An Integrated Model to Predict Corporate Failure of Listed Companies in Sri Lanka

Nisansala Wijekoon[1], A. Abdul Azeez[2]

ABSTRACT

The primary objective of this study is to develop an integrated model to predict corporate failure of listed companies in Sri Lanka. The logistic regression analysis was employed to a data set of 70 matched-pairs of failed and non-failed companies listed in the Colombo Stock Exchange (CSE) in Sri Lanka over the period 2002 to 2010. A total of fifteen financial ratios and eight corporate governance variables were used as predictor variables of corporate failure. Analysis of the statistical testing results indicated that model consists with both corporate governance variables and financial ratios improved the prediction accuracy to reach 88.57 per cent one year prior to failure. Furthermore, predictive accuracy of this model in all three years prior to failure is above 80 per cent. Hence model is robust in obtaining accurate results for up to three years prior to failure. It was further found that two financial ratios, working capital to total assets and cash flow from operating activities to total assets, and two corporate governance variables, outside director ratio and company audit committee are having more explanatory power to predict corporate failure. Therefore, model developed in this study can assist investors, managers, shareholders, financial institutions, auditors and regulatory agents in Sri Lanka to forecast corporate failure of listed companies.

1.0   INTRODUCTION

Interest in corporate failure prediction has grown rapidly in recent years with the global increase in the number of corporate failures. The motivation to undertake this study was provided following the corporate failures in Sri Lankan companies during last decade. Examples of such failures include Vanik Incorporation Limited, Ferntea Ltd, Lanka Cement Limited, Associated Hotels co. Ltd and the Galadari Hotels (Lanka) Ltd.

[1] University of Kelaniya, Sri Lanka. Email: nisansala@kln.ac.lk
[2] University of Colombo, Sri Lanka. Email: aazeez72@yahoo.com

The two notable works of corporate failure prediction are Beaver's (1966) univariate approach and the seminal work of Altman's (1968) Z-score using multiple discriminant analysis (MDA). Thereafter, these two approaches were widely used by researchers to develop models to predict corporate failure. All these research were based on financial ratios.

Several researches pointed out that weakness in corporate governance as one of the major causes for Asian Financial Crisis that occurred in 1997. For example, Rajan and Zingales (1998) and Prowse (1998) conclude that poor corporate governance on top of concentrated ownership structure paved the way to the crisis. The failure of Enron in 2001 was due to weak corporate governance mechanisms that provided an opportunity to the firm's executives to commit the fraud. The WorldCom had also reported that its earnings were subject to earning management. In Sri Lanka, Pramuka Savings and Development Bank Ltd (PSDB) failed due to lack of corporate governance practices. Hence, these events have raised the attention of individuals about the corporate governance.

Therefore, it can be evident that an early warning system cannot be developed without incorporating the corporate governance characteristics. The reason is that poor corporate governance can increase the probability of corporate failure even for firms with good financial performances. Only a few researchers tried to develop an early warning system that incorporates corporate governance variables so far. However, theses researchers did not incorporate financial ratios into their failure prediction models. To the author's best knowledge, no research to the date was found in Sri Lanka which incorporates both corporate governance variables and financial ratios to predict corporate failure.

The researcher intended that a new modelling approach presented in this study would fill existing gaps in the research. Therefore, primary purpose of this study is to develop a failure prediction model by incorporating both financial ratios and corporate governance variables. The researcher developed three models to test the predictive accuracy of each model using financial ratios and corporate governance variables. Analysis of the statistical testing results indicated that model consists with both corporate governance variables and financial ratios improved the prediction accuracy to reach 88.57 per cent one year prior to failure. Furthermore, predictive accuracy of this model in all three years prior to failure is above 80 per cent. Hence it is robust in obtaining accurate results for up to three years prior to failure. Final model includes two financial ratios, working capital to total assets and cash flow from operating activities to total assets, and two corporate governance variables, outside director ratio and company audit committee.

The rest of this paper is structured as follows. The next section reviews previous research studies in the area of corporate failure prediction. The methodology section illustrates the research hypotheses used in the study, measurement scales of both independent variables and dependent variable, modelling approach, sample selection, and data collection methods used in the study. Section 4 and 5 provides results and discussions respectively. Finally, section 6 concludes the paper.

2.0   LITERATURE REVIEW

The literature about corporate failure prediction methodologies is substantial. Many authors during the last 40 years have examined several possible realistic alternatives to predict corporate failures. The seminal works in this field were Beaver (1966) and Altman (1968), who developed univariate and multiple discriminant models to predict corporate failures using a set of financial ratios.

Beaver (1966) is the pioneering academician who used financial ratios with a univariate technique to predict financial failure. Beaver found that cash flow to total debt ratio is the best predictor for five years preceding failure. Although the simplicity of the univariate model is appealing, this model shows some important disadvantages. As univariate analysis involves an individual financial ratio as a single predictor of failure, an inconsistency problem can occur. The model may give inconsistent and confused classifications results for different ratios for the same firm (Altman 1968).

To overcome the problems resulting from the univariate analysis method, Altman (1968) improved on Beaver's univariate method of analysis by introducing a multiple discriminant approach. Altman developed the well-known Z score model with financial ratios based on multiple discriminant analysis (MDA). The results found that five financial ratios are significant predictors in corporate bankruptcy prediction model. These ratios are working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, market value equity to par value of debt and sales to total assets.

A subsequent study by Deakin (1972) examined fourteen financial ratios used by Beaver (1966), but used multiple discriminant analysis (MDA). The results indicated that it is possible to identify a large number of potential failures correctly up to three years before the firm files for bankruptcy. Altman, Haldeman and Narayanan (1977) formulated the ZETA R credit risk model, which contained several enhancements compared to the original Z score model. Instead of five variables, seven variables were entered into the updated version, namely: return on assets, stability of earnings measured using a normalized standard error, interest coverage ratio, retained earnings to total asset, current ratio, equity to total capital, and Log of total assets. Since many years, multiple discriminant analysis (MDA) was the prevalent statistical technique applied to the failure prediction models. It was used by many authors (see for example: Deakin 1972; Edminster, 1972; Blum, 1974; Eisenbeis, 1977; Taffler and Tisshaw, 1977; Altman 1977; Micha, 1984; Gombola et al., 1987; Lussier, 1995; Altman et al., 1995).

Financial ratios previously deployed are accrual accounting financial ratios that cannot reflect the ability of a firm to manage its future cash flows. Cash flow has been an important determinant of failure. Scott (1981) claimed that cash flow variables involve estimates of the firm's future cash flow distribution, and that past and present cash flow should be able to predict probability of failure. The value of cash-flow measurement was also supported by Earl and Marais (1982), who regarded the single ratio of cash flow to current liabilities as being a successful discriminator.

Other scholars have also included cash flow characteristics in their predictive models (Casey and Bartczak, 1985; Gentry et al., 1985; Gombola et al., 1987; Aziz et al., 1988). Gombola and Ketz (1983) reported that cash flow from operation ratios provide certain information that is not explained by other accrual ratios. Moreover, Gentry, Newbold, and Whitford (1987) asserted that in addition to the accrual ratios, the cash flow ratios can be accounted for in order to explain the financial health or illness of a particular firm. Furthermore, Charitou et al. (2004) evidenced that the bankruptcy prediction model containing the three financial variables: a cash flow ratio, profitability variables, and a financial leverage variable, provide a relatively high accuracy rate of classification one year prior to the actual bankruptcy.

Although the financial ratios, both accrual-based and cash flow-based ratios, are claimed to be decent variables comprised in the financial distress models, they have been criticized. The limitations of financial ratio analysis highlighted by Lee and Yeh (2004). They argued that the financial ratios, derived from financial statements, may be subject to earning management; the management manipulates the firm's financial results to meet predetermined earnings targets. Particularly, some financially distressed firms may improperly change their underlying accounting policies to temporarily increase operating income and prevent firms from failures (Opler and Titman, 1994). In addition, different firms may apply differing accounting treatments; thus the identical ratios from different firms may not be compared. Next, the financial ratios are calculated using the financial data over a fixed period, but the corporate failure is dynamic event representing the inability of firms to meet the obligations.

Hence, it is questionable whether it is useful to include only the financial ratios in predicting the corporate failure (Johnson, 1970). Moreover, Gilbert et al., (1990) argued that using the financial ratios alone may lead to the lack of information content and model misspecifications for prediction purposes. Several researches pointed out that weakness in corporate governance as one of the major causes for Asian Financial Crisis that occurred in 1997. For example, Rajan and Zingales (1998) and Prowse (1998) conclude that poor corporate governance on top of concentrated ownership structure paved the way to the crisis. Therefore, Corporate governance mechanisms have received extensive attention in corporate failure

prediction researches since the occurrence of a series of corporate collapses in the late 1990s (Becht, Bolton and Roell, 2002).

The size of the board can determine the quality of managerial monitoring and controlling. Evidence to support this argument is found in an empirical study by Chaganti, Mahajan and Sharma (1985), which found that non-failed retailing firms tend to have bigger boards than failed ones. On the other hand, some researchers have argued that small boards can improve firm performance while large boards are ineffective because of the coordination and process problems that often exist when there are many people involved in the decision making process (Lipton and Lorsch, 1992; Jensen, 1993). The other corporate governance variable under the board structure is the representation by outside directors on board. Inside directors cannot be relied on to impartially monitor their own performance. In contrast, outsiders are seen to be independent, and therefore impartial, as well as benefiting a company by representing alternative perspectives and enhancing the expertise of directors in general (Zahra and Pearce, 1989). Hence, boards dominated by many outsiders may be superior to other boards in contributing to managerial effectiveness (Wagner, Stimpert, and Fubara, 1998) and reducing the probability of corporate failure. An effective board should be truly independent from the CEO (Fama and Jensen, 1983). To be independent, the chairman of board should not be the same person as the CEO, implying that decision control and decision management functions are separated (Jensen, 1993). Hence, it is reasonable to believe that the probability of corporate failure tends to increase with the presence of CEO duality.

Various studies have examined the explanatory power of audit opinions. Typically, evidence supports a relationship between audit opinions and event of financial distress. For example, Altman and McGough (1974) and Menon and Schwartz (1986) found that about 50 percent of their samples received a going-concern qualification opinion before the distress really occurred. Flagg et al. (1993) found positive relationship between going-concern qualification opinion and the distress event.

Moreover, presence of an audit committee is also a significant corporate governance variable in past literature. DeFond and Jiambalvo (1991) found that the overstatement of earnings is less likely among firms which have audit committees. Kinney and Martin (1994) showed that auditors detect and reduce overstatements of earnings and assets.

Considering prior corporate failure studies, it is found that the primary problem of those studies is that these models were heavily relying on financial ratios in predicting corporate failure. It is therefore logical to search for more information other than financial ratios when building early warning systems for corporate failures. Furthermore, it is observed that none of prior empirical studies proposes a model that uses the vital causes of failure, which are the financial ratio and corporate governance to predict the corporate failure of firms in Sri Lanka. Researchers have found that firms failed even though they presented fairly good financial ratios as close as two years prior to the actual failure. This argument has seriously questioned the validity and reliability of using financial information in isolation from other non-financial variables like corporate governance. Moreover, it is found that previous studies used statistical corporate failure prediction models including univariate analysis, multiple discriminant analysis (MDA) and conditional probability models. It can be seen that in order to avoid some limitations presence in univariate analysis and multiple discriminant analysis, previous researchers used logistic regression analysis extensively. Hence, this study will employ logistic regression analysis to develop the corporate failure prediction model.

3.0   METHODOLOGY AND METHOD

3.01   RESEARCH HYPOTHESES

The research intends to test the following hypotheses:

H₁A: corporate failure prediction model consists with financial ratios is more accurate than the model consists with two classes of variables.
-   To test this hypothesis, financial ratios based on accrual and cash flow have been used in the model.

H₁B: corporate failure prediction model consists with corporate governance variables is more accurate than the model consists with two classes of variables.
-   To test this hypothesis, corporate governance variables categorized as board structure, ownership structure and disclosure and transparency have been incorporated in the model.

H₁C: corporate failure prediction model consists with two classes of variables is more accurate than the model consists with either financial ratios or corporate governance variables.
-   To test this hypothesis, both financial ratios based on accrual and cash flows and corporate governance variables incorporated in to the model.

3.02   OPERATIONALIZATION

Table 1 presents selected variables in this study with their measurement scale.

Table 1: Operationalization of variables

Variable	Indicator	Measurement
Dependent variable Corporate failure		Binary variable 1 = Failed , 0 = otherwise (Probability)
Independent variables		
1.Financial variables		
1.1 Accrual based	Profitability	Net income/Total assets
		Operating profit/Sales
		{Net profit (after tax) – preference dividend}/average ordinary share holders' equity.
	Leverage	Total liabilities/Total equity
		Total liabilities/Total assets
	Liquidity	Currentassets/Currentliabilities
		(Currentassets – Inventories)/currentliabilities
		(currentassets-currentliabilities)/Total assets
	Efficiency	Revenue/Total assets
		Revenue/Total capital employed
1.2 Cash flow based		Cash flow from operations/Net income
		Cash flow from operations/Liabilities
		Cash flow from operations/Current liabilities
		Cash flow from operations/Total assets
		Cash flow from operations/Total debt
2. Corporate governance variables		
	Outside directors	Number of outside directors/Total directors
	CEO duality	Binary variable 1 = CEO duality, 0 = otherwise
	Board size	Total number of directors in the board
	Outsiders' ownership	Percentage of shares owned by outside directors, institutions and public
	Audit report	Binary variable 1=qualified opinion,0=otherwise
	Presence of an Audit committee	Binary variable 1 = Presence , 0 = otherwise
	Remuneration of board members	Directors remuneration/ Revenue Directors remuneration/Profit or Loss

Based on reviewing literature, the present study employs a failure definition adapted from Hopwood et al. (1988), Lee et al. (2003), Sori and Jalil (2009), and Abou (2008). A company is considered among the failing companies if and only if one of the following conditions is satisfied. (1) the companies that had been incurring losses for three years continuously or more, (2) the companies that had illustrated negative position in cash flow for three years continuously or more.

3.03   MODELLING APPROACH - LOGISTIC REGRESSION

The statistical-analysis package used for developing the model is E –views. The primary tool used is logistic regression. Logistic regression is a statistical tool used for predicting an event's probability of occurrence. As it only became available in the 1970s, logistic regression was not considered in the development of early models such as Altman's Z-score, which was based on discriminant analysis. A logit model is estimated using the maximum likelihood method. The empirical testing of the present study attempts to improve prediction accuracy of corporate failure by introducing corporate governance variables besides financial ratios based on accounting information.

For empirical purposes, a model utilizing financial ratios is developed (Model I) and test the prediction accuracy. Then, a model utilizing corporate governance is developed (Model II) and tests the prediction accuracy. Finally, all variables: financial ratios and corporate governance variables are to be combined in Model III to test for the overall predictive power of the two classes of variables combined.

The function in logit analysis is called the logistic function and can be written as follows. Researcher used 3.1 logistic function to build the model consists with financial ratios, 3.2 logistic function to build the model consists with corporate governance variables and 3.3 logistic function to build the model consists with both variables.

$$P_i(Y=1) = 1/(1+e^{-z})$$

$$= 1/\{1+\exp[-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots + \beta_{15} X_{15})]\} \tag{3.1}$$

$$= 1/\{1+\exp[-(\beta_0 + \beta_1 G_1 + \beta_2 G_2 + \ldots\ldots + \beta_8 G_8)]\} \tag{3.2}$$

$$= 1/\{1+\exp[-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_{15} X_{15} + \beta_{16} G_1 + \beta_{17} G_2 + \ldots + \beta_{23} G_8)]\} \tag{3.3}$$

Where,

$P_i(Y=1)$ = Probability of failure for firm i;

$\exp$ = exponential function;

$\beta_1, \beta_2, \ldots$ = slope coefficients;

$X_1, X_2, \ldots$ = financial ratios $G_1, G_2, \ldots$ = corporate governance variables

3.04   SAMPLE SELECTION

All the listed companies in Colombo Stock Exchange (CSE) that had been failed during the period 2002 to 2008 were taken for the study and the matched sample design method was applied for this analysis. Each failed company has a non-failed partner in the sample. The failed companies were paired to the non-failed companies using the following criteria: same industry; same failure year; and closest asset size.

This matching design is consistent with the vast variety of prior corporate failure prediction studies (Altman, 1968; Aziz and Lawson, 1989; Beaver, 1968; Casey and Bartczak, 1985; Charitou et al., 2004). In addition, financial industry as a whole is excluded from the selected sample due to their different financial and business nature. Financial firms are structurally different from the others on the general accounting policies (Gilbert et al., 1990) and the financial firms have different failure environment (Ohlson, 1980).

A total of 70 failed companies were identified during the years of determination and with the match sample criteria, total sample consist with 140 companies; 70 failed and 70 non failed.

3.05   DATA COLLECTION

Relevant financial information and corporate governance information collected through the annual reports of both failed and non-failed companies for the years one year before the failure, two years before the failure and three years before the failure. One year before the failure data used to develop the failure prediction model and two years before the failure and three years before the failure data used to test the validity of the model.

4.0   RESULTS

In order to develop a more reliable and accurate corporate failure prediction model, three models were developed using logit analysis which is available in E-views.

4.01   MODEL WITH FINANCIAL RATIOS

Table 2 presents the logit regression results for the estimated model one together with their coefficient values, Z statistic, McFadden R squared, log likelihood ratio and the significance of the log likelihood stat. Model one has only three significant variables namely working capital to total assets (WCTA) debt ratio (DR) and cash flow from operating activities to total assets (CFFOTA).

For the logit model, the coefficients are calculated through the use of Maximum Likelihood Estimation (MLE) method as opposed the Original Least Squares (OLS) method employed by linear regression. While OLS seeks to minimize the sum of squared distances between the data points and the regression line, MLE seeks to maximize the log likelihood. This reflects how likely the observed values of the dependent variable can be predicted from the observable values of the independent variables. Hence, model fit can be ascertained through the log likelihood ratio of the model. Log likelihood ratio of the model I is 62.02 and it is statistically significant at 1 per cent level. Further, McFadden R squared is the likelihood ratio index. As the name suggests, this is an analog to the R squared reported in linear regression models. It can be seen that the value of Mcfadden R squared in the model I is 32 per cent. The final selected variables and related regression coefficients as shown in table 2 are used to derive the logistic regression function for model consists with financial ratios as follows. Z = -0.228 -5.190WCTA + 1.844DR -10.089CFFOTA

Table 2: Model I with selected financial ratios

Variable	Coefficient	z-Statistic	Prob.
C	-0.228	-0.488	0.625
WCTA	-5.190***	-3.807	0.000
DR	1.844**	2.160	0.030
CFFOTA	-10.089***	-4.253	0.000
McFadden R-squared **0.320**			
LR statistic **62.020**			
Prob(LR statistic) 0.000			

**Denotes 5% significant level; ***Denotes 1% significant level
WCTA=working capital to total assets; DR=debt ratio; CFFOTA= cash flow from operating activities to total assets.

4.02   MODEL WITH CORPORATE GOVERNANCE VARIABLES

Table 3 shows results of logit analysis for corporate governance variables, which are found to be significant in initial multivariate logit analysis. Both OUDR and REBMPL are statistically significant at 1 per cent level. Further, CEODUL and COAUCOM are statistically significant at 5 per cent level. Log likelihood ratio of the model II is 77.07 and it is statistically significant at 1 per cent level. Further, McFadden R squared of the model is 40 per cent. The final selected variables and related regression coefficients as shown in table 3 are used to derive the logistic regression function for model consists with corporate governance variables. Z = 4.899 – 7.540OUDR + 1.464CEODUL -1.021COAUCOM – 0.090REBMPL

Table 3: Model II with selected corporate governance variables

Variable	Coefficient	z-Statistic	Prob.
C	4.899	4.797	0.000
OUDR	-7.540	-4.815	0.000***
CEODUL	1.464	2.214	0.026**
COAUCOM	-1.021	-2.186	0.028**
REBMPL	-0.090	-2.675	0.007***
McFadden R-squared **0.400**			

LR statistic **77.070**
Prob(LR statistic) 0.000

**Denotes 5% significant level; ***Denotes 1% significant level, OUDR=outside director ratio; CEODUL=CEO duality; COAUCOM=company audit committee; REBMPL=remuneration of board members to profit and loss

4.03   MODEL WITH FINANCIAL RATIOS AND CORPORATE GOVERNANCE VARIABLES

Table 4 shows selected significant financial and corporate governance variables in model three, together with their regression coefficients. Initially, all the financial ratios and corporate governance variables entered to the multivariate logit model. Then, by dropping all insignificant financial ratios and corporate governance variables from the multivariate logit model, it remains with all significant financial ratios and corporate governance variables. Logistic function 3.3 presented in section 3.3 used to derive the model consists with financial ratios and corporate governance variables.

Table 4: Model III with selected financial ratios and corporate governance variables

Variable	Coefficient	z-Statistic	Prob.
C	10.675	4.726	0.000
WCTA	-12.456***	-4.349	0.000
CFFOTA	-18.148***	-4.018	0.000
OUDR	-13.872***	-4.450	0.000
COAUCOM	-2.494***	-3.156	0.001
McFadden R-squared **0.640**			
LR statistic **124.620**			
Prob(LR statistic) 0.000			

***Denotes 1% significant level
WCTA=working capital to total assets; CFFOTA= cash flow from operating activities to total assets; OUDR=outside director ratio; COAUCOM=company audit committee.

Significant variables among financial ratios are working capital to total assets, cash flow from operating activities to total assets, while significant corporate governance variables are outside director ratio and company audit committee. However, out of three financial ratios which are significant in model I, only two financial ratios are deem to be significant in model III. Even though debt ratio is significant in model I, it is found to be insignificant when combined with corporate governance variables. Further, out of four corporate governance variables which are significant in model II, only two variables are found to be significant in model III. Remuneration of board members to profit and loss and CEO duality variables are not statistically significant when combined with financial ratios. The parameter estimate of OUDR and COAUCOM indicates that outside director ratio and company audit committee has a significant negative effect on the probability of corporate failure.

Therefore, model III consists with two financial ratios and two corporate governance variables. All the variables are significant at 1 per cent level. Log likelihood ratio of the model III is 124.62 and it is statistically significant at 1per cent level. Further, McFadden R squared of the model is 64 per cent. The final selected variables and related regression coefficients as shown in table 4 are used to derive the logistic regression function of model consists with financial ratios and corporate governance variables.

Z= 10.675 – 12.457WCTA – 18.149CFFOTA – 13.872OUDR – 2.494COAUCOM

4.04   TEST OF GOODNESS OF FIT

Table 5 presents results of Loglikelihood ratio test, McFadden R squared and Hosmer and Lemeshow test that are applied to test the goodness of fit of three models. The likelihood ratio statistic tests whether the null model, i.e. the model that only includes the constant term, fit the data as well as the full model. In other words, it tests whether the set of variables included in the model explains a significant portion of the variability in the data. In all three models, the test is significant at 1 per cent level. Likelihood ratio is 62.02 for model I. it increases to 77.07 in the model consists with corporate governance variables. Further, it has been increased to 124.63 when both classes of variables entered in to a one model (Model

III). Similar results obtain with respect to McFadden R squared. It increases from 0.319 for Model I, to 0.397 for Model II to 0.642 for Model III. Again results shown that higher McFadden R squared is achieved when financial ratios and corporate governance variables entered into a one model.

Finally, Hosmer and Lemeshow test is useful in testing the difference between model – predicted values and observed values. If the statistics is large enough to reject the null hypothesis: that predicted values equal observed values, then the model may not be good enough. For three models, none of them is rejected at 10 per cent level. Therefore, it could be noticed from the analysis that combining the two classes of variables in Model III improves the log likelihood ratio, McFadden R squared and Hosmer and Lemeshow test compared to other two models. So, it is reasonable to consider that the goodness of fit of the Model III is quite acceptable, and expect a well performed forecast ability.

Table 5: Results of the tests of goodness of fit

Model	McFadden R-squared	LR stat	Hosmer & Lemeshow test
I	0.319	62.02***(0.000)	5.960(0.65)
II	0.397	77.07***(0.000)	9.825(0.27)
III	0.642	124.63***(0.000)	5.52 0(0.70)

Numbers in parenthesis are p-values
***Denotes 1% significant level
Model I consists with financial ratios; Model II consists with corporate governance variables; Model III consists with financial ratios and corporate governance variables.

4.05   CLASSIFICATION ACCURACY

Table 6 presents the classification accuracy for three prediction models for failed and non-failed companies based on data one year prior to the corporate failure. To ensure that the corporate failure prediction model obtained above is the "reliable" prediction model, the classification accuracy test is employed by using Type I and Type II analysis (Altman, 1968; Casey & Bartczak, 1985; Gilbert et al., 1990, Ohlson, 1980). Type I refers to the probability of accurate classification of failed company, while Type II refers to the probability of accurate classification of non-failed company. Hence, in the "reliable" corporate failure model should have the joint maximization of Type I and Type II.

Once the probability of corporate failure is obtained, each company is classified into failed or non-failed based on a cutoff estimated probability of 0.5. As the estimated probability is more than 0.5, the firm is classified as failed company and if less than 0.5, the firm is classified as non-failed company (Casey and Bartczak, 1985; Gilbert et al., 1990, Ohlson, 1980; Lee &Yeh, 2004). Results show that the Type I and Type II accuracy rates of the model III are higher than the other two models. This means that model III has the discriminating power to classify correctly the failed companies about 92.9 per cent (only 5 misclassification out of 70) and to classify correctly the non-failed companies about 84.3 per cent (only 11 misclassification out of 70). The results show the overall accurate classification rate of the model III for the first year before the failure is about 88.6 per cent.

Table 6: Classification accuracy for failed and non failed companies
Using in –the sample data, to classify a firm whether it is failed or non-failed, the probability of corporate failure for each firm is calculated from the cumulative probability function P = 1/ {1+e$^{-logit\ function}$}.

Model	Firms	Prediction accuracy
I	Failed	78.57%
	Non failed	77.14%
	Entire sample	77.86%
II	Failed	81.43%
	Non failed	84.29%
	Entire sample	82.86%
III	Failed	92.86%
	Non failed	84.29%
	Entire sample	**88.57%**

Model I consists with financial ratios; Model II consists with corporate governance variables; Model III consists with financial ratios and corporate governance variables.

4.06   VALIDATION OF THE LOGIT MODEL

Table 7 shows the validation results of the three logit models. The external validity of the multivariate logit model is tested using different data set. Three models were tested using two years before the failure data and three years before the failure data. Validity of the model depends on its applicability for multi period. That is, the longer the accuracy of the model could be maintained, the better the model becomes. The overall correct classification results for one, two and three years prior to failure are 88.57 per cent, 82.86 per cent, and 82.14 per cent respectively for the model consists with both financial ratios and corporate governance variables (Model III). As the predictive powers of the model III in all three years prior to failure are above 82 per cent, it can be concluded that the model III is robust. Further, it indicates that valuable results could be obtained for up to three years prior to failure.

Table 7: Validation test results for three models

	1 year before the failure	2 years before the failure	3 years before the failure
Model I	77.86%	72.14%	74.29%
Model II	82.86%	73.57%	80%
Model III	**88.57%**	**82.86%**	**82.14%**

Model I consists with financial ratios; Model II consists with corporate governance variables; Model III consists with financial ratios and corporate governance variables.

5.0   DISCUSSION

Model III includes both financial ratios and corporate governance variables. Based on the goodness of fit results, it can be seen that model III is the well fitted model among other two. Log likelihood ratios for model I, II and III are 62.02, 77.07 and 124.63, respectively. All these ratios are significant at 1 per cent level. However, it is evident that model III which consist with financial ratios and corporate governance variables is having the more explanatory power over the other two models as per the incremental log likelihood ratio. Similar results obtain with respect to McFadden R squared and Hosmer and Lemeshow test. Therefore, it could be noticed that combining the two classes of variables in Model III improves the log likelihood ratio, McFadden R squared and Hosmer and Lemeshow test compared to other two models.

This final model (Model III) provides an impressive results in which it yields an overall correct classification accuracy 88.57 per cent, 82,86 per cent and 82.14 per cent for one year before the failure, two years before the failure and three years before the failure, respectively. Prediction accuracy for all three years for the model consists with both variables is higher than the other two models. Hence, there seems to be an appropriate ground on which to accept the third hypothesis H_{1C} which states that, "model consists with financial ratios and corporate governance variables is more accurate than the model consists with either financial ratios or corporate governance variables" and reject hypothesizes H_{1A} and H_{1B}.

The results of model III appear to be high compared to the 86.95 per cent for one year before the failure reported by Lee, Yeh and Liu (2003). They also found that when the financial ratios based model combined with corporate governance variables, it adds more explanatory power to the model and predicts corporate failure more accurately than model including financial ratios alone. Further, this is consistent with Abou (2008). He also found that it significantly increases the explanatory power of the model consists with financial ratios, when it combined with corporate governance variables and macroeconomics variables.

Therefore, results indicate that model consists with both variables can be used to predict corporate failure up to three years prior to failure occurs. Final model (Model III) includes two financial ratios namely working capital to total assets (WCTA) and cash flow from operating activities to total assets (CFFOTA) and two corporate governance variables namely outside director ratio (OUDR) and company audit

commit (COAUCOM). Those ratios are found to be the most explanatory variables in predicting corporate failure. It can be seen that when financial ratios are combined with corporate governance variables, debt ratio (DR) is insignificant.

It is interesting to note that none of the models include profitability ratios as predictors of corporate failure of listed companies in Sri Lanka. Results revealed that company's ability to generate profits appears to be insignificant in ensuring a firms' continued survival. This result is consistent with the Shirata (1998). He found that profitability ratios have no significant importance in determining firm health. These results appear to refute Beaver' s (1966) findings that profitability ratio as proxy by ROA was the second best predictor of potential failure.

Further, all three models emphasize the significance of working capital to total assets and cash flow from operating activities to total assets in predicting corporate failure. Liquidity as measured by WCTA is a good predictor of corporate failure. Most of the failed companies were unable to generate sufficient liquidity during the period under study. Further, they were inefficient in utilizing companies' assets to generate cash flows. For the corporate governance variables, it is found that out of four variables which were significant in model II, two variables are found to be significant predictors in model III. Outside director ratio and company audit commit have the significant predictive ability over other variables. Therefore, it can be seen that CEO duality and remuneration of board members to profit and loss are not significant predictors of corporate failure when it is combined with financial ratios. It is evident that most of the failed companies did not pay remuneration to their directors due to insufficient earnings during the period under study. Further, some of the non-failed companies also did not pay remuneration due to the same reason. Therefore, it cannot find a direct relationship between directors' remuneration and probability of corporate failure or the survival.

Moreover, when corporate governance variables combined with financial ratios, it is found that CEO duality is not a significant predictor of corporate failure. Research finding is consistent with Chaganti et al, (1985). He found no difference in the incidence of CEO duality in each of the five years preceding failure for failed as compared to non-failed companies. Further, Daily and Dalton (1994) also found that CEO duality was not a significant predictor of bankruptcy at either three or five years prior to failure.

6.0   CONCLUSION

Research results indicate that an early warning system cannot be completed without incorporating the corporate governance characteristics. The reason is that poor corporate governance can increase the probability of corporate failure even for firms with good financial performance. Therefore, financial data alone may not be good enough for the purpose of predicting corporate failure. It can be seen that bad corporate governance as one of the key factors leading to the corporate failures in both developed and developing economies. However, only a few researchers have tried to develop an early warning system that incorporates corporate governance variables so far.

Estimating probability of failure is valuable for credit rating agencies and financial institutions to consider granting loans to companies. Furthermore, investment decisions in listed companies could be enhanced through predicting probability of failure. As the value of listed firms are often supported by the use of funds supplied by the general public, the potential loss in equity value as a direct or indirect result of firm distress, bankruptcy, and reorganization could have wide ranging effects. Similarly, it is vitally important for an auditor to be able to assess whether or not a company is a going concern in preparing the audit report. Therefore, model developed by this thesis could be used by credit rating agencies, financial institutions, auditors and investors to predict the probability of corporate failure in advance. Investors can use this model as a valuable technique for screening out undesirable investments. If an investor already owns stock in a firm whose future appears uncertain, he should sell the stock in order to avoid further price declines. Further, investment analysts can utilize these predictions to recommend appropriate investment policy. Management and other regulatory institutions can use the model to predict the probability of firm's failure. So, thereby they can take either preventive or corrective actions

to mitigate the risk of further collapses. If the management of the firm utilizes the model correctly and periodically, they can predict corporate problems early enough. As a result, this will enable management to realize the severity of the situation in time to avoid failure. If failure is unavoidable, the firm's creditors and stockholders may be better off if a merger with a stronger enterprise is negotiated before bankruptcy. Moreover, investors and other credit granting institutions should take in to account both financial soundness and corporate governance mechanisms of the organization. The reason is that poor corporate governance can increase the probability of corporate failure even for firms with good financial performance.

This study has a number of implications for managerial practices. Strengthening the corporate governance mechanism would help to reduce the likelihood of corporate failure. To enhance the performance of companies and mitigate the probability of corporate failure, the companies should employ more outside directors to their board of directors. Based on agency perspective, it can be suggested that if the majority of directors in the board are outside directors, then the opportunity for the CEO and inside directors to exercise behaviors that are self-serving and costly to the firm's owners will be reduced. Further, companies should appoint an audit committee to oversight the firm's financial reporting process and credibility of audited financial statements. However, ownership structure, audit opinion and remuneration of board members have no impact on listed companies' failure. So, these factors are not guaranteed the survival of listed companies. As the working capital to total assets ratio and the cash flow from operating activities to total assets are the only significant financial ratios influencing failure of listed companies, management needs to consider carefully the level of liquidity and cash flow positions of the company in order to prevent possible failure of listed companies.

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