Corporate Failure Prediction: A Fresh Technique for Dealing Effectively With Normality Based On Quantitative and Qualitative Approach

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Abstract
This study uses a combination of quantitative and qualitative models to predict business failure with an appreciable degree of accuracy and/or precision. Quantitatively, the study used Factor Analysis (FA) to reduce the dimensionality of the data and further employed the Generalised Linear Modelling (GLM) technique which skips and/or relaxes the use of the normality assumption test that must be used by the General linear models. Qualitatively, the study adopted the most notable qualitative A- score model of Argenti (1976), which suggests that business failure process follows three predictable sequences: Defects, Mistakes made and Symptoms of failure. Among the three link functions (models) of GLM, the Logit model provides the highest overall accuracy rate with the lowest Akaike Information Criteria (AIC): 49.484. Regarding the 19 corporate determinants classified into 5 distinct categories, namely: Profitability and Employee Efficiency, Leverage and Liquidity, Asset utilization, Growth ability and Size, the significant variables that have appeared as a consistent indicator of financially distressed companies in the best model (logit) are Profitability ratio (Return on total assets) and Leverage ratio (Solvency, Gearing and Interest cover).In terms of the qualitative analysis, it was revealed that organizations that are prone and susceptible to corporate failure display high scores in defects usually in the range of 40 which is a high rate in the scale of 43 (highly unsatisfactory). As far as the three main mistakes are concerned (high gearing, overtrading and the big project) which failed companies exhibit, high gearing had a higher score of 15 which validates the findings in the quantitative analysis. Among symptoms of failure (Financial signs, Creative accounting, Non-financial signs – various signs include frozen management salaries, delayed capital expenditure, Terminal signs – at the end of the failure process, the financial and non-financial signs become so obvious and debilitating that even the casual observer recognises them), Financial signs holds sway posting a higher score of (16).

Keywords: Solvency, Generalized Linear Modelling, Factor Analysis, Financial Ratio, quantitative models, qualitative analysis

1. Introduction
Business failure prediction (BFP) has been an interesting subject in finance for both researchers and practitioners for decades (Oki, 2004). The investigations of corporate failure prediction research (Altman 1983; Ballantin 1992; D'Aveni 1989; Dugan and Zavgren 1989; Koh and Killough 1990; Pech and Alistair 1993; Shumway 2001; Chava and Jarrow 2004; Bunyaminu and Mohammed 2012) usually implement binary classification into one of the distinguished groups – Distress or non-Distress companies. Using various statistical techniques, BFP 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), than internal

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(endogenous, or caused by mismanagement) and others argue that various industries could exhibit characteristics involving high grades of failure.

While there has been a lot of prior work in this area, much is still needed to be done; for example (Gaskill et al, 1993 P12) argue: “There are many studies to better understand business success versus failure”. As a result, there are many questions still to be answered that warrant additional ‘exploration’. Despite this, little research has been done to investigate empirically a technique that encompasses financial and non-financial (managerial) variables to solve the problem of normality assumption test that can be used to predict corporate failure.

Prior empirical studies of failure have focused almost exclusively on financial ratio data that are mostly based on quantitative models, although studies of failure usually mention managerial variables as being crucial (Scherr, 1989). However, most of these models do suffer from the problem of normality. The usefulness of ratio-based business failure prediction models in providing accurate predictions has been questioned (Alves 1978; Corman and Lussier 1991; Gilbert, Menon, and Schwartz 1990). For instance, El-Zayaty (1986) found ratio models to be unreliable predictors of bankruptcy: in his study of 132 businesses predicted to fail, only 5 were discontinued over a five-year period. Storey et al. (1987) indicated that qualitative data can provide at least as good predictions as traditional financial ratios (quantitative models). Bunyaminu A. & Mohammed I. (2012) suggested that a combination of quantitative and Qualitative models has the propensity to predict business failure with an appreciable degree of accuracy.

Consequently, several attempts have been made to develop a model that capitalises on both financial and non-financial variables but this effort has stumbled on enormous challenges, creating a research problem in corporate failure prediction.

2. Literature Review

The meaning of Corporate Failure

Corporate failure like many models does not lend itself to a single, universally accepted definition. There is however the need to provide a concise definition of corporate failure to promote understanding of the phenomenon. In situations where corporate failure is inappropriately defined or given a generic definition, difficulties may emerge in the effort of predicting corporate bankruptcy. The study undertaken by Bahnson and Bartley (1992) reveal that the definition of corporate failure influences the construction of prediction models adding that the provision of a concise but robust attention should engage the attention of researchers. Corporate failure describes a situation where an entity continues to rake in a rate of return on investment that is below prevailing rates of return by comparable firms in similar industries (Bibeault, 1982:10). Form a legal standpoint, corporate failure is a phenomenon in which a company is unable to settle its current financial commitments and lacks the financial muscle to defray its outstanding debts.

In the UK., the Insolvency Act 1986 defines an insolvent company as a corporate entity that is unable to settle its debt as and when they fall due (the cash flow Test) or the value of its assets is less than liabilities taking into account its contingent liabilities and impending liabilities (the balance sheet test). The Insolvency Act provides five spheres of actions that firms dabbling in insolvency must take namely: administration, company voluntary arrangement (CVA), receivership, liquidation and dissolution. Within the parameters of this study, corporate failure is defined as a firm navigating into a state of liquidation, CVA, administration and receivership. Dissolution as a kind of corporate failure is jettisoned on grounds of difficulties associated with accessing annual financial statements of firms that file under dissolution. This definition finds support in the definition proffered Neophytou et al (2000) and Neophytou and Molinero (2001) stressing that efforts at acquiring the distressed firms’ financial statements proved futile.
Post Z-Score Model Development

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).

Business failure prediction has been 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. However, the development of corporate failure models is generally agreed to have been started with Univariate analysis, pioneered by William Beaver (1966) followed by Altman’s Multiple Discriminant Analysis (MDA) in 1968.

With major shift from univariate to multivariate corporate failure prediction models in 1968, MDA became the standard method for predicting corporate failure for almost one and half decades (Hossari, 2007). However, researchers including Altman continue to either extend Altman’s original MDA model or develop new statistical models that will accurately predict corporate failure with little assumptions (Altman and Hotchkiss, 2006).

Ohlson (1980) observed that there were some limitations with the MDA model with respect to the assumptions of normality and group dispersion. He developed Logistic regression model (logit) to take care of the assumptions and the limitations of the MDA. He examined 105 bankrupt and 2058 non-bankrupt companies from 1970 to 1976. The logit model uses a single period where an average data is normally used. As a result, for each failed and non-failed company there is only one company-year observation. Ohlson (1980) observed that the most important determinants of corporate failure are size, financial structure, performance and current liquidity.

One of the advantages of Ohlson’s studies is that it has not been affected by the MDA’s basic assumptions, such as the normality of the variables which are violated (Altman, 1993). Another advantage is that, the logit model calculates the weight each coefficient contributes to the overall prediction of failure and produces a probability score which makes the results more accurate (Ohlson, 1980). In view of these advantages, the logit model was extended to include different industries, sectors and countries, these extensions include (Zavgren, 1985; Gilbert et al, 1990; Johnsen and Melicher, 1994; Ciampi and Gordini, 2008; Wang and Campbell, 2010).

Hillegeist et al (2004) identified two econometric problems with the logit model. The first econometric problem is the sample selection bias that arises from using only one, non-randomly selected observation for each bankrupt company. The second econometric problem is in relation to time varying changes that reflect the underlying risk of bankruptcy. This has not been included in the model and has a potential for inducing cross-sectional dependence in the data. The problem with the logit model could result in biased, inefficient, and inconsistent coefficient estimates (Shumway, 2001).

Ciampi and Gordini (2008) used both MDA and logistic regression on a representative sample of manufacturing firms based in Italy with the aim to construct prediction models for small enterprise default, their overall prediction accuracy rate for the two models is highly satisfactory (75.5% for discriminant analysis and 80% for logistic regression).

Another interesting multivariate technique applied in corporate failure prediction for the past few decades is factor analysis, especially a branch called principal component analysis (Taffler, 1983). The technique identifies factors that can be used to predict failure and can also be used to study interrelationships between a large number of variables in terms of their common underlying dimensions or factors. Variables that are believed to predict failure are condense into smaller set of variables without losing valuable information and these factors can then be applied in further statistical approaches such as MDA, Logit and MDS. (Hair et al., 1998).

In 1990, research studies on Neural Network (NN) started with Coats and Fant (1993), Fletcher and Goss (1993), Altman et al. (1994), and continue recently with Gritta et al. (2000) and Charitou et al. (2004). NN relaxes a number of MDA’s assumptions and are non-linear architectures that discriminate patterns
which are not linearly separable and do not require data to follow any specific probability distribution (Balcaen and Ooghe, 2004). Coats and Fant (1993) discovered that NN is a better classifier than the MDA. However, Boritz and Kennedy (1995) compared two NNs (Back-Propagation and Optimal Estimation Theory) methods to MDA, Probit and Logit and found out that the classification rates of the two NNs are not superior. They identified that, the main problems with the NN models are the difficulty of building up the model, the required time to accomplish iterative process and the difficulty of model interpretation.

In recent years many types of statistical approaches such as Probit analysis (Bongini et al., 2000), ID3 approach (Kim and McLeod Jr., 1999), Going Concern Advisor (Lenard et al., 1998), Recursive Partitioning Algorithm (Frydman et al., 1985), Rough Sets Analysis (Dimitras et al., 1999), Tabu Search (Drezner et al., 2001), Mixed Logit Analysis (Jones and Hensher, 2004) and Decision Trees (Zheng and Yanhui, 2007) have also been used in predicting corporate failure in an attempt to developing models that would generate predictive accuracies that are at least as good as MDA (particularly with respect to reducing Type I error, which is classifying a failed company as non-failed), but that rely on fewer assumptions (Hossari, 2007).

Hossari (2007), in his study of benchmarking new statistical techniques concluded that, during the early state of the literature (1968-1979), 100% of studies adopted MDA as the primary tool for modelling corporate failure. However, as researchers started to develop new methodological approaches, the usage rate of MDA as the primary tool dropped to 29%. However, MDA did not lose prominence. Researchers turned to MDA once again, but this time as the preferred benchmark methodology, where 87% of studies that used some sort of benchmark chose MDA.

**Failure Prediction approaches in the UK**

Studies in connection with prediction of corporate failure in the UK revolve around the use of models based on MDA. Taffler and Tishaw (1977) utilize the MDA model anchoring it on a sample of 92 manufacturing concerns. They posit a 99% classical and plausible classification using 92 companies. However, a critical test on the model by Taffler (1983) capitalizing on a sample size of 825 leads to results that leaves a lot to be desired. Taffler then proceeds to undertake a couple of failure classification models based on the MDA techniques (1982, 1984).

The outcome of Taffler’s Z-score model attracted a wave of assessments by Agarwal and Taffler (2007). They arrive at the conclusion that Taffler’s Z-score model is a potent technique that can be utilized in the endeavour of predicting failure regarding UK firms. Agarwal and Taffler (2008) in their attempt to draw comparison between Taffler Z-score and the market oriented Black-Scholes-Merton (BSM) model adopted Hillegeist et al. (2004) and the narrow market-centred model used in Bharath and Shumway (2008) and find that both the Z-score and BSM are efficacious models that can used in predicting corporate failure. On the evidence of their findings, they place a weighty premium on the potency of the twin models of the BSM and the Z-score to foresee corporate failure in the UK.

Neophytou et al. (2000) join the fray and produce a corporate failure classification model regarding UK public industrial organizations utilizing Logit analysis and Neural Networks. The outcome of their study points to the fact that a thrifty model that encompasses three financial elements namely; profitability, an operating cash-flow and a financial leverage element can provide insights that equip financial experts to with the information to predict the financial woes of a company in advance of one year before the failure occurs. They credit this approach with 83% accuracy adding that the Neural Networks can be credited with the highest overall classification compared to the Logit models across the entire three years duration.

In yet another study conducted by Ezzamel et al. (1987) using factor analysis to analyse 53 ratios. They identify five broad facets of corporate failure: Capital intensity, profitability manifested in earnings, working capital status, liquidity position and Asset turnover. They suggest that it is possible to determine and identify financial trends that show corporate bodies heading precariously toward financial ruin. They however admit that, a reduction in the number of ratios was worth considering.

Researchers such as Neophytou and Molinero (2001), apply multidimensional scaling (MDS) to predicting corporate failure, an approach that draws some strength from providing pictorial representations
of the structures of the data, thereby opening the doors of an intuitive understanding of its structure. The technique has an inherent linkage with principal component analysis (a branch of factor analysis), suffice it to say it is more general in its approach. The strength of MDS over traditional analysis in that it is more amenable to comprehension by a non-initiated user. Its downside is reflected in its lack of robustness making it less convincing than traditional models (Neophytou and Molinero, 2001). They conclude that

“MDS maps have been produced and it has been shown that failed and non-failed companies fall in clearly distinct areas within the maps”. P.22

Researchers in the UK continue to make inroads in corporate failure studies using logistic regression and probit techniques and these include; Storey et al. (1987), Peel and Peel (1988), Keasy and McGuinness (1990) and Neophytou et al. (2000). Other UK researchers (Ketz, 1978; Norton and Smith, 1979; Keasey and Watson, 1986) use adjusted historic cost accounting ratios for either general price level changes (inflation) or for specific price changes (current cost accounting) to assist in predicting corporate failure with an appreciable degree of certainty.

It is important to state that, majority of the UK corporate failure prediction work centred on using MDA and in the works of Charitou and Vafeas, (1998) as cited by Neophytou et al (2000) they relegate the growing influence of operating cash flow information in building foresight into the subject of corporate failure to the back burner despite increasing interest in cash flow reporting in the UK in the recent past.

The design of corporate failure predictions models over the past four decades hinge on financial ratios as predictor variables. The reliance on financial ratios emanates from their popularity and efficacy in predicting corporate failure. However, the use of financial ratios in the exercise of foreseeing corporate ignores economic theory which can also be instrumental in igniting corporate failure. (Morris,1997; Storey, 1994 and Keasey and Watson, 1991).

Consensus on the most potent statistical model for predicting corporate collapse appears to be a distant dream. The assumptions underlying the various approaches to predicting corporate failure are far from becoming uniform. Chung (2008, p. 22) observes that “Despite the long heritage of corporate failure prediction modelling, there are disagreements over which ratios and methods (multivariate analysis or ANN or hybrid) are appropriate for predicting corporate failure and the accuracy of results have varied considerably….”. The differences and disagreements notwithstanding, there are prediction concepts (MDA, Logit, NN and MDS) which have given deeper understanding in the phenomenon of corporate failure and have served as instruments for predicting corporate demise with a fair degree of certainty across several sectors of the economy within specific timelines (Taffler, 1983; Storey et al. 1987).

3. Research Design and Methodologies

Data

The study uses quantitative data comprising 50 failed and 50 non-failed listed companies on the London Stock Exchange (LSE) for both Main Market and the Alternative Investment market (AIM). For each failed company, a non-failed match is identified during the period from 2000 to 2010 with the firms operating in one of the industry sectors listed in the Table below. The qualitative information was obtained by interviewing managers of both failed and non-failed companies belonging to the same industry and having operated in the same fiscal year.
<table>
<thead>
<tr>
<th>Categories</th>
<th>Sectors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Primary Sector (agriculture, mining, food etc.)</td>
</tr>
<tr>
<td>2</td>
<td>Chemicals, rubber, plastics, non-metallic products, textiles</td>
</tr>
<tr>
<td>3</td>
<td>Construction</td>
</tr>
<tr>
<td>4</td>
<td>Wholesale and retail trade</td>
</tr>
<tr>
<td>5</td>
<td>Hotels and restaurants and real estate activities</td>
</tr>
<tr>
<td>6</td>
<td>Post and telecommunications</td>
</tr>
<tr>
<td>7</td>
<td>Machinery, equipment, furniture and recycling</td>
</tr>
<tr>
<td>8</td>
<td>Education, health and computing</td>
</tr>
<tr>
<td>9</td>
<td>Other services</td>
</tr>
</tbody>
</table>

**Methods**

**Factor Analysis (FA)**

Quantitatively, the study uses the Factor Analysis (FA) to reduce the dimensionality of the initial financial data in order to allow visual description of the total sample of failed and non-failed companies and also to check if the financial ratios used in the study can be useful enough to predict corporate failure.

Misra & Vikram (2008) identified Factor Analysis as a mathematical model which attempts to reduce a large number of inter-correlated variables to a smaller number of unobserved and uncorrelated latent factors or dimensions. Another interesting definition by Words, I. (n.y) is it being a Statistical technique that can uncover relationship patterns underlying hundreds of interacting phenomenon such as changes in interest rates, inflation, and/or oil prices.

FA 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, 2009). The Factor Analysis algorithm used in this study was adopted from Bunyaminu & Mohammed (2012) but with some adjustments as indicated below:

**STEP 1:** Identifying missing values or “abnormal” values (extreme values which affect the average).

**STEP 2:** Centering and reducing the initial observations - necessary due to heterogeneity of measurement units.

**STEP 3:** Calculating the correlation matrix of the initial variables.

**STEP 4:** Calculating linear combinations of the initial variables (the eigenvectors) in order to maximise the variance and to generate uncorrelated factor variables.

**STEP 5:** Calculating the communalities and the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy (MSA) and Bartlett’s Test.

**STEP 6:** Choosing the number of factors based on Kaiser's criterion: ordering the eigenvectors in a descending eigenvalues order, and then retaining those factors which have their eigenvalues greater than 1, meaning they bring more information than the original variables (centered and reduced).
STEP 7: Interpretation of Factors.

STEP 8: Plotting individuals on the retained Factors space. If the data are concentrated in a linear subspace, this provides a way to compress data without losing much information and simplifying the representation.

**Generalised Linear Modelling (GLM)**

Further analysis was conducted by the use of a Generalised Linear Modelling (GLM) technique which relaxes the assumption of normality usually confronted by previous studies. GLM is anchored on the critical principle that observations (variables) may emerge from a very general class of distributions and any twice differentiable one-to-one function of the mean is represented via a linear function of unknown parameters (Crawley, 2004).

The study used R programming language to model the popular link functions (models) of GLM:

- Logit (model) link:
  \[
g(p) = \ln \left( \frac{p}{1-p} \right).
\]

- The probit (model) link:
  \[
g(p) = \Phi^{-1}(p).
\]

- The complementary log-log (Clog-log) function (model): \( \log(-\log(1-p)) \)

From the above, a best model was considered to be the one with the lowest AIC (Akaike Information Criteria).

**Qualitative Analysis**

Qualitatively, the study adopts the most notable qualitative A- score model of Argenti (1976), which suggests that business failure process follows three predictable sequences:

- Defects
- Mistakes made
- Symptoms of failure

**4. Results of the Analysis**

**Factor Analysis**

The SPSS 19.0 software was first used to run the Factor Analysis (FA). The initial sample of 100 companies was divided into a 70% estimation sample, 30% holdout sample and the overall prediction for a cumulative three-year data set. The study examined the financial ratios to check on the seriousness of the multicollinearity problem in the data by looking at the Factor Analysis. The data was first standardised before applying the Factor Analysis Technique, this is due to the presence of missing values in the variables. The final variables selected for the Factor Analysis for the cumulative three-year data set were: X1, X2, X3, X4, X7, X8, X9, X10, X14 and X15; which mean Return on Shareholders’ Fund, Return on Capital Employed, Return on Total Assets, Profit Margin, Current Ratio, Liquidity Ratio, Solvency Ratio, Gearing Ratio, Net Assets Turnover, Fixed Assets Turnover respectively.

The correlation matrix in the analysis revealed that Net Assets Turnover (X14) and Fixed Assets Turnover (X15) have a correlation matrix value of 0.893. Similarly, Liquidity Ratio (X8) and Current Ratio...
(X7) have a correlation matrix value 0.982. This is an indication that those financial ratios are likely to suffer from the problem of multicollinearity; hence were eliminated in the future analyses.

Table 4.1 Total Variance Explained

<table>
<thead>
<tr>
<th>Factor</th>
<th>Initial Eigenvalues</th>
<th>% of Variance</th>
<th>Cumulative %</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.615</td>
<td>43.589</td>
<td>43.589</td>
</tr>
<tr>
<td>2</td>
<td>1.426</td>
<td>23.772</td>
<td>67.361</td>
</tr>
<tr>
<td>3</td>
<td>.932</td>
<td>15.531</td>
<td>82.892</td>
</tr>
<tr>
<td>4</td>
<td>.591</td>
<td>9.855</td>
<td>92.747</td>
</tr>
<tr>
<td>5</td>
<td>.299</td>
<td>4.977</td>
<td>97.724</td>
</tr>
<tr>
<td>6</td>
<td>.137</td>
<td>2.276</td>
<td>100.000</td>
</tr>
</tbody>
</table>

Extraction Method: Principal Axis Factoring.

In the end only six (6) factors were used further analysis. The first factor has the highest contribution of 43.59% of the total gain of recovered information, followed by a 23.77% contribution of the second factor, totalling 67.36%. The third factor contributed 15.53% and with this inclusive, led to a total of 82.89% of the variability of the initial space as shown in Table 4.1. This means that three (3) factors have accounted for the higher variability while the rest have lower variability, as such the total variance explained has accounted for 82.89%, which is a proof of higher accountability and a manifestation that a lot of the variables or ratios have been accounted for.

The scree plot, Figure 4.1 shows the eigenvalues for the factors. Using Cattell’s criteria it appears from the plot that just three (3) factors would be sufficient to represent the data. Considering all three criteria for excluding components, it would be most appropriate to represent the data with just three components.

![Figure 4.1 The Scree Plot](image)

Table 4.2 is the Rotated Factor Matrix; each number represents the partial correlation between the financial ratios and the rotated factor. The rotation had the effect of associating the Solvency Ratio (86.40%) and Gearing Ratio (79.70%) more with the first factor; Return on Total Assets (87.30%) with the second
factor; Return on Capital Employed (71.40%) and Return on Shareholders’ Funds (70.60%) with the third factor and Profit margin (63.70%) with the fourth factor.

Table 4.2: Rotated Factor Matrix

<table>
<thead>
<tr>
<th></th>
<th>Factor 1</th>
<th>Factor 2</th>
<th>Factor 3</th>
<th>Factor 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solvency ratio (%)</td>
<td>.864</td>
<td>.300</td>
<td>-.146</td>
<td>-.190</td>
</tr>
<tr>
<td>Gearing (%)</td>
<td>-.797</td>
<td>-.032</td>
<td>.290</td>
<td>-.095</td>
</tr>
<tr>
<td>Return on Total Assets (%)</td>
<td>.230</td>
<td>.873</td>
<td>-.012</td>
<td>.401</td>
</tr>
<tr>
<td>Return on Capital Employed (%)</td>
<td>-.192</td>
<td>.086</td>
<td>.714</td>
<td>.075</td>
</tr>
<tr>
<td>Return on Shareholders Funds (%)</td>
<td>.240</td>
<td>.482</td>
<td>-.706</td>
<td>.194</td>
</tr>
<tr>
<td>Profit margin (%)</td>
<td>-.051</td>
<td>.202</td>
<td>-.003</td>
<td>.637</td>
</tr>
</tbody>
</table>

Extraction Method: Principal Axis Factoring.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 6 iterations.

Figure 4.2 is the Factor Plot in Rotated Factor Space of which the first factors represents the Liquidity/Leverage and Assets variables, the second one is Profitability and proportion of Liquidity Ratios, and the third factor as well is centred around Liquidity/Leverage and Profitability elements, whilst the fourth and the fifth factors represent Profit Growth and Assets elements respectively.

Table 4.3 summarises the outcome of the Factor Analysis computed for the purpose of this study:

Table 4.3 Summarised Factor Analysis Result

<table>
<thead>
<tr>
<th>Data Set</th>
<th>Initial Set of Variables</th>
<th>Variables Excluded</th>
<th>Factors Retained</th>
<th>% of Gained Information</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulative Three-Year Data Sets</td>
<td>X1, X2, X3, X4, X7, X8, X9, X10, X14, X15</td>
<td>X2, X4</td>
<td>X1, X9, X10, X3</td>
<td>92.75%</td>
</tr>
</tbody>
</table>

The Generalised Linear Modelling (GLM)

Among the three linked functions (models) of the GLM, the Logit model provides the highest overall accuracy rate with the lowest AIC: 49.484.
Among the 19 corporate determinants classified into 5 distinct categories, namely: Profitability and Employee Efficiency, Leverage and Liquidity, Asset utilisation, Growth ability and Size, the significant variables that have appeared as a consistent indicator of financially distressed companies in the best model (logit) of the GLM are Profitability ratio (Return on total assets) and Leverage ratio (Solvency, Gearing and Interest cover). This shows that financially distressed companies post low profitability, a situation made worse by an irreversibly high debt regime (High Gearing). The probability of defaulting on debt contracts is accentuated if the company continuous to dabble in losses or not creating shareholder value through profits. This is consistent with the results reported by Charitou et al., (2004); Abdullah et al., (2008); Neophytou et al., (2000); Ciampi and Gordini, (2008) and Bunyaminu A. and Mohammed I. (2012).

The predictive accuracy of the GLM in this study is by far better than the findings of Charitou et al. (2004), with an average overall prediction accuracy of 76% by the cumulative three year data comparison. Ciampi & Gordini (2008) reported 80% accuracy for the overall prediction while Bunyaminu & Mohammed (2012)’s predictive ability was 83.80%, way below the overall predictive power of this research by 14.50% and 10.70% respectively when the cumulative three year results were analysed.

Qualitative Analysis

In terms of the qualitative analysis, the study divides Defects into management weaknesses (autocratic chief executive, failure to separate role of chairman and chief executive, passive board of directors, lack of balance of skills in management team – financial, legal, marketing, etc, weak finance director, lack of ‘management in depth’, poor response to change) and accounting deficiencies (no budgetary control, no cash flow plans, no costing system). In the study, it is revealed that organisations that are prone and susceptible to corporate failure display high scores in defects usually in the range of 40 which is a high score in the scale of 43 (highly unsatisfactory). Per the scale used, a score of 0-10 is deemed satisfactory meaning that, a firm with such a score is engaged in best practices and the danger of corporate failure is constantly diminished. On the other hand, a score above 10 means, a company is entering the threshold of corporate failure and this scenario aggravates in the region of 40-43. Thus a firm that scores 40 and above is on the palpable brink of collapse and operational salvation will be a distant prospect.

As far as the three main mistakes are concerned (high gearing, overtrading and the big project) which failed companies exhibit, high gearing has a higher score of 15 which authenticates the findings in the quantitative analysis.

Among symptoms of failure (Financial signs, Creative accounting, Non-financial signs – various signs include frozen management salaries, delayed capital expenditure, Terminal signs – at the end of the failure process, the financial and non-financial signs become so obvious that even the casual observer recognises them), financial signs holds sway posting a higher score of (16). These findings are consistent with previous studies reported by Argenti (1976), Alves 1978; El-Zayaty (1986); Corman and Lussier 1991; Gilbert, Menon, and Schwartz 1990.

5. Conclusion

Based on the qualitative and quantitative findings of this work, the following conclusions have been drawn.

Low profitability

Firms at the brink of corporate failure post negative profits over sustained periods of time. Dwindling sales and rising operational expenses inevitably leads to operational losses in failing firms. As exhibited in this work, the financially distressed firms face a twin difficulty of poor sales and high cost of sales and operational expenditure resulting in sustained losses. The financial statements of firms on the pathway to failure exhibit spiralling costs and sales decline which eventually impacts negatively on the bottom line of the distressed firms.
Inability to settle debts

This study uncovers a disturbing trend of financially distressed firms’ incapacity to settle both short term and long term debts as and when they fall due. The downward trend in sales means a major source of cash is drying up and as stocks build up owing to the poor sales, the chances of raking in cash continue to diminish. Creditors are therefore constantly snapping on the heels of firms that are heading towards failure.

Weak Finance Director

A common feature of firms on the verge of failure is the existence of a weak Finance Director. The Finance Director in most firms exhibiting failure attributes appear to kowtow to the demands of the Chief Executive by authorising payments that are outside the stipulations of the budget. Such Finance Directors, this study concludes obviously fail to offer sound financial advice to management thereby putting the finances of the firm in jeopardy. Internal controls in such firms are ignored because the Finance Director is not able to play his watchdog role over the financial administration of the ailing firms.

Poor response to change

From the findings, it is imperative to conclude that, firms which do not realise the realities of the time and make the necessary changes to enable them operate efficiently and effectively are prone to fail. Most firms with traits of corporate failure have maintained old structures, procedures and systems despite changes in market environment and industry norms. By sticking to old ways and frowning on innovation and creativity, the firms cascading towards failure get steeped in outmoded management practices and strategies which weaken their competitive standing.

6. Recommendations

The study recommends that future research should delve into corporate failure prediction using both quantitative and qualitative managerial factors that is based on multi-state approach which classifies companies into four distinct categories known as Financially healthy (1st state), Cash Dividend reduction > 40% (2nd state), Debt accommodation (3rd state) and Bankruptcy and Liquidation (4th state) instead of the commonest dichotomous approach (distressed and non-distressed states). Beside, future research can focus on firms in different EU nations to provide insights into the dynamics of corporate failure in those countries.

References

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