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A Model to Predict Corporate Failure in the Developing Economies: A Case of Listed Companies on the Ghana Stock Exchange

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Abstract

The study aimed at developing a model that predict the probability of failure of companies operating in the developing economies using financial ratios and non-financial ratio. The logit model was the main statistical tool applied. A matched sample design was used. Three models were developed and compared; a model consisting of financial ratios only (Model 1), non-financial ratios only (Model 2) and both financial and non-financial ratios (Model 3). From the study, comparatively Model 3 is more efficient in predicting the corporate failure status in one year from now. Prediction of failure status of a corporate entity therefore should consider both financial and non-financial variables.

JEL classification numbers: G3
Keywords: Corporate failure, corporate governance, logit model, log-likelihood, Ghana Stock Exchange.

1 Introduction

1.1 Background of the study

Every business regardless of size of asset and nature of operations is exposed to the risk of insolvency. This study was necessitated by the various corporate failures in in Ghana during last decade. Among the companies that has failed include Ghana Co-operative Bank Limited (failed in 2015), West African Mill Company Limited (failed in 2014), Juapong Textiles Ltd (failed in 2005), Bonte Gold Mines (failed in 2004), Bank for Housing & Construction Ltd (failed in 2000), Ghana Cooperative Bank Ltd (failed in 2000), etc. Most work on corporate failure attributes failure to poor management of corporate financial

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resources hence based their studies on financial ratios only. The pioneer works of corporate failure prediction are Beaver's (1966) and Altman's (1968) were all based on only financial ratios. Thereafter, several researchers has develop models to predict corporate failure using different approaches but they were all based on only financial ratios.

However, some researches has pointed out that, weakness in corporate governance (a non-financial indicator) is a major cause financial distress as evidenced in the work of Rajan and Zingales (1998) and Prowse (1998) who concluded that, poor corporate governance on top of concentrated ownership structure paved the way for financial crisis. The failure of the famous Enron in 2001 was due to weak corporate governance mechanisms that provided an opportunity to the firm's executives to commit the fraud. Again, the Pramuka Savings and Development Bank Ltd in Asia failed due to lack of corporate governance practices. In Ghana, the collapse of companies such as Tano Agya Rural Bank, Tana Rural Bank Ltd, Meridian BIAO Bank, Bank for Credit and Commerce International can be largely be attributable to poor corporate governance in the parent banks which eventually led to their collapse (Appiah, 2011).

It is therefore evident that, a model to predict early warning signs of failure cannot be developed without incorporating the non-financial factors particularly, corporate governance characteristics. This is because, poor corporate governance contribute greatly to the probability of corporate failure even for firms with good financial performances. Very few researchers have develop a failure prediction model that incorporates non-financial factors such as corporate governance variables. A notable study in this area are Nisansala and Abdul (2015) and Bunyaminu (2015) where the latter perform the study in Ghana but used only managerial factors as the non-financial factors other than corporate governance characteristics.

To the authors' best knowledge, apart from Nisansala and Abdul (2015), no research was found in the developing economies which combines both corporate governance variables and financial ratios to predict corporate failure hence creating a gap in the literature for which the authors' aimed at filling.

1.2 Objective of the study

The primary objective of the study is to develop a model for predicting the failure status of corporate entities in the developing economies based on both financial and non-financial ratios.

1.3 Hypothesis of the study

The study is premised on the following null hypotheses;

a) There is no difference between corporate failure prediction model based on only financial ratios and model based on both financial and non-financial ratios in terms of their validity and predictive power.

b) There is no difference between corporate failure prediction model based on only non-financial ratios and model based on both financial and non-financial ratios in terms of their validity and predictive power.

The rest of this paper is organised as follows. The next section reviews relevant literature in the area of corporate failure prediction. Section three explains the methods adopted for the study, measurement of both predictor variables and the response variable, description of the modelling approach, sample selection, and data collection methods used in the study. Section four presents the results from the empirical analysis and finally section five concludes the paper.

2 Review of Relevant Literature

Corporate failure prediction is an area widely studied by numerous writers. However, majority of these studies are carried out in a well developed economies. For instance, researchers contend that the UK provides a financial environment 'ideal' for the successful development of statistical models that could facilitate the assessment of corporate solvency and performance (Taffler, 1984). Again, a considerable volume of the corporate failure literature has mainly employed US data which is evidenced form Beaver's (1966) who employed a univariate approach and then Altman's (1968) using linear multiple discriminant analysis model based on UK data. From this time, there has been extensions to these studies which include the assignment of prior probability membership classes (Deakin, 1972), the use of a more appropriate quadratic classifier (Altman et al., 1977), the use of cash flow-based models (Casey and Bartczak, 1985), the use of quarterly information (Baldwin and Glezen, 1992); and the use of current cost information (Aly et al., 1992). Though the classification accuracy of these studies is considerably high, they all based their studies on the multiple discriminant analysis which is based on some assumptions which are frequently violated. Besides, all these studies were contextualised in a well developed economies and also did not consider non-financial factors.

Altman (1968) for instance used five ratios which includes working capital to total assets - a liquidity indicator; retained earnings to total assets – firm aging indicator; earnings before interest and taxes to total assets - profitability; market value of equity to book value of total debt – solvency indicator; and sales to total assets – volume of activity indicator. The aim was to examine whether the five-variable set can be used to predict the probability of bankruptcy in UK companies using sixty-six firms grouped into failed and non-failed made up of 33 companies in each group. Altman, however, tested the predictive ability of the variables by means of linear discriminant analysis. To avoid the limitations of this technique and the reliance on only financial ratios, the current study applies the logistic regression analysis and also includes non-financial indices in the Ghanaian setting which is a developing economies.

3 Methodology

In this section, we describe the method of selecting the data for the study, selection of the predictor variables and the modelling approach and specifications for the study.

3.1 Description and method of selecting the data

3.1.1 Population and sample

The study population constitutes the equity stock listed companies on the Ghana Stock Exchange from 1994 to 2015 (the study period) which numbered forty (40) as at 31 December, 2015 and selected failed companies in Ghana up to 31 December 2015. In selecting the sample from this population, a matched sample design was applied where major companies that has failed in Ghana during the study period (not necessarily listed) were selected and paired to the non-failed companies on the stock exchange with reference to turnover size and in the same financial year. This sampling method is consistent with the methods applied by Beaver (1966), Altman (1968) and Bunyaminu & Issah (2012) in a similar study. However, this study focus much on industrial groupings and the inclusion of non-financial factors in corporate failure prediction which were not considered in these studies. In total, twenty (20) matched-pair (forty (40) companies in total) of failed companies and non-failed listed companies on the Ghana Stock Exchange was used for the study. Each of the 20 failed companies were matched with a corresponding non-failed company on the Ghana Stock Exchange with reference to turnover size and industrial groupings.

3.1.2 Data Collection

Relevant financial and non-financial (specifically on corporate governance issues) data was collected from the published annual reports of the forty companies for the period; in the case of the failed companies, data for one year before failure was used to develop the corporate failure prediction model, in the case of the non-failed companies, the same year data for which it corresponding company was selected.

3.2 Modelling Approach and Specification

The modelling approach adopted for the study is based on the logit model and is considered as most appropriate model for the study as it utilizes the coefficients of the independent variables to predict the probability of occurrence of a dichotomous dependent variable (Dielman, 1996). This method was adopted by Demirguc-Kunt and Detragiache (1998) to estimate of the probability to a threatened economy which is undergoing a banking crisis, hence well applied in the literature and has produced a valid and verified result.

3.2.1 The logit model

In applying the logit model, bivariate data $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$used are assumed to be independent and identically distributed (*iid*) such that $x_1, y_1 \in R$. The predictor variables $(x_i) \in R$ is a combination of financial ratios (quantitative variables) computed from the financial statements of the selected companies and corporate governance indexes (qualitative variable) obtained from the activities of the selected companies whereas the response variable $(y_i) \in R$ follows random law of Benoulli which takes the value of 1 if the entity survives or 0 otherwise. On this basis, the probability of a corporate entity failing using the Logit model is denoted by;

$$P(f) = P(Y\_i = 0/X\_i \quad = x) \tag{1}$$

Since Y_i follows the Benoulli processes, we formulate linear regression model using the Generalized Linear Model (GLM) introduced by Nelder and Wedderburn (1972). In the context of failure prediction, the Logit model weighs the financial ratios and the corporate governance indexes and creates a score for each company in order to be classified as either failed or non-failed. The score are calculated by *z* in the first phase of the analysis which is a linear combination of financial ratios and corporate governance indexes where;

$$z = \beta_0 + \beta_i^T X_i \tag{2}$$

In the second phase, we estimate the failure probability using equation (1) by means of the function G where;

$$P(f) = P(Y\_i = 0/X\_i \ = x) = G(z) \tag{3}$$

Where G(z) $\in$ (0,1) defined by;

$$G(z) = \frac{1}{1+e^{-z}} \tag{4}$$

The parameters β_i are estimated through the method of maximum likelihood procedure and Lagrangian function as follows;

$$L(\beta_0, \beta_1, \dots, \beta_{n+1}) = \prod[Y_i G(z) + (1 - Y_i)\big(1 - G(z)\big)] \tag{5}$$

Taking the log of equation (5)

$$logL(\beta_0, \beta_1, \dots, \beta_n) = \sum[Y_i logG(z) + (1 - Y_i)log\big(1 - G(z)\big)] \tag{6}$$

Maximising the β_i, the first order condition for maximisation is obtained as;

$$\frac{\partial logL}{\partial z} = G(\hat{z}) = G(\widehat{\beta_0} + \widehat{\beta_i^T} X_i \tag{7a}$$

This must also satisfies the second order condition as;

$$\frac{\partial^2 logL}{\partial z^2} < 0 \tag{7b}$$

In estimating the parameters, it is necessary to choose the most performing predictor variables to model the prediction of probability of failure. This helps in fitting a parsimonious model that explains variation in the dependent variable with a small set of predictors. We apply the Akaike's (1973) Information Criterion (AIC) where stepwise logistic regression method is applied by introducing all the predictor variables and in each step, those variables that do not contribute to the model is removed until we obtain the model with the minimum AIC thereby selecting the model that best fits the data and at the same time maintaining the number of estimated parameters at minimal, thereby avoiding over fitting. For *n* number of estimated parameters based on a maximum likelihood of the fitted model, L, the AIC is given as;

$$2n - 2logL \tag{8}$$

3.2.2 Selection of variables

In our study, the response variable represents the state of the selected company and it assumes a binary response such that, it takes the value of 1 if the entity survives or 0 if the entity fails. Eleven financial ratios and six non-financial ratios were initially used as the predictor variables each category representing different indicators of operational and liquidity vulnerability measure. The financial ratios are regrouped into four groups; profitability – a measure of the extent to which companies assets generate returns, liquidity – a measure of cash generating ability of the entity, efficiency – a measure of the volume of activity perform by the entities using their assets and gearing – a measure of the effect of debt in the capital structure of the company. Table 1 shows the definition of the operational variables used for the study.

Table 1: Operation definition of study variables

Variable Type	Category	Indicator	Measurement	Variable label
Response: Corporate failure		State of the company	1 – Failed 0 – Non – failed	Y
Predictors: Financial Ratio	Profitability	Return on Investment	$\frac{Net\ operating\ income}{Net\ Asset}$	x_1
		Net operating margin	$\frac{Net\ operating\ income}{Sale}$	x_2
	Liquidity	Current ratio	$\frac{Current\ Asset}{Current\ liabilities}$	x_3
		Acid test ratio	$\frac{Current\ Asset - inventories}{Current\ liabilities}$	x_4
		Cash ratio	$\frac{Cash}{Current\ liabilities}$	x_5
	Efficiency	Asset turnover	$\frac{sales}{total\ asset}$	x_6
		Receivable collection period	$\frac{receivables}{sales}$	x_7
		Payables payment period	$\frac{payables}{purchases}$	x_8
	Gearing	Debt – equity ratio	$\frac{long\ term\ debt}{equity}$	x_9
		Interest cover	$\frac{profit\ before\ interest\ and\ tax}{interest\ on\ debt}$	x_{10}
		Liability to Asset ratio	$\frac{long\ term\ liability}{Total\ Asset}$	x_{11}
Non-Financial Ratios	Corporate Governance	Non-Executive Director ratio	$\frac{No.\ of\ External\ Directors}{Total\ No.\ of\ Directors}$	x_{12}
		Board size	No. of directors on the board	x_{13}

External ownership	% of shares owned by non-executive directors and public	x_{14}
Quality of audit report	1 – unqualified report 0 – qualified report	x_{15}
Presence of audit committee/ internal audit	1 – present 0 – absent	x_{16}
Directors remuneration per GHS of sales	$\frac{Directors\ renumeration}{Sale\ revenue}$	x_{17}

4 Empirical Analysis and Results

4.1 Preliminarily analysis

Preliminary analysis of the predictor variables indicates a skewed towards the performance of the non-failed firms, indicating that the performance indicators are greatly influenced by the performance of the non-failed firms. For instance, the worse performance in assessing the returns companies generate on their investment was -10% in the last year before the year of failure which was achieved by a failed company as against 19% during the same year made by a non-failed company with an average performance of 3.2%. It can be noted that there is a high standard deviation with a positive skweness of 0.2 clearly indicating the impact of the high performing ratios. The result in table 2 indicates that, general performance of companies reduces towards the time of their failure. Similarly, the non-financial indicators exhibits similar characteristics such that, companies that shows high risk of managerial deficiencies and corporate governance lapses shows their distribution tending to be negatively skewed. Table 2 shows the summary of the descriptive analysis of the predictor variables.

Table 2: Descriptive statistics of predictor variables

	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Financial Indicators						
Return on Investment (%)	-10.0	19.0	3.2	8.1	0.2	-1.1
Net operating margin (%)	-13.0	29.0	4.8	11.9	0.2	-1.0
Current ratio : 1	0.0	7.0	2.9	2.1	0.4	-1.2
Acid test ratio : 1	0.0	5.0	1.5	1.4	0.8	-0.3
Cash ratio : 1	0.0	1.0	0.4	0.3	0.5	-1.3
Asset turnover (Times)	1.0	9.0	5.0	2.8	-0.1	-1.5
Receivable collection period (days)	10.0	90.0	56.2	23.7	-0.5	-0.6
Payables payment period (days)	10.0	59.0	36.7	15.8	-0.2	-1.3
Debt – equity ratio (%)	51.0	112.0	83.8	17.9	-0.1	-1.2
Interest cover (Times)	1.0	13.0	4.7	3.7	0.9	-0.5
Liability to Asset ratio (%)	49.0	81.0	64.1	9.8	0.4	-1.2
Non-Financial Indicators						
Non-Executive Director ratio (%)	23.0	75.0	48.1	16.8	0.1	-1.4
Board size (Number)	9.0	19.0	14.0	3.2	-0.1	-1.4
External ownership (%)	50.0	100.0	73.9	15.1	-0.1	-1.2
Quality of audit report (Dummy)	0.0	1.0	0.5	0.5	0.0	-2.1
Presence of audit committee/ internal audit (Dummy)	0.0	1.0	0.5	0.5	-0.1	-2.1
Directors remuneration per GHS of sales (GHS)	5.0	25.0	14.7	5.5	0.3	-0.7

4.2 Model Specification

In building the model for the prediction of the variable of interest, we aimed at achieving a great efficiency, such that, the variation in the dependent variable would be well explained with the minimum variables as possible. Using a backwards step by step procedure in the choice of the most discriminating variables shows a criterion of the weakest AIC of 195.06 for the model that regroups the variables $x_1, x_4, x_5, x_7, x_8, x_9, x_{10}, x_{14}, x_{15}$ and x_{17} as shown in table 3.

Table 3: Selected variables on the basis of least AIC

Variable Type	Category	Indicator	Measurement	Variable label
Response: Corporate failure		State of the company	1 – Failed 0 – Non – failed	Y
Predictors:				
Financial Ratio	Profitability	Return on Investment	$\frac{Net\ operating\ income}{Net\ Asset}$	x_1
	Liquidity	Acid test ratio	$\frac{Current\ Asset - inventories}{Current\ liabilities}$	x_4
		Cash ratio	$\frac{Cash}{Current\ liabilities}$	x_5
	Efficiency	Receivable collection period	$\frac{receivables}{sales}$	x_7
		Payables payment period	$\frac{payables}{purchases}$	x_8
	Gearing	Debt – equity ratio	$\frac{long\ term\ debt}{equity}$	x_9
		Interest cover	$\frac{profit\ before\ interest\ and\ tax}{interest\ on\ debt}$	x_{10}
Non-Financial Ratios	Corporate Governance	External ownership	% of shares owned by non-executive directors and public	x_{14}
		Quality of audit report	1 – unqualified report 0 – qualified report	x_{15}
		Directors remuneration per GHS of sales	$\frac{Directors\ renumeration}{Sale\ revenue}$	x_{17}

4.3 Corporate failure prediction Models

In order to achieve the stated objective and also test the stated hypothesis, three models were constructed, i.e., model in which corporate failure status is predicted based on financial ratios only, model based on non-financial ratios only and model based on both financial and non-financial ratios.

4.3.1 Model based on financial ratios

Based on the financial ratios identified in table 3, the probability that a corporate entity in Ghana would fail one year from now is predicted by model (labelled model 1);

$$p(f) = \frac{1}{1+e^{-(2.468+0.112x_1+1.022x_4-1.301x_5+0.027x_7-0.035x_8-0.058x_9+0.188x_{10})}} \quad (9)$$

The model is based on logistic regression, with the coefficients calculated through the use of Maximum Likelihood Estimation (MLE) method, where we seeks to maximize the log likelihood which in this case is 37.48 after the 6th iteration and is significant at 1%. This shows that the observed values of the dependent variable can be predicted from the observable values of the independent variables. The Cox-Snall R squared shows a 36.2% fit. The classification accuracy of the model is 80% as 17 failed firms were correctly classified as failed and 15 non failed firms were also classified as non-failed. The result of the logistic regression of the financial ratios is shown in table 4.

Table 4: Binary regression of financial ratios

	Coefficient	Standard error	Z-statistic	Sig. level
X1	0.112	0.063	1.790	0.037
X4	1.022	0.533	1.920	0.025
X5	-1.301	1.586	-0.820	0.048
X7	0.027	0.018	1.470	0.040
X8	-0.035	0.029	-1.200	0.046
X9	-0.058	0.031	-1.860	0.035
X10	0.188	0.157	1.200	0.046
Constant	2.468	2.237	1.100	0.051

Log Likelihood – 37.48 *Cox-Snall R^2 – 36.2%*

4.3.2 Model based on Non-financial ratios

Based on the non-financial ratios (specifically, corporate governance variables identified in table 4), the probability of a company in Ghana failing one year from now is predicted by the model (labelled model 2);

$$p(f) = \frac{1}{1+e^{-(-2.551+0.045x_{14}-0.491x_{15}+0.116x_{17})}} \tag{10}$$

The logistic regression co-efficients are obtained as per table 5 where all the variables are statistically significant at 1% except for the ratios x_{15} which is significant at 5%. The coefficients are calculated MLE method, with log likelihood of 20.99 after the fourth iteration and is significant at 1%. The classification accuracy of the model is however lesser than that of the financial ratio at 70% as 14 failed firms were correctly classified as failed and 14 non failed firms were also classified as non-failed. The result of the logistic regression of the financial ratios is shown in table 5. The classification accuracy of the model with non-financial ratios tends to be relatively lower than the model with financial ratios indicating clearly that, the corporate failure status of an entity cannot be exhaustively be explained by only non-financial ratios.

Table 5: Binary regression of non-financial ratios

	Coefficient	Standard error	Z-statistic	Sig. level
X14	0.045	0.023	1.957	0.005
X15	-0.491	0.679	0.720	0.020
X17	0.116	0.066	1.770	0.007
Constant	-2.551	2.005	-1.270	0.203

Log Likelihood – 20.99 *Cox & Snall R^2 – 21.6%*

4.3.3 Model based on both financial and non-financial ratios

Combining both the financial and non-financial ratios yielded the following corporate failure prediction model (labelled model 3);

$$p(f) = \frac{1}{1+e^{-(-6.379+0.143x_1+1.680x_4-4.393x_5+0.048x_7-0.057x_8-0.047x_9+0.279x_{10}+0.078x_{14}-2.442x_{15}+0.178x_{17})}} \quad (11)$$

All the predictor variables, as determine in table 3, are statistically significant at 5%. However, as in equation (9) and (10), X5(cash ratio), X8 (payable payment period), X9 (debt-equity ratio) and X15 (quality of audit report) relates negatively with the corporate failure status of the firm. So a firm is likely to fail one year from now if it have a poor cash management practices, short payable payment period, high debt equity ratio and auditors have been qualifying their report on the company. The result of the logistic regression for both financial and non-financial ratios is shown in table 6.

Table 6: Binary regression of financial and non-financial ratios

	Coefficient	Standard error	Z-statistic	Sig. level
X1	0.143	0.084	1.710	0.037
X4	1.680	0.800	2.100	0.006
X5	-4.393	2.642	-1.660	0.041
X7	0.048	0.030	1.620	0.042
X8	-0.057	0.038	-1.500	0.045
X9	-0.047	0.033	-1.430	0.047
X10	0.279	0.219	1.270	0.049
X14	0.078	0.047	1.660	0.040
X15	-2.442	1.432	-1.700	0.037
X17	0.178	0.117	1.520	0.044
Constant	-6.379	5.025	-1.270	0.048

Log Likelihood – 69.89 *Cox & Snall R^2 – 49.2%*

The log likelihood of this model is 69.89 which out-perform the previous models which was obtained after the 8^{th} iteration and is significant at 1%. The Cox and Snall R squared shows a 49.2% fit with a classification accuracy of 89% as 18 failed firms were correctly classified as failed and 17 non failed firms were also classified as non-failed. This clearly shows that, a model to predict corporate failure predict better if both quantitative and qualitative factors are duly considered.

4.4 Evaluation of the models

In this section, we adopted three major techniques, i.e. testing goodness of fitness of the models and assessing the classification accuracy. this is consistent with the method adopted by Nisansala and Abdul (2015).

4.4.1 Test of Goodness-of-fit

In testing whether the model duly fit the data used for the study, we employed the Log-likelihood ratio test, Cox-Snall R squared and Hosmer and Lemeshow test. Our main objective here was to test which of the models in equation (8) to (10) fit the data and to test the hypothesis of the study. The result of the three fitness test is summarised in table 7.

Table 7: Test result of Goodness-of-fit

Model*	Log-likelihood ratio	Cox-Snall R squared	Hosmer and Lemeshow test
1	37.48 (0.0119)	36.2%	22.97 (0.003)
2	20.99 (0.2150)	21.6%	7.955 (0.438)
3	*69.89 (0.0021)*	*49.2%*	*25.91 (0.000)*

*Model 1 consist of financial ratios only, model 2 consist of non-financial ratios only and model 3 consist of both financial and non-financial ratios. p-values are shown in parenthesis.

The log-likelihood ratio statistic tests whether the reduced model (which is defined as the model that only includes the constant term) fit the data than any of the three models. Thus, it explore whether it worth including the set of variables in included in the model by examining whether the set of variables explains a significant portion of the variability in the data. The log-likelihood ratio for model 1 is 37.48 and is significant at 5%, reduced to 20.99 in the case of model 2 insignificant at 5% but significant at 25% but increased to 69.89 which is significant at 1%. We therefore reject the null hypothesis at 1% level of significance for both hypothesis 1 and hypothesis 2 and conclude that, the model that combines both financial and non-financial variables fits the data much more than the model that uses financial data only or non-financial data only.

Again using the Cox-Snall R squared, 49.2% of the variation in the dependent variable is explained by the variation in both the financial and non-financial variables as against 36.2% in the case of model 1 and 21.6% in the case of model 2. Thus, higher predictive precision is achieved when both financial and non-financial variables are entered in a single model.

In testing whether there exist a significant differences between the models' predicted values and observed values, we applied Hosmer and Lemeshow test and with model 3 have a larger value at 1% significant level, it implies model 3 predicts better as compared to model 1 and model 2. It must however be stated that, model 1 also produced a significant value of Hosmer and Lemeshow test which indicates that it is a better model but comparatively model 3 is more acceptable as it improves interms of log-likelihood test ratio, cox-snall R square and Hosmer and Lemeshow test. So it is more acceptable to consider model 3 as being more efficient in fitting the data as well as it forecast ability as compared to model 1 and 2.

4.4.2 Classification Accuracy Rate

In other to ensure the *reliability* of any of the models in equation 8 to equation 10, we employed the classification accuracy test applied by Altman (1968) and Casey & Bartczak (1985). This test is based on the ability of the model to correctly classify a company as whether failed or non-failed using in-sample data. So a model is preferred and considered *reliable* if it classification rate for both failed and non-failed company is relatively higher. Table 8 shows the result of the accuracy test based on in-sample data, predicting the state of the company one year before failure.

Table 8: Accuracy test based on in-sample data

State of company	Model 1		Model 2		*Model 3*	
	Failed	Non-Failed	Failed	Non-Failed	*Failed*	*Non-Failed*
Failed	17	3	14	6	*18*	*2*
Non-Failed	5	15	6	14	*3*	*17*
Accuracy rate	80%		70%		*89.0%*	

The results show that, the accuracy rate of model 3 is higher as compared to model 1 and 2. This implies that model 3 has the discriminating power to classify correctly with a classification accuracy rate of 89% as against 80% and 70% in model 1 and 2 respectively.

5 Conclusion

The objective of this paper is to develop a corporate failure prediction model based on both financial ratios and non-financial variables for companies operating in the developing economies. The result of the study clearly shows that, early warning sign of failure cannot exhaustively be identified without considering non-financial variables with particular reference to corporate governance characteristics. The study has bring out the fact that, a poor corporate governance practices increases the probability of failure even if for companies with satisfactory financial performance. This confirms the study by Nisansala and Abdul (2015) that, modelling corporate failure prediction should not be based on financial data alone neither on non-financial data but a fair combination of the two.

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