failed or non-failed) was minimized as a result of the identification of an optimal cut-off point, misclassification could either be a Type I error (classifying a failing firm as non-failing), or Type II error (classifying a non-failing firm as failing). Beaver's approach explored 79 failed and 79 non-failed companies between 1954 and 1964. The study examined the predictive power of 30 ratios when applied five years prior to failure. Beaver (1966) identified that the most significant ratio in predicting failure is 'Cash flow to total debt' ratio with 78% success rate for five years before failing. Each failed company was matched with a non-failed company in terms of size and industry.

Even though Beaver's univariate approach was simple and serves as a platform for further research and development of corporate failure prediction models, there are a number of potential problems. It could be argued that Beaver's company classification was based on a single financial ratio at the time and the classification result for different ratios used on the same company could be confusing and misleading (Poque, 2008).

Altman (1968) considered that the adoption of univariate results for assessing bankruptcy potential of a firm is both theoretically and practically questionable and that ratio analysis presented in univariate fashion is susceptible to faulty interpretation and potentially confusing. To correct these deficiencies in univariate models, Altman (1968) came out with a multivariate analytical method; Multiple Discriminant Analysis (MDA) in 1968. Altman (1968) conducted his research on 33 bankrupt companies and 33 non-bankrupt companies during the period 1946 to 1965 and a total of 22 ratios were identified from 5 different categories: Profitability; Liquidity; Leverage; Solvency and Activity. According to Altman's original Z-score model, a company is considered relatively safe when its Z-score exceed 2.99; Companies with Z-scores of less than 1.8 would be considered as potential failures. Until 1980's discriminant analysis was the dominant method in failure prediction. However, it suffered from the normality assumption test, particularly for the failing firms.

Despite these limitations, researchers seem to turn deaf ear and continued to advance Altman's model, hoping to achieve higher classification accuracy. Some of the studies that have sought to advance Altman's model include: application of prior probability membership classes (Deakin, 1972); using appropriate 'quadratic classifier' (Altman, Haldeman & Narayanan, 1977); use of cash flow based models (Gentry, Newbold & Whitford, 1987); application of quarterly financial statement information (Baldwin & Glezen, 1992) and analysis of the use of current cost information (Aly, Barlow & Jones, 1992; Keasy & Watson, 1986). Nonetheless, none of these studies have been able to achieve higher statistically significant results than Altman's earlier work. Furthermore, in most cases, these models appeared so complex and difficult to apply in real life applications.

Due to the well-documented restrictions of the linear discriminant analysis approach, Ohlson (1980) employed logistic regression to predict company failure, a technique that evades some of the problems of the MDA approach. Since then, logistic regression has been extensively used for the development of bankruptcy models. Extensions to Ohlson's study include, among others, the following: (a) the investigation of the effect of industry-related ratios on the likelihood of corporate failure (Platt & Platt, 1990); (b) the attempt to discriminate between firms in financial distress and failed firms (Gilbert et al., 1990); (c) the development of industry-specific models (Platt et al., 1994); (d) the adoption of a multinomial logit approach to reduce misclassification error by adding, to the outcome space used to predict bankruptcy, a 'weak' state of financial distress (Johnsen & Melicher,1994) multicriteria decision aid methodology (Zopounidis & Doumpos, 1999); (e) a comparative predictive power of MDA and logistic Regression model using UK's listed companies (Bunyaminu & Issah, 2012) and (f) the use of Generalized linear modeling (GLM) to solve the problem of normality assumption test to predict business failure (Bunyaminu & Bashiru, 2014).

To avoid the deficiencies of the traditional normality prone approaches in corporate failure prediction, there is an urgent need to model non-linearities using Generalised Linear Models instead of single-period static models (Shumway, 2001; Chava & Jarrow, 2004; Hillegeist et al., 2004). The GLM are considered to be broader in scope in the sense that they apply to all industry sectors; Financial and non-financial institutions to handle non-linear modelling and evaluate the forecast performance based on static and non-linearity (Bunyaminu & Bashiru, 2014).

Types of Business Failure

Type 1

This is a type of business failure that mostly occurs to newly established firms or small companies. Failure of this kind indicates that performance never arose above poor before it sank. These companies mostly collapse within five years of its establishment. This type of failure mostly does not attract attention. 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, cost 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.

Type 2

With this type of corporate failure, it occurs to young companies that have survived longer than the type one companies. This type of companies' performances shoots 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.

Type 3

This type of failure affects companies that are mature and have been in existence for years. These businesses before failure experience 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).

Causes of Business Failure

Failure is a phenomenon every individual or entity would wish to avoid completely but this threat is inevitable if situations are not analyzed and monitored. The distress and fall of businesses are as a result of many factors. Firstly, companies would fail as a result of inadequate financing and poor financial planning. Businesses need cash flow to float them through sales and the natural flow of business. Funds for business operation may be obtained internally through contributions or externally through the floating of shares and taking loan advances.

In sourcing for funds from financial institutions, companies face the problem of competing with the government for loans. The financial institutions would prefer to extend credit to the government since they view the government to be of no risk when it comes to loan repayment as compared to the companies. If the companies are able to get these credit facilities, they may have to pay a much higher interest rate on the loans. This problem worsens when the company also suffers poor cash flow management. Where the company fails to properly manage its inflows and outflows, getting sufficient money from banks will be of little benefit to business growth.

Secondly, businesses fail due to the lack of proper management and leadership. Management of a business entails a number of activities which include planning, organizing, controlling, directing and communication. There is said to be poor management of the company when the owners of the firm fail to recognize their shortfalls and seek help followed by insufficient relevant business experience. Business failure can be attributed to the problem of wrong delegation and hiring the wrong people for the right job. Poor leadership is also a contributing factor to the failure of businesses. Leadership is a key component of management. Businesses run down as a result of insufficient leadership skills and techniques to coordinate and synchronize the activities of the employees.

Also, some companies fail as a result of poor marketing strategies. It is essential to provide the necessary information and product idea to the customers. Businesses are at risk of failure when they apply the wrong marketing strategy towards a particular product and target market.

Finally, businesses fail as a result of fraudulent activities. Some of the businesses suffer some fraudulent acts such as mismanagement and embezzlement of funds, illegal fund transfers etc. These acts can wear out the financial stability of the company, reducing their cash holding and making it difficult for the firm to run its normal business operations.

Theories on Business Failure

For the purpose of this research, the researchers adopted two (2) theories. These include:

1. Lussier's theory and
2. Life cycle theory

Lussier's Theory

Preceding success and failure model studies have been conducted by Carter and Van Auken (2006) and Cooper et al. (1990). The Lussier (1995) model was selected to be used in this study for the following reasons. Lussier's model was the most extensive because the study examined the efficacy of 15 variables identified from 20 prior studies. The Lussier (1995) model has been published in more journals (Lussier 1995; 1996a, 1996b; Lussier & Corman, 1996; Lussier & Pfeifer, 2000) and has been used to predict success and failure cross-nationally in the USA (Lussier, 1995), Croatia (Lussier & Pfeifer, 2001), and in Chile (Lussier & Halabi, 2010). The Lussier model includes human capital variables—industry experience, management experience, and education. It is designed to determine which variables are more and less important to success and failure. Thus, the Lussier (1995) model was selected for the purpose of this research.

Lussier (1995) researched the literature to better understand why some businesses succeeded and others failed. To be included in the Lussier (1995) S/F model, a variable had to have been included in a study that had at least three variables identified as contributing factors to success and failure. Fifteen variables were identified in the literature and for each of the variables a hypothesis was developed to explain the relationship between the independent variable and the dependent variable performance—success vs. failure.

Life Cycle Theory

The stage model or life cycle theory of the firm originates in economics literature (Penrose, 1952, 1959; Rostow, 1960), and is used to describe the progression of the successful firm through growth phases. A biological analogy is sometimes used to describe "the cyclical quality of organizational existence. Organizations are born, grow, and decline. Sometimes they reawaken, sometimes they disappear" (Kimberly & Miles, 1980). The life cycle model describes the development and progression of the firm as a linear sequential process through a number of stages. Numerous stage models have been developed in the management and organizational studies literature (d'Amboise & Muldowney, 1988; Poutziouris, 2003), although the number of stages is not standardized (Lester et al., 2008). For example, Steinmetz (1969) proposes a model based on three phases of growth, whilst Lester et al. (2008) propose a five-stage model of organizational growth and development. In deriving taxonomy of growth stages for high-technology organizations, Hanks et al. (1994) identify common developmental stages based on the comparison of a number of stage models, namely start-up, expansion, maturity, diversification, and decline. Specifying age categories for each developmental stage in a universal life cycle model is difficult because of intra industry differences. Attempts to assign specific age groups thus tend to be confined to particular sectors (Hanks et al., 1994). Similar to the stage model developed in the organizational studies literature, the financial life cycle theory models firm resourcing across a number of development stages. Presented as a descriptive concept in early textbooks (Weston & Brigham, 1978), it outlines sources of finance typically available at various growth stages of the firm, along with potential financing problems that may arise at each stage. The financial life cycle model incorporates elements of trade-off, agency (Jensen & Meckling, 1976), and pecking order theories (Myers, 1984; Myers & Majluf, 1984), and describes sources of finance typically advanced by funders at each stage of a firm's development. The commonly held view is that nascent and start-up firms have difficulty accessing external finance, as this is when problems related to information opacity are most severe (Huyghebaert & Van De Gucht, 2007). The most important sources of finance at this stage are personal savings of the firm owner, and finance from friends and family (Ullah & Taylor, 2007). These informal sources of equity exceed venture finance as the main source of capital for start-up companies, even in the US which is considered the most advanced economy in the world in the provision of venture capital (Bygrave & Quill, 2007). The contribution of the firm owner in nascent firms is not confined to equity, but commonly includes the provision of quasi-equity in the form of personal assets used as collateral to secure business debt (Basu & Parker, 2001). Whilst a firm may obtain sufficient capital to initiate trading, a lack of planning may lead to problems of under-capitalization in the earliest stages. In extreme cases, particularly in the face of competition, the firm may not be able to continue in business (Cressy, 2006). As successful firms survive nascent and start-up phases and matures through growth stages, personal funding becomes relatively less important as investment finance is increasingly sourced from retained profits.

Furthermore, accumulation of a trading history facilitates access to increased sources and amounts of external financing, particularly bank finance and trade credit. Rapidly expanding firms lacking adequate working capital to meet increased costs may experience liquidity problems at this stage (Bates & Bell, 1968). Firms faced with the problem of overtrading often seek to alleviate these liquidity problems by increasing their overdraft facility. Thus, it is common for SMEs to have high levels of short-term debt (Ray & Hutchinson, 1983; Michaelas et al., 1999). Short-term debt is neither sufficient nor appropriate for firms requiring large amounts of additional external finance for investment; however, these requirements are more suitably fulfilled by long-term debt, or by raising external equity through a private placement or an initial public offering of common stock. Firms requiring large amounts of external equity are characterized by the pursuit of a high growth strategy, and may be involved in the development of products or services based on new technology (Ullah & Taylor, 2007). A consequence of the sale of firm equity for the owner is loss of control and managerial independence, although a number of authors indicate that this outcome may be compatible with the firm owner's goals (Berggren et al., 2000; Hogan

& Hutson, 2005). On reaching maturity, firms have acquired a trading history, and typically have access to a broad range of resources. Sources of finance accessed at this stage are generally determined by preferences of firm owners, rather than supply side restrictions. The life cycle theory has been applied to predict a probable path of firm development. They have been used to suggest managerial skills, knowledge, attitudes (Lippett & Schmidt, 1967; priorities (Smith, Mitchell & Summer, 1985); efficient ways of problem solving (Lyden, 1975); provide a model for small business growth (Scott & Bruce 1987); identify internal (Churchill & Lewis, 1983) and external (Quinn & Cameron, 1983) factors of success and failure for business. The role of innovation and entrepreneurial activity has been analyzed in the early stage of firm development by Kimberly (1979) using this framework. The life cycle phenomenon has been found meaningful by SME owner managers and evidence has been provided for the sequential nature of life cycles (Lester et al., 2008).

Empirical Review

Various concepts of failure have been reviewed in previous studies but the design for the research adopted failure as defined in the UK Insolvency Act 1986 which states that an insolvent company is a company with inability to pay debts when they fall due or the value of its assets is less than liabilities taking into accounts its contingent liabilities and prospective liabilities. The Act further outlined five courses of action for companies to follow if they end up insolvent and these are: administration, company voluntary arrangement, receivership, liquidation and dissolution. Failed companies in this study were considered from this point of view. Receivership which is a type of bail out was not considered since none of the companies benefited from such government facilities.

Beaver (1966), one of the pioneers of quantitative models, 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 within the years of 1946 and 1965, using a combination of ratios into one score to determine the financial stability of the firm. He concluded 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) in their study applied the multidimensional scaling (MDS) 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 by new users. Its robust nature makes it more convincing. They concluded that the MDS results showed that both 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 artificial neural network 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.

In a study using Altman's Z-score, Mohammed (2016) showed that current ratio, retained earnings to total asset, earnings before interest and taxes to total assets and book value of equity to total liabilities can be used to successfully predict failures.

In his article in Interdisciplinary Journal of Contemporary Research in Business, Orabi (2014) studied and 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 concluded 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. 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.

Mahama (2015) conducted research in assessing the financial distress of listed companies understanding 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

In addition to the Altman Z-score, this study employs an alternative technique to the corporate failure prediction models, Cluster Analysis (CA).

Cluster Analysis (CA)

Cluster Analysis (CA) is defined as a family of data reduction techniques employed for separating cases, observations, or variables of a given dataset into homogeneous classes that are distinct from each other (Yim & Ramdeen, 2015). CA is a term given to a set of multivariate techniques that starts with a data set containing information about entities/objects and attempts to reorganize these into relatively homogenous groups. Also, because of the frequent instability of the results arising from standard statistical techniques, the user needs to supplement statistics with judgement. CA however, offers simple visual appealing graphical representation which does not require in-depth statistical knowledge.

Clustering techniques can be divisive or agglomerative:

(a) A divisive method begins with all cases in one cluster. This cluster is gradually broken down into smaller and smaller cluster.

(b) Agglomerative techniques start with (usually) single member clusters. These are gradually fused until one large cluster is formed. This study specifically focuses on hierarchical agglomerative cluster analysis. The hierarchical agglomerative cluster analysis is a statistical technique where groups are serially formed by systematically merging similar clusters together, as dictated by the distance and linkage measures chosen by the researcher (Yim & Ramdeen, 2015). The present paper focuses on hierarchical clustering, that has the goal of increasing within-group homogeneity and between-groups heterogeneity.

Clustering techniques can also be monothetic or polythetic:

(i) In *monothetic* scheme cluster membership is based on the presence or absence of a single characteristic.

(ii) *Polythetic* schemes use more than one characteristic (variable)

Five basic steps that characterize all CA methods have been used in this study:

(i) Selection of factors (financial variables) to be clustered
(ii) Definition of a set of variables on which to measure the entities in the sample
(iii) Computation of similarity/dissimilarity among companies
(iv) Use of a cluster analysis method to create groups of similar entities
(v) Validation of resulting clusters

Proximity-dissimilarities and Similarity Measures

To create clusters, we have to measure how near or farther our objects are; their proximities. This study has done this using either similarity or dissimilarity measures and shall refer to both of these as distances.

The SPSS has a multitude of distance measures that are appropriate for each type of data; interval, count or binary. The commonest measure is the Euclidean distance. In this connection, the study has used the Euclidean distance measure based on Pythagoras's theorem applied to points whose co-ordinates are given by the financial ratios used in the research. To find the distance from company a to company b, we find the difference on financial factor 1 and square it, distance on financial factor 2 and square it…add up all the squared differences and take the square root.

Mathematically the Euclidean distance between company a to company b when we have p number of financial ratios (factors) is:

$$d_{ab}\sqrt{\sum_{k=1}^{p}\left(x_{ak}-x_{bk}\right)^{2}}$$

One issue about the Euclidean distance is that they can be greatly influenced by variables that have the largest values. To overcome this issue, this study has standardized variables to bring them to equal scale. The study used the SPSS software that has its in-built function of transforming all the variables to z-scores, such that their means = 0 and Standard deviation = 1.

There are various clustering methods, but the one used in this study is Agglomerative Hierarchical method, specifically the between group single linkage.

The Agglomerative Hierarchical clustering method operates on the principle that each organization is considered to be a single member cluster to the final state where there is a single cluster containing all n number of financial factors.

Single Linkage: Nearest Neighbor

The form of clustering method used in this study is the type of single linkage known as the nearest neighbor. Suppose we have n objects. We treat each one as being a 'cluster' containing one object at the moment. The study conducted the following in carrying out the nearest neighbor technique:

(i) Start with n clusters. Each contains one individual.

(ii) Find the distances between all pairs of clusters. This is presented as a matrix. Unite the two closest financial ratios, say a and b. into a single group so that there are then (n-1) clusters.

(iii) Find all the pairwise dissimilarities again. The dissimilarity between this cluster and any other individual is defined by min ( ). In this case, we used the shortest distance from a cluster to another cluster to form the new matrix of distances

(iv) Find the shortest distance in the revised distance matrix. Unite these two closest 'clusters' which will either be two singletons or will be one singleton and the group of two formed in (ii).

(v) Construct a new dissimilarity/distance matrix for the (n-2) clusters.

As studies by many researchers have shown that financial insolvency models are basically unstable, in that the coefficients of a model will differ base on the economic health of a country (Moyer, 1977; Mensah, 1984), hence the need to use an accurate model with current data sets is paramount (Keasy & Watson, 1991). As a result, a more recent data set spanning from 2011 to 2015 of public listed companies (both failed and healthy) on Ghana Stock Exchange (GSE) is used. The study adapted the Z-Score bankruptcy model based on three (3) distinct dimensions namely - non-distress, semi-distressed and distressed with small refinements as follows:

Z Score Bankruptcy Model

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5$$

Based on our categorization, those companies having a z-score to be greater than 2.99 are considered as Non-distressed (Safe Zone), those between 1.81 to 2.99 are classified as Semi-distressed (Gray Zone) and those having the Z-Score to be less than 1.81 are considered as Distressed (Distressed Zone).

Zones of Discrimination

$Z > 2.99$ – "Safe" Zone
$1.81 < Z < 2.99$ – "Gray" Zone
$Z < 1.81$ – "Distress" Zone

The following symbols X1, X2, X3, X4, and X5 are define as follows. The symbol " / " means the same thing as " ÷ ", representing division.

X_1 = working capital / total assets
X_2 = retained earnings / total assets
X_3 = earnings before interest and taxes / total assets
X_4 = market value of equity / total liabilities
X_5 = sales / total assets
Z = overall index.

Variable Categorization

The study collected data from the financial statement of selected firms using five cooperate determinants (ratios) or variables for analysis. The variables are categorized into five standard ratio classification as: liquidity, profitability, leverage, solvency, and activity. The ratios are chosen on the basis of their popularity in the literature and their potential relevancy to the study. The Beaver study (1967) affirmed that the cash flow to debt ratio was the best single ratio predictor. However, this ratio was not considered in this study due to its lack of consistent and precise depreciation and cash flow data. In order to attain the final profile of variables, the following steps were considered:

1. Analysis of the statistical significance of various alternative functions, including evaluation of the relative contributions of each independent variable;
2. determination of inter-relationships among the relevant variables;
3. determination of the predictive accuracy of the various profiles; and
4. judgment of the analyst.

X1, Working Capital/Total Assets (WC/TA)

The working capital/total assets ratio, often found in corporate failure researches, is calculated using the net liquid assets of the firm relative to the total capitalization. Working capital is considered as the difference between current assets and current liabilities. Liquidity and size characteristics are explicitly considered. Usually, a firm having constant operating losses will have dwindling current assets in relation to total assets.

X2, Retained Earnings/Total Assets (RE/TA)

Retained earnings is considered as the account which reports the total amount of reinvested earnings and/or losses of a firm over its entire life. The account is also considered as earned surplus. It is worth mentioning that the retained earnings account is subject to "manipulation" via corporate quasi-reorganizations and stock dividend declarations. Although this issue is not apparent in this study, it is plausible that a bias would be formulated by a considerable reorganization or stock dividend and suitable

readjustments should be made to the accounts. The longevity of a firm is unreservedly considered in this ratio. For instance, a relatively young firm will probably show a low RE/TA ratio because it has not stayed for long to build up its cumulative profits. It is an undisputable fact that the younger firms are susceptible to failure and their chances of being classified as bankrupt is relatively higher than that of older firms. Indeed, this is precisely the situation in the real world. The situation of failure is much higher in firms with earlier years than newer years. In 1993, nearly 50% of all firms that failed were all within the first five years of their existence (Altman, 2000).
Furthermore, the RE/TA ratio determines the leverage of a firm. Those firms with high RE, relative to TA, have financed their assets through retention of profits and have not made use of much debt.

X3, Earnings Before Interest and Taxes/Total Assets (EBIT/TA)

This ratio is the amount of true productivity of the firm's assets, independent of any tax or leverage factors. Since a firm's main existence is relative to the earning power of its assets, this ratio appears to be particularly relevant for studies dealing with corporate failure.
Furthermore, insolvency in a bankrupt sense occurs when the total liabilities exceed a fair valuation of the firm's assets with value determined by the earning power of the assets (Altman & Rijken, 2011).

X4, Market Value of Equity/Book Value of Total Liabilities (MVE/TL)

Equity is determined using the combined market value of all shares of stock, preferred and common, whereas liabilities encompasses the current and long term liabilities. The ratio indicates how much the firm's assets can drop in value (determined by market value of equity plus debt) before the liabilities exceed the assets and the firm becomes insolvent. This ratio includes a market value component which most other failure studies did not consider. The ratio also appears to be a more active predictor of bankruptcy than a similar, more commonly used ratio; net worth/total debt (book values). The equity market value serves as a proxy for the firm's asset values.

X5, Sales/Total Assets (S/TA)

The capital-turnover ratio is a standard financial ratio depicting the sales generating capability of the firm's assets. It is one measure of management's capacity in handling competitive conditions of the business. This last ratio is quite relevant as it is the least important ratio on an individual basis. The ratio has a unique relationship to other variables in the model, the sales/total assets ratio ranks second in its contribution to the overall discriminating ability of the model.

The Data

The data consist of six industry sector categories on the Ghana Stock Exchange from 2011 to 2015 and were matched during the same time span. Below is a table showing the industry sector categories:

TABLE 1
INDUSTRY SECTOR CATEGORY

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

Source: GSE Fact Book (2018)

The data employed were the published annual financial statements of both distressed and non-distressed companies obtained from the Internet, Ghana Stock Exchange and its Fact Books. Financial ratios were computed from the available financial reports.

Data Analysis and Key Findings

Descriptive Statistics

The study explored the effects of the following ratios of Altman Z-score model: X1 = working capital / total assets, X2 = retained earnings / total assets, X3 = earnings before interest and taxes / total assets, X4 = market value of equity / total liabilities and X5 = sales / total assets on survival or otherwise of 23 companies. For anonymity, the companies have been given pseudo names: C1 - C23.

When the data were subjected to critical analysis, it emerged that some of the companies were classified as distressed, semi-distressed and non-distressed. Out of the total number of 23 companies considered for the study, 16 were classified as non-distressed companies (i.e. C4, C5, C6, C10, C11, C14, C15, C19, C9, C16, C3, C18, C17, C7 and C8); 6 companies were classified as distressed (i.e. C1, C23, C2, C13, C12, C22 and C21) and only 1 was considered as semi-distressed (i.e. C20). Table 2 shows the calculation and classifications of the companies.

TABLE 2
RATIOS

Company	X1	X2	X3	X4	X5	Z Score	Remarks
C4	0.115	0.045	4.4920	18.318	0.132	26.147	Non-distressed
C5	0.115	4.523	4.522	34.048	0.132	41.955	Non-distressed
C6	0.116	4.334	4.334	0.032	0.106	20.636	Non-distressed
C10	0.059	4.720	4.720	0.077	0.148	22.449	Non-distressed
C11	1.778	5.681	5.681	0.080	0	28.884	Non-distressed
C14	0.208	1.968	1.967	0.008	0.072	9.574	Non-distressed
C15	0.209	2.227	2.227	0.008	0.074	10.799	Non-distressed
C19	0.078	2.737	2.737	11.367	0.144	19.923	Non-distressed
C9	0.220	21.525	21.525	0.169	1.423	102.959	Non-distressed
C16	-0.126	0.010	1.024	0.021	1.034	4.289	Non-distressed
C1	-0.062	-4.998	-4.998	0.992	0.630	-22.341	Distressed
C3	0.311	0.001	21.567	0.999	0.924	73.067	Non-distressed
C23	-0.071	0.0002	10.563	0.963	1.782	37.133	Distressed
C18	0.311	3.686	3.686	0.989	1.261	19.549	Non-distressed
C2	0.096	-7.108	-7.108	0.219	11.918	-21.256	Distressed
C13	-0.061	-30.810	-30.810	0.021	1.036	-143.829	Distressed
C12	-0.038	5.722	5.722	0.958	4.091	-31.509	Distressed
C17	0.051	4.693	4.693	1.221	0.614	23.464	Non-distressed
C22	0.023	-1.606	-1.606	0.011	0.206	-7.307	Distressed
C7	0.915	29.401	29.401	2972.668	0.386	1923.272	Non-distressed
C8	0.846	12.485	12.485	0.009	0.119	59.822	Non-distressed
C20	0.043	0.005	0.523	0.153	0.647	2.524	Semi-distressed
C21	0.051	-0.0001	-0.014	0.108	0.502	0.581	Distressed

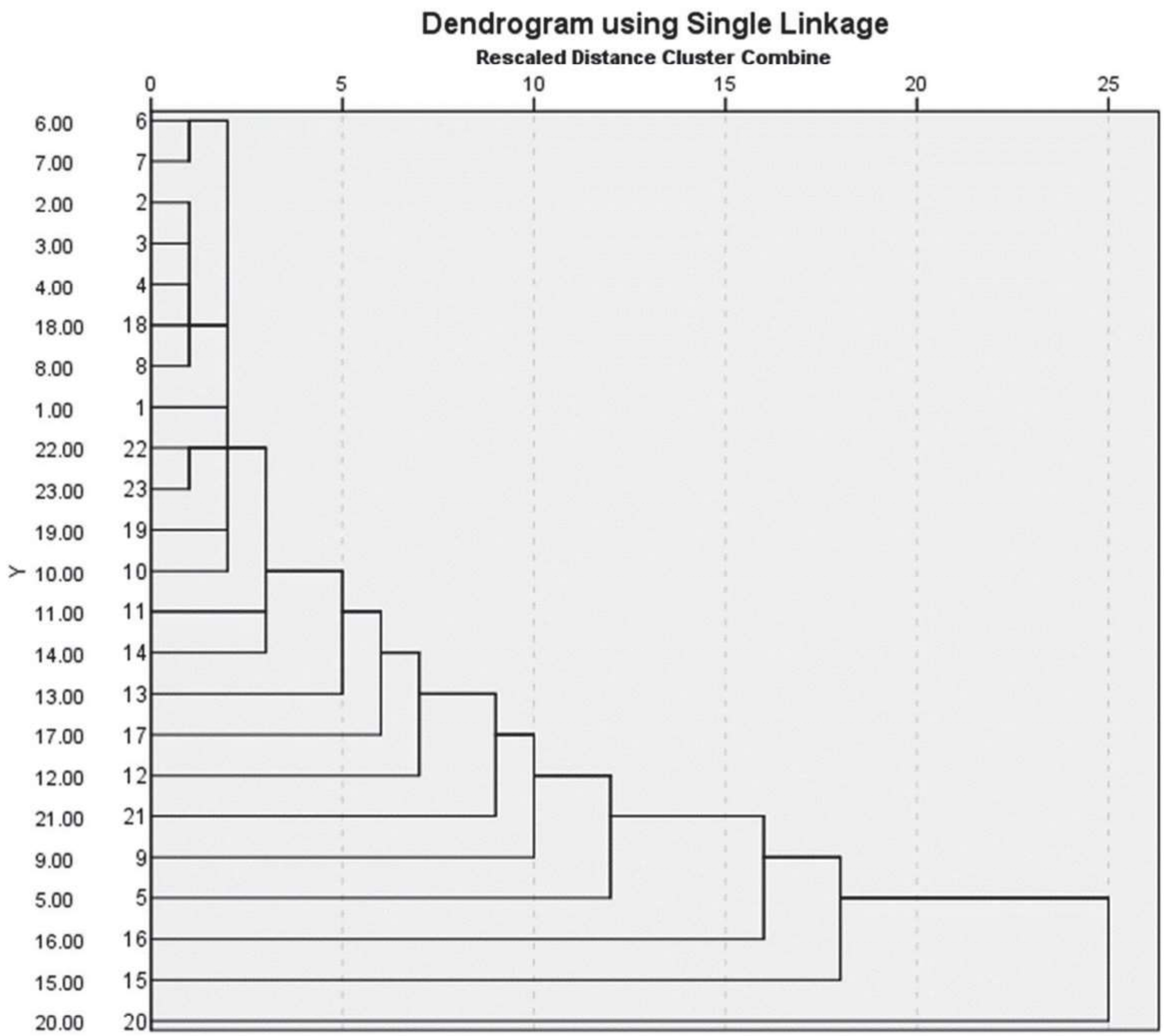
The researchers tried comparing the results of the classification based on the Altman Z-Score with that of the hierarchical clustering technique to ascertain if it will provide the same classification results. The following analysis of the hierarchical clustering method were therefore conducted

Hierarchical Clustering Method

Dendrograms

The results of a hierarchical clustering are presented as a dendrogram (tree diagram). This is a display of the hierarchical structure implied by the dissimilarity matrix and clustered by a linkage rule. If we use nearest neighbor clustering method with the Euclidean distance measure, then the following dendrogram is the main output.

FIGURE 1
DENDOGRAMS



The dendrogram shows relative similarities between cases. Notice how the 'branches' merge together as you look from left to right in the dendrogram.

The vertical line superimposing on the dendrogram produces a solution that has small within-cluster distance, but large between-cluster distances. The dendrogram suggests three cluster solution comprising one singleton and two other clusters. The branch that is separated and bigger at the upper part of the dendrogram is the singleton.

Proximity Matrix

From the analysis, the Euclidean distance proximities indicate how dissimilar the case study companies are. The study has classified companies with similar Euclidean distance proximities into three (3) groups. This is similar to the three-cluster solution earlier discovered on the dendrogram.

From the proximity matrix table in Table 3, companies that are different from each other have Euclidean distances that are dissimilar. For instance, C4 which is taken as Case 1 has an Euclidean distance of 0.418. This is different from the following companies in terms of proximity as follows: C11 (2.559), C3 (1.595), C2 (4.865), C13 (4.254), C12 (1.711), C17 (6.208) and C8 (2.190). Table 4 provides a summary of all companies with similar Euclidean distances. Those that are in the same group are similar in proximity and bear similar Euclidean distances and are likely to be classified under one group. Based on the Altman Z-score classification, the study can classify the companies into three (3) clusters: those with Euclidean distance from 0.418 - 1.5 (non-distressed); 1.6 - 6.40 (semi-distressed) and 6.50 – 9.35 (distressed).

TABLE 3
PROXIMITY MATRIX

	Euclidean Distance																						
Case	1.00	2.00	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00	11.00	12.00	13.00	14.00	15.00	16.00	17.00	18.00	19.00	20.00	21.00	22.00	23.00
1.00	0.000	0.418	0.401	0.457	3.952	0.361	0.362	0.307	2.559	0.738	1.060	1.595	0.953	0.733	4.865	4.254	1.711	0.498	0.597	6.208	2.190	0.439	0.448
2.00	0.418	0.000	0.061	0.146	3.918	0.398	0.372	0.247	2.247	0.852	1.302	1.648	1.042	0.656	4.940	4.548	1.631	0.250	0.815	6.015	2.000	0.611	0.619
3.00	0.401	0.061	0.000	0.146	3.915	0.372	0.347	0.225	2.272	0.842	1.282	1.659	1.050	0.655	4.943	4.525	1.643	0.258	0.791	6.071	2.009	0.592	0.597
4.00	0.457	0.146	0.146	0.000	4.050	0.499	0.477	0.258	2.239	0.782	1.288	1.678	0.987	0.754	4.942	4.562	1.598	0.187	0.813	6.088	2.103	0.607	0.621
5.00	3.952	3.918	3.915	4.050	0.000	3.725	3.719	4.021	4.227	4.550	4.549	3.777	4.462	3.499	6.407	6.375	4.577	4.073	4.235	6.031	2.360	4.150	4.135
6.00	0.361	0.398	0.372	0.499	3.725	0.000	0.033	0.325	2.557	0.899	1.117	1.774	1.224	0.576	4.882	4.253	1.774	0.551	0.633	6.174	2.015	0.503	0.481
7.00	0.362	0.372	0.347	0.477	3.719	0.033	0.000	0.318	2.524	0.908	1.144	1.754	1.214	0.563	4.889	4.286	1.765	0.532	0.659	6.155	1.992	0.520	0.500
8.00	0.307	0.247	0.225	0.258	4.021	0.325	0.318	0.000	2.477	0.666	1.060	1.783	1.041	0.718	4.871	4.313	1.646	0.319	0.570	6.195	2.196	0.387	0.384
9.00	2.559	2.247	2.272	2.239	4.227	2.557	2.524	2.477	0.000	2.814	3.468	2.026	2.329	2.290	5.573	6.721	2.363	2.211	3.031	5.187	1.944	2.768	2.804
10.00	0.738	0.852	0.842	0.782	4.550	0.899	0.908	0.666	2.814	0.000	0.737	2.072	0.896	1.113	4.488	4.002	1.410	0.705	0.556	6.540	2.780	0.430	0.476
11.00	1.060	1.302	1.282	1.288	4.549	1.117	1.144	1.060	3.468	0.737	0.000	2.531	1.511	1.438	4.535	3.302	1.948	1.267	0.507	6.903	3.099	0.716	0.693
12.00	1.595	1.648	1.659	1.678	3.777	1.774	1.754	1.783	2.026	2.072	2.531	0.000	1.361	1.607	5.128	5.476	2.118	1.661	2.162	5.750	1.916	1.949	1.992
13.00	0.953	1.042	1.050	0.987	4.462	1.224	1.214	1.041	2.329	0.896	1.511	1.361	0.000	1.153	4.404	4.628	1.149	0.869	1.265	6.240	2.545	1.024	1.095
14.00	0.733	0.656	0.655	0.754	3.499	0.576	0.563	0.718	2.290	1.113	1.438	1.607	1.153	0.000	4.506	4.494	1.422	0.675	1.045	5.998	1.749	0.807	0.831
15.00	4.865	4.940	4.943	4.942	6.407	4.882	4.889	4.871	5.573	4.488	4.535	5.128	4.404	4.506	0.000	5.312	3.546	4.764	4.737	8.353	5.624	4.604	4.653
16.00	4.254	4.548	4.525	4.562	6.375	4.253	4.286	4.313	6.721	4.002	3.302	5.476	4.628	4.494	5.312	0.000	4.825	4.547	3.751	9.358	5.940	3.979	3.950
17.00	1.711	1.631	1.643	1.598	4.577	1.774	1.765	1.646	2.363	1.410	1.948	2.118	1.149	1.422	3.546	4.825	0.000	1.412	1.819	6.278	2.757	1.556	1.624
18.00	0.498	0.250	0.258	0.187	4.073	0.551	0.532	0.319	2.211	0.705	1.267	1.661	0.869	0.675	4.764	4.547	1.412	0.000	0.824	6.094	2.128	0.569	0.602
19.00	0.597	0.815	0.791	0.813	4.235	0.633	0.659	0.570	3.031	0.556	0.507	2.162	1.265	1.045	4.737	3.751	1.819	0.824	0.000	6.569	2.644	0.301	0.245
20.00	6.208	6.015	6.071	6.088	6.031	6.174	6.155	6.195	5.187	6.540	6.903	5.750	6.240	5.998	8.353	9.358	6.278	6.094	6.569	0.000	5.268	6.414	6.427
21.00	2.190	2.000	2.009	2.103	2.360	2.015	1.992	2.196	1.944	2.780	3.099	1.916	2.545	1.749	5.624	5.940	2.757	2.128	2.644	5.268	0.000	2.462	2.465
22.00	0.439	0.611	0.592	0.607	4.150	0.503	0.520	0.387	2.768	0.430	0.716	1.949	1.024	0.807	4.604	3.979	1.556	0.569	0.301	6.414	2.462	0.000	0.077
23.00	0.448	0.619	0.597	0.621	4.135	0.481	0.500	0.384	2.804	0.476	0.693	1.992	1.095	0.831	4.653	3.950	1.624	0.602	0.245	6.427	2.465	0.077	0.000

This is a dissimilarity matrix

TABLE 4

Companies	**Range of Euclidean distance proximities**	**Remarks**
C4, C5, C6, C10, C11, C14, C15, C19, C9, C16, C3, C18, C17, C7 and C8	0.41 - 1.5	Cluster 1/non-distressed
C1, C23, C2, C13, C12, C22 and C21	6.50 – 9.35	Cluster 2/distressed
C20	1.6 - 6.40	Cluster 3/semi-distressed

The agglomeration schedule in Table 5 shows how the cases are clustered at each stage of the analysis. For example, at stage 1 cases 6 and 7 are joined with a coefficient of 0.033, at stage 2 cases 2 and 3 are joined with a coefficient of 0.061 etc., all the way to case 14 which all have coefficients less than 1.0. Thereafter, there is sudden jump from case 15 with a coefficient of 1.149 to case 21 that has a coefficient of 3.546. However, the coefficient of case 22 is unique with a value of 5.817, implies that case also belong to its own classification. We may say that case 1 to 14 belong to one cluster which will be considered as group of non-distressed companies. Similarly, case 15 to 21 also belongs to another set of clusters and may be regarded as distressed and finally only one case, case 22 is unique in its coefficient. It will then be classified as the only company that was picked by Altman (1968) classifier as semi-distressed. According to Yim and Ramdeen (2015), the coefficient values of agglomeration schedule are dependent on the proximity measure and the linkage method used. The more homogeneous the two clusters are the smaller the coefficient values, the larger the values the more dissimilar or distant the clusters being combined.

TABLE 5
AGGLOMERATION SCHEDULE

	Cluster Combined			Stage Cluster First Appears		
Stage	Cluster 1	Cluster 2	Coefficients	Cluster 1	Cluster 2	Next Stage
1	6	7	0.033	0	0	9
2	2	3	0.061	0	0	4
3	22	23	0.077	0	0	7
4	2	4	0.146	2	0	5
5	2	18	0.187	4	0	6
6	2	8	0.225	5	0	8
7	19	22	0.245	0	3	10
8	1	2	0.307	0	6	9
9	1	6	0.318	8	1	10
10	1	19	0.384	9	7	11
11	1	10	0.430	10	0	12
12	1	11	0.507	11	0	13
13	1	14	0.563	12	0	14
14	1	13	0.869	13	0	15
15	1	17	1.149	14	0	16
16	1	12	1.361	15	0	17
17	1	21	1.749	16	0	18
18	1	9	1.944	17	0	19
19	1	5	2.360	18	0	20
20	1	16	3.302	19	0	21
21	1	15	3.546	20	0	22
22	1	20	5.187	21	0	0

TABLE 6
CLUSTER MEMBERSHIP

Case Number	Company	Cluster	Distance
1	1.00	1	15.210
2	2.00	1	30.430
3	3.00	1	4.005
4	4.00	1	3.901
5	5.00	1	4.379
6	6.00	1	5.671
7	7.00	1	5.414
8	8.00	1	8.397
9	9.00	1	23.918
10	10.00	1	7.155
11	11.00	3	13.740
12	12.00	1	16.410
13	13.00	1	6.749
14	14.00	1	3.477
15	15.00	3	12.580
16	16.00	3	23.604
17	17.00	1	4.735
18	18.00	1	2.835
19	19.00	1	9.925
20	20.00	2	.000
21	21.00	1	11.542
22	22.00	1	7.428
23	23.00	1	7.846

Table 6 shows cluster membership for each case. Cluster membership attempts to group individual constituents or items into homogeneous sub-sets. This can be interpreted by looking for the cases that are grouped together. From Table 6, it is evident that companies 1-10, 12-14, 17-19, 21-23 are grouped under cluster 1 as follows: C4, C5, C6, C10, C11, C14, C15, C19, C9, C16, C3, C23, C18, C12, C17, C22, C8, C7, C21. These companies will then be considered as non-distressed. Similarly, companies C1, C2 and C13 are also classified under cluster 2 and can then be considered as distressed companies. Finally, only one company, company C20 is classified under cluster 3 and that may also be considered as semi-distressed company.

From the hierarchical clustering it is evident that, out of the 23 companies considered in the study, 19 companies (C4, C5, C6, C10, C11, C14, C15, C19, C9, C16, C3, C23, C18, C12, C17, C22, C7, C8, C21) have been distinctively categorized as non-distressed. Similarly, 3 companies (C1, C2 and C13) have been classified as distressed and only 1comapny C20 is classified as Semi-Distressed.

CONCLUSION

This study applied both Z-score classifier and hierarchical clustering technique to classify companies into: non-distressed, semi-distressed and distressed. In both instances, companies are distinctively categorized into three dimensions instead of the binary classifications employed by previous studies.

From the results, the Altman z-score model has been able to classify the 23 companies into three dimensions; non-distressed, semi-distressed and distressed. Out of which 16 were classified as non-distressed companies; 6 were classified as distressed and only 1 was considered as semi-distressed.

In the same vein, out of the 23 companies considered in the study, the Hierarchical Cluster method has distinctively categorized 19 companies as Non-distressed. The method also chose 3 companies as distressed and only 1 company was classified as semi-distressed.

In both methods, there was slight misclassification. While the Altman method classified 16 companies as non-distressed, the Hierarchical Cluster method categorized 19 companies as non-distressed. Similarly, the Altman method classified 6 companies as distressed and 1 as semi-distressed respectively, whereas, the Hierarchical Cluster method categorized 3 companies as distressed and 1comapny as semi-distressed. In both cases, the misclassification occurs in either non-distressed or distressed, but there has been consistent classification for the semi-distressed. This could be as a result of different ratio calculations in various industries or sectors. However, future research could help explore this further.

The study has therefore formulated a simple to use scale in company's classification. This scale can then be used as benchmark to incorporate any new company into the structure. Even though this technique may not offer an optimum solution, however, it is simple and effective. Bearing in mind that a precise result is not actually required, hence this technique can be simply used by practitioners wanting to assess an organization's financial health.

DISCLAIMER

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

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