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Predicting Corporate Financial Distress in Sri Lanka: An Extension to Z-Score Model

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ABSTRACT

The main purpose of this study is to develop a better financial distress prediction model for the Sri Lankan companies using the Z-score model. Fourteen variables have been selected consisting of accounting, cash flow and market based variables. Multivariate Discriminate Analysis (MDA) was used as the analytical technique and stepwise method was used to select the variables with the best discriminating power to a dataset of sixty-seven matched pairs of failed and non-failed quoted public companies over the period 2002 to 2011. The final models are validated using the cross validation method. The results indicate that a model with four predictors of earnings before interest and taxes, cash flow from operations to total debts, retained earnings to total assets, and firm size have achieved the classification accuracy of 85.8% in one year prior to the distress with a very low type I error. Moreover, the model has correctly classified the cases by 79.9% and 69.4% in two year and three year prior to distress respectively. The study has further revealed that the companies with negative cutoff value fall into distress zone while the companies with positive cutoff values fall into safety area. Hence, the study concluded that the companies with cutoff values approximately zero should be considered on mitigating actions for financial distress not only on the accounting information but also on the cash flow and market data.

Keywords: Financial distress, market variables, multivariate discriminant analysis, Z-Score.
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1.0 INTRODUCTION

The prediction of financial distress or bankruptcy has been recently characterized one of the most important problems facing businesses. Because the problem may causes the companies to get bankrupt or to reduce the reputation in the industry. Due to the gravity of the issue to the corporate sector, the influenced parties raised the question on a way to identify the financial distress in advance. With that, many researchers attempted to find a solution to the problem by developing models that able to provide early signals. However, the issue of identifying the distress in advance is still remained unsolved. While there is abundant literature describing prediction models of corporate bankruptcy, few

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research efforts have sought to predict corporate financial distress. The lack of work on financial distress results in part from difficulty in defining objectively the onset of financial distress. Financial distress is defined as a late stage of corporate decline that precedes more cataclysmic events such as bankruptcy or liquidation. Information that a firm is approaching distress can precipitate managerial actions to forestall problems before they occur, can invite a merger or takeover by a more solvent or better-managed enterprise, and can provide an early warning of possible future bankruptcy. Further many studies on developing countries focus on testing the available models in their context rather than developing a country specific model. According to Mensah (1984) the failure prediction research could vary from context to context. Therefore, in this study, we attempt to develop a financial distress prediction model with advance predicting accuracy for the quoted public companies in Sri Lanka.

Even though there are ample studies available internationally, only few published studies could be found in the area of predicting financial distress in Sri Lanka. As an example, Samarakoon & Hasan (2003) empirically tested the three versions of Altman's Z-Score model with the financially distressed companies in Sri Lanka while Nanyakkara & Azeez (2013) developed a context specific model using the Altman's Z-Score model. According to Samarakoon & Hasan (2003) US based Altman Z"- Score model has a remarkable degree of accuracy in predicting distress in the year prior to distress. Since that study is not adjusted the loadings (weights) of the accrual based ratios for the Sri Lankan context, the conclusion is based on the original Z-score formula which was derived from USA bankrupted companies. Nanyakkara & Azeez (2013) developed a new model by adjusting the loadings of the Altman's model with better accuracy rate for three years in advance. Bellovary et al (2007) indicate that a model to become more valuable it should be able to accurately predict bankruptcy earlier. However, both studies conclude that the Z-Score model as a suitable model in predicting financial distress in Sri Lanka.

Even though these studies concluded in favour of Z-Score model, the limitation of independent variables in the Altman's Z-Score model has not been addressed by those studies. They are purely accrual based accounting ratios, and in purely accounting based approaches, there is an issue of timeliness as accounting data is essentially out of date and distress firms likely to be late reporting (Christidis & Gregory, 2010). Also market variables which provide a sound theoretical model for bankruptcy (Agarwal & Taffler, 2008) have not been tested in previous studies in Sri Lankan context. In addition to that we have not found any single study conducted locally which used one of the most popular and promising method for financial distress, Multivariate Discriminant Analysis and Z-Score model, in developing a distress model integrating non-accrued based ratios. This study will contribute not only to the theoretical knowledge, but also to the practical world. Because this study will help for the potential investors in making decision on whether to invest or not in a particular stock, for the lenders to make sure the return and the recoverability of the investment, for the managers to make corrective actions prior to company suffer from financial distress and for shareholders to ensure the return on their investment in the future periods.

Hence the objective of this study is to test the financial distress predicting accuracy of market base variables and cash flow base variables together with accrual base accounting ratios and develop a suitable model for Sri Lanka using Z-Score model, which could be able to provide a better sense in advance about the financial distress of companies. In order to develop the model the study has selected fourteen variables consisting accrual based, cash flow based and market based variables for the period 2002 to 2011. A sample of 134 companies were tested which includes 67 distressed and 67 non-distressed companies. Multivariate Discriminant Analysis (MDA) used as the analytical technique and stepwise method used to enter the variables in the analysis. The study has tested up to three years prior to distress in order to get an idea about the possibility of use the model in advance. In addition, the result of the model validated using the cross validation method. Our results provide evidence that the derived model which consists of four variables is able to predict financial distress of Quoted public companies in Sri Lanka by 85.8% accurately one year prior to distress. Further, the model has correctly classified the cases by 79.9% and 69.4% in two year and three year prior to distress respectively. The study also exposes that the companies with negative cutoff value will fell into distress zone while companies with positive cutoff values fell into safety area. Hence, we suggest that the companies with cutoff values near to zero should consider on mitigating actions for financial distress.

The balance part of the paper is organized as follows. The next section deals with prior research studies in relation to prediction of financial distress of companies using accrued based accounting ratios, cash flow ratios and market variables. The methodology section discusses the selected variables, dataset, model and method of model validation. The fourth section presents the empirical results and data analyses. Finally, conclusion of the study is presented.

2.0 LITERATURE REVIEW

The distress prediction models starts with the ratio analysis in 1930s and it has evolved with various methodologies and variables later (Bellovary et al., 2007). The purpose of certain approaches is to find the best predictors that lead to minimum misclassification errors while others tend to select the statistical method that would lead to improved correct classification accuracy (Yap, Yong & Poon, 2010). From 1930s with the publication of Bureau Business Research (BBR) the ratio analysis is used by other researchers as a technique for predicting failure (eg: FitzPatrick: Smith & Winakor: Merwin: Jacendoff, as cited in Bellovary et al., 2007). When we look at the development of bankruptcy prediction model, instead of simple ratio analysis, the use of univariate analysis was introduced by Beaver (1966), followed by multivariate discriminant analysis by Altman in 1968. Beaver's (1966) univariate analysis used individual financial ratios to predict distress. By using 79 failed and non-failed companies that were matched by industry and assets size in 1954 to 1964, his results from the prediction error tests suggested that cash flow to total debt, net income to total asset and total debt to total assets have the strongest ability to predict failure. These ratios differed from the MDA model proposed by Altman (1968). By utilizing 33 bankrupt companies and 33 non-bankrupt companies over the period 1946 to 1964, five variables were selected on the basis that they did the best overall job in predicting bankruptcy. Those are Working capital to total assets, Retained earnings to total assets, Earnings before interest and taxes to total assets, Market value of equity to Book value of total debt, and Sales to total assets. Using the same technique as the analytical tool Taffler & Tishaw (1977)[3] develops a Z-score model in order to predict company failure based on UK companies. Altman (1983; 1993) further revise the original Z score model targeting private firms (Z' score model or private firm model) by substituting the book value of equity for the market value and using non-manufacturing companies (Z" score model). Revised model with Book value of equity to Book value of total liabilities probably less reliable than the original, but only slightly less (Altman, 2000). Since the Sales to total assets ratio is an industry sensitive variable, it is excluded in the third revision in order to minimize the potential industry effect. Recently, Yap, Yong & Poon (2010) develop a model to predict company failure for Malaysia based on manufacturing companies and constructs a strong discriminant function with 7 ratios which has a predictive accuracy for five years prior to actual failure. Among the seven ratios two ratios are in all three versions of Altman's Z-Score model. Further, Bhunia, Khan & Mukhuti (2011) develop a model to predict the financial distress of Indian companies under the Z-score model with a classification accuracy of 81%.

Many research works during 1960's & 1970's consider only the accrual based variables using companies' historical financial data. According to Sharma (2001), the basic purpose of the creative accounting is to mislead and even defraud users of financial reports in extreme circumstances. Based on this purpose it can be argued that since companies manipulate and mislead the referees, the problem of using accrual based financial information solely in predicting financial distress has a significant doubt. Hence, time to time researchers criticize the models with accrued based financial ratios (eg. Deakin, 1972; Ohlson, 1980; Beaver, McNichols, & Rhie, 2005 etc) due to certain issues associated with them, and emphasize the need of incorporating other variables to the model. Owing to the criticisms over accrued based ratios, Beaver (1966) and some other researchers (eg. Deakin, 1972: Blum, 1974: Norton & Smith, 1979

[3] A most prominent model developed based on UK companies and all the variables used are different from Altman's Model.

etc) emphasize the importance of including cash flow based variables in developing models for predicting company failures and they highlight the importance of Cash flow from operation ratios in their studies.

However, according to Sharma (2001), studies which use cash flow based variables as predictors of company failure are not conclusive due to the limitations such as improperly measured cash flow operations, research studies which are not validated using a validation sample, research studies not consider about the caution of Gombola et al., (1987) regarding the importance of conducting time series analysis using cash flow information, studies focus mainly on cash flow from operations and ignoring other potential cash flow variables, and studies become difficult with large variety of cash flow ratios investigated with different measurements, research methods and statistical techniques employed in different paradigms. According to Beaver et al., (2005) since financial statement variables are correlated, the effect of selecting independent variables may have only marginal fluctuation. Further, mainly due to the changes happening over time in the financial statement measurement tools and standards the informative power of financial statement variables decrease and this loss of informative power in accounting information can compensate with the usage of market variables. Supporting to that argument Christidis & Gregory (2010) emphasize that combining accounting data with information in market prices help to overcome the timeliness problem in accounting data. Hence, researchers focus on incorporating market data in developing models for predicting company failure. Accordingly, the researchers identify the importance of market variables such as firm market return, past excess return, idiosyncratic standard deviation, standard deviation of stock return, and firm stock return in predicting company failure (ex: Shumway, 2001; Chava & Jarrow, 2004; Hillegeist, Cram, Keating, & Lundstedt, 2004; Campbell, Hilscher, & Szilagyi, 2011; Agarwal & Taffler, 2008)

In Sri Lanka, Samarakoon & Hasan (2003) test the original Altman's Z-score models and concludes that the third version of score model (Z"-score model) gives the highest overall success rate and it seems that Z-score models have a very good potential in predicting financial distress of companies in emerging markets, but with a declining overall accuracy at the two consecutive years prior to distress. This study provides evidence that Altman's Z-score model is a suitable analytical tool for Sri Lankan companies in predicting financial distress. Owing to that conclusion Nanyakkara & Azeez (2013) develops a model specific to Sri Lanka with a predicting ability of financial distress for three years in advance using the Altman's Z" score model. But no further evaluations have been done using a latest dataset to derive a model specific to Sri Lanka with a high predicting accuracy level by addressing the limitations with purely accrued based variables.

3.0 METHODOLOGY AND DATA

This section describes the data set, selected variables, and the statistical models. In this study financial distress is defined as the companies suffering with losses continuously for three years or more and/or, suffering with negative cash flow position continuously for three years or more and/ or, have a negative net worth continuously for three years or more. Dependent variables are categorical as financially distressed or non- distressed. The companies which satisfied one of these three criteria are defined as 'financially distressed' Companies.

This study uses the financial ratios, cash flow ratios and market based variables as the independent variables. Table 1 present all the variables with their definitions. These ratios are incorporated for the studies of company failure by many research studies to date (ex: Altman, 1968; Samarakoon & Hasan, 2003; Beaver et al., 2005 etc).

The data are collected from the annual reports of the listed companies in the Colombo Stock Exchange for the period from 2002 to 2011. There are 20 industries and 246 companies quoted in CSE as of 31st March, 2011. In determining the population Banking, Finance and Insurance industry is excluded since it has separate characteristics than the other industries by its nature. Out of the remaining 206 quoted public companies, the companies that satisfied one of the above mentioned three criteria have been selected as distressed company. Certain companies which satisfied the criteria as distressed has to be ignored from the sample due to the unavailability of previous years data, listed in CSE at least not more than three years from the distressed year, or unavailability of healthy company for matched sample (ex: Information technology industry). Finally, the study used total sample size of 134 quoted public companies registered in CSE. The sample size comprised with sixty seven (67) numbers of financially distressed companies and the same number of non-distressed companies as the matched sample which has been selected based on the industry and/or asset size following the literature (eg. Altman, 1968; Beaver, 1966; Altman, Baidya & Dias, 1979 etc.)[4].

Table 1: Operationalization of the variables

	Variables	Indicators	Measurement
Dependent variables	Financially distressed Financially not distressed	Net worth Annual profitability Soundness of the Cash flow	1= if distressed, 0 = otherwise
Independent variables	Accrual based financial ratios	Profitability/Leverage Liquidity Profitability/Efficiency Liquidity/Efficiency Solvency Solvency	RE/TA WIC/TA EBIT/TA MVE / BV of TD TD/TA EBIT/Interest expense
	Cash flow based financial ratios	Soundness of the cash flow	CFFO/NW CFFO/TA CFFO/CL CFFO/TD CFFO/Interest paid
	Market based variables	Firm return Firm size Stock volatility	Stock return[5] ln (Market capitalization) Std deviation of stock return over past 12 months

Data are collected for each company in the sample for one year, two year and three year separately. As mentioned in Altman (1968) and later studies, data collected for the non-distressed companies from the same years as of relative distressed companies. Data of one year prior to distress were considered in developing the discriminant function while two year and three year prior data are used to test the predicting ability of the derived function in advance.

Accordingly, the following discriminant function is used for the analysis[6].

$$Z = \beta_1 WICTA + \beta_2 RETA + \beta_3 EBITTA + \beta_4 MVEBVTD + \beta_5 TDTA + \beta_6 EBITINT + \beta_7 CFFONW + \beta_8 CFFOTD + \beta_9 CFFOTA + \beta_{10} CFFOCL + \beta_{11} CFFOI + \beta_{12} StkRtn + \beta_{13} FS + \beta_{14} StkVol$$

Where: Z = Discriminant score value, WICTA = Working Capital to Total Assets, RETA = Retained Earnings to Total Assets, EBITTA = Earnings Before Interest and Taxes, MVEBVTD = Market Value of Equity to Book Value of Total Debts, TDTA = Total Debts to Total Assets, EBITINT = Earnings before Interest and Taxes to Interest, CFFONW = Cash flow from Operations to Net Worth, CFFOTD = Cash flow from Operations to Total Debts, CFFOTA = Cash flow from Operations to Total Assets, CFFOCL = Cash flow from Operations to current Liabilities, CFFOI = Cash flow from Operations to Interest, StkRtn = Stock return, FS = Firm Size, StkVol = Stock Volatility

[4] Refer appendix A for the sample of two groups

[5]Adjusted stock return= $R_{i,t} = \frac{\left[\left[\frac{Pc}{Pc + R_r P_r}\right](1 + R_r + D_r + B_r)\right] P_{i,t} - P_{i,o}}{P_{i,o}} \times 100$

[6] In Altman's original model the constant term cannot be seen due to the statistical package (which was developed by W. Cooley and P. Lohnes) used to develop the model.

The study has satisfied with the major two assumptions namely, multivariate normality of the independent variables, and Unknown (but equal) dispersion and covariance structures (equal covariance matrices). In analyzing the model stepwise method is applied to see the discriminating power of the predicting variables and Mahalanobis Distance is used as a criterion in selecting the variables to the function which is computed in the original space of the explanatory variables rather than as a collapsed version.

In order to determine the relevant zone the function should derive a common cutting score. Optimum cutting score could be calculated considering the defined prior probabilities of the groups (Altman, 1968; Hair et al., 2011). Since there is an equal prior probability, the following formula is applied to calculate the cutting score (Optimum Z-score) of the discriminant function[7].

$Z_{CE} = (Z_A + Z_B)/2$

Where,

Z_{CE} = Critical cutting score value for equal group sizes

Z_A = Centroid for Group A, Z_B = Centroid for Group B.

The classification matrix[8] was developed for the sample using SPSS software and to construct the classification matrix each observation were classified into distress or non-distress following the rule in Hair et al., (2011) as follows.

Classify a company into group distress if $Zn < Zct$

Classify a company into group non-distress if $Zn > Zct$[9]

After calculating the hit ratio[10] the standard of comparison and Press's Q statistic are used to satisfy with the hit ratio of the model. Majority of the researchers accept the hit ratio if it is 25% greater than the standard of chance (Burns & Burns, 2009; Hair et al., 2011), and we adopt the same method. The Press's Q statistic is applied as a test to ensure the classification accuracy more statistically. We used cross-validation method to externally validate the model.

4.0 DATA ANALYSIS AND FINDINGS

This section discusses descriptive statistics, test of assumptions, estimation results, validation of model, analysis of advance classification accuracy of the model and discussion of results.

Table 2 indicates the descriptive statistics of all fourteen variables in the study under two main groups in equal size as financially distressed and non-distressed companies. Even though there are high standard deviations in variables the mean differences among the two groups are statistically significant according to F test (Table 3).

4.01 TEST OF ASSUMPTIONS

The study analyzed and satisfied the assumptions of normality, the equal covariance, multicollinearity and differences between the groups. Kolmogorov-Smirnov test results become insignificant for each variable by accepting the null hypotheses of the test and plots of the Q-Q diagram are laid on or nearly on the diagonal line. Box's M statistic and the Log determinants within the groups used to test the assumption of equal covariance matrix. Even though the Box's M test do not support to the assumption with 45.364 M value and 4.388 F value and significant p value of 0.000, the test of log determinants satisfied the test of equal covariance with similar log determinants for the two groups.

[7] This formula could be applied only with the equal prior probabilities.
[8] Classification matrix is a table with rows of dependent categories and columns of predicted categories (Burns & Burns., 2009).
[9] Zn = Discriminant Z score for the individual, Zct = Critical cutting score value
[10] Percent correctly classified the two groups by the function

According to Burns & Burns (2009) with significant M statistic the assumption could be hold if the log determinants become similar.

Table 2: Descriptive statistics

	Group 1				Group 2			
Variable	Mean	Standard Deviation	Minimum	Maximum	Mean	Standard eviation	Minimum	Maximum
WICTA	.0109	.2583	-.5180	.6501	.1712	.2517	-.3026	.7993
RETA	-.0574	.2935	-.4961	.6122	.1933	.1912	-.2634	.6693
EBITTA	.0279	.0837	-.0843	.2440	.1061	.0753	-.0800	.2491
TDTA	.5252	.3099	.0244	1.1791	.3536	.2171	.0125	.7600
MVEBVTD	2.9290	2.3761	-1.77	8.31	4.8626	1.8754	1.66	10.53
EBITINT	.9275	4.9427	-10.957	19.028	6.1506	4.6658	-5.000	19.314
CFFONW	-.0229	.2288	-.3397	.5363	.1147	.1840	-.3428	.5101
CFFOTA	-.0239	.0777	-.1838	.1724	.0559	.0910	-.1800	.2576
CFFOCL	-.0718	.2470	-.6067	.6226	.1968	.3241	-.6850	.8127
CFFOTD	-.0518	.1737	-.3613	.4628	.1780	.2647	-.6850	.5160
CFFOI	-.7389	3.4783	-7.9538	8.8153	2.7014	4.8359	-9.9489	13.6130
StkRtn	.0286	.0488	-.0700	.1200	.0276	.0358	-.0312	.1204
FS	8.5920	.4876	7.7126	9.9000	8.9281	.5019	7.8893	10.0032
StkVol	.1434	.0688	.0000	.2981	.1342	.0666	.0000	.2957
No of observations	67				67			

Note: Group 1 = Distress, Group 2 = Non-distress

The results of correlation matrix show the absence of multicollinearity among the independent variables. Descriptive statistics (group means) and values in ANOVA Table (Wilks' Lambda) as in Hair et al (2011) and Burns & Burns (2009) were used to test the significance differences between groups on each predictor. According to the results, stock return and stock volatility reported the highest Wilks' Lambda with F values of .019 and .608 respectively. Meanwhile, EBITINT recorded the highest Mahalanobis D^2 (1.181) among the fourteen variables with the lowest Wilk's Lambda. When smaller the Wilks' Lambda, the independent variable will be more important for discriminating purpose (Yap et al, 2010). When comparing the group means it can be seen a significant difference between mean values of two groups for all variables and all the variables other than the stock return and stock volatility are significant under the equality test of group means (Table 3).

Table 3: Group descriptive statistics and test of equality of group means

	Dependent variable Group Means		Test of Equality of Group Means			Minimum Mahalanobis D^2	
	Financially distress (Group 1) (n=67)	Financially not distress (Group 0) (n=67)	Wilks' Lambda	F Value	Significance	Minimum D^2	Between Groups
RETA	-.0574	.1933	.794	34.318	.000	1.024	0 and 1
WICTA	.0109	.1712	.909	13.219	.000	.395	0 and 1
EBITTA	.0279	.1061	.804	32.264	.000	.963	0 and 1
MVEBVTD	2.9289	4.8625	.828	27.336	.000	.816	0 and 1
TDTA	.5252	.3536	.905	13.777	.000	.411	0 and 1
EBITINT	.9275	6.1506	.769	39.561	.000	1.181	0 and 1
CFFONW	-.0229	.1147	.900	14.727	.000	.440	0 and 1
CFFOTA	-.0239	.0559	.816	29.835	.000	.891	0 and 1
CFFOCL	-.0718	.1968	.819	29.103	.000	.869	0 and 1
CFFOTD	-.0518	.1780	.789	35.336	.000	1.055	0 and 1

CFFOINT	-.7389	2.7014	.855	22.348	.000	.667	0 and 1
StkRtn	.0286	.0276	1.000	.019	.890	.001	0 and 1
FS	8.5920	8.9281	.895	15.455	.000	.461	0 and 1
StkVol	.1434	.1343	.995	.608	.437	.018	0 and 1

4.02 ESTIMATION OF THE MODEL

After satisfied with the main assumptions of discriminant analysis the study has developed the model using stepwise method. When selecting the predictors for the model we considered the largest mahalonibis D^2, decreasing Wilks' Lambda, significance of the variables and the structure matrix coefficients to identify the relative importance of the predictors in each step. Table 4 shows the results under the variables in the analysis at each step with their significance and Table 5 shows the standardized and unstandardized coefficients along with the discriminant loadings. The study is proceeded four steps with largest D^2 value until Wilks' Lambda decreases at each step presenting a high discriminating power and including all the significant variables in to the model.

The canonical unstandardized coefficients shown in Table 5 are used to develop the model after considering all above criteria.

Z = -5.983+ 1.626 *RETA*+ 0.097 *EBITINT*+ 2.849 *CFFOTD*+ 0. 611 *FS*

The results in Table 5 shows that the earnings before interest and taxes to interest expenses has the best discriminating power for the two groups while cash flow from operations to total debts, retained earnings to total assets and firm size also provide better discriminating power respectively. All variables remain in the model identify by the literature also as good predictors in the predicting company financial distress over the others (ex: Altman 1968; Beaver, 1966, Campbell et al., 2011 etc).

Table 4: Variables in the analysis at each step

Step	Variable	Tolerance	F to remove	Min D^2	Wilks' Lambda	Significance	Between Groups
1	EBITINT	1.000	39.561		0.769	.000	
2	EBITINT	.997	34.183	1.055	0.626	.000	0 and 1
	CFFOTD	.997	30.115	1.181			0 and 1
3	EBITINT	.870	13.881	2.211	.579	.000	0 and 1
	CFFOTD	.995	29.069	1.624			0 and 1
	RETA	.869	10.527	2.358			0 and 1
4	EBITINT	.865	11.747	2.558	0.556	.000	0 and 1
	CFFOTD	.995	28.286	1.875			0 and 1
	RETA	.862	8.547	2.709			0 and 1
	FS	.978	5.332	2.868			0 and 1

Table 5: Discriminant function and discriminant loadings

	Discriminant Function			Structure Matrix
Independent Variable		Unstandardized	Standardized	Discriminant Loadings
RETA		1.626	.403	.570
EBITINT		.097	.466	.612
CFFOTD		2.849	.638	.579
FS		.611	.302	.383
Constant	-5.983			

Wilks' Lambda of the model explains that the overall model is unexplained about the variance in the grouping variables by 55.6%. The canonical correlation of .667 with an eigenvalue of 0.799 of the model suggested that the model explains 44.48% variation in the grouping variable of financially distress or not distress. However, chi-square of 76.366 and a significant p (p =.000) value reported in Table 6 indicates a highly significant function in the model. Hence, it can be concluded that the model developed by us is a significant discriminant function in discriminating financially distressed and non-distressed firms.

Table 6: Eigenvalue and Wilks' Lambda

	Percent of variance						
Eigenvalue	**Function %**	**Cumulative %**	**Canonical Correlation**	**Wilks' Lambda**	**Chi-Square**	**Df**	**Significance**
.799	100.0	100.0	.667	.556	76.366	4	.000

Z-Score[11] of the model also calculated in order to develop the classification matrix using the group centroids presented in Table 7. According to the critical Z-score the companies with <0 (negative) has classified as distressed while companies with Z-score > 0 (positive) has classified as non-distress group in the classification matrix in Table 8.

Table 7: Group centroids and prior probabilities of groups

	Functions at Group Centroids	Prior probabilities for groups
Group		
0= Not distress	.887	0.5
1= Distress	-.887	0.5

Based on the cutting score values the study has analyzed the classification accuracy of the derived function as the next step. According to the results it can be seen that the developed model is able to correctly classify the distress companies 91% and non-distress companies 80.6% accurately. Further in overall the model has a hit ratio of (overall classification accuracy) 85.8% (Table 8).

When analyzing the cost of misclassification the model provides better result showing very low type I error (9%). Further, type II error is also in a lower percentage as 19.4%. Since type I error is much lower than the type II error the model provides a high promise to the users. Accordingly not only with a high hit ratio, with a low type I error also the developed model shows better results in discriminating the two groups.

Table 8: Classification results: Hit Ratio of the model

	Predicted Group Membership					
	Number			Percentage		
	0	1	Total	0	1	Total
0= Non-distress	54	13	67	80.6	19.4	100
1=Distress	06	61	67	9.0	91.0	100

85.8% of original grouped cases correctly classified [(115/134) x 100].

The results of both tests used in the study to accept the hit ratio [standard of comparison by chance (25% into the standard of chance = 50% x 1.25) and the Press's Q statistics] provide evidence in favor of the derived model as a discriminate model with better prediction accuracy (i.e., 25% into the standard of chance = 50% x 1.25 < hit ratio and the Press's Q statistics, 38.68).

Since there is a model with better prediction accuracy we have tested the validity of the model using cross validation method. According to the cross validation results the model has predicted the cross validation cases 85.1% accurately. Further in cross validation the distressed firms are correctly classified by 91% and non distressed firms are correctly classified by 74.6%. Even with a repeated process of withholding the cases of the sample better accuracy results are obtained and hence we can satisfy with the validity of the model.

4.03 ANALYSIS OF ADVANCE CLASSIFICATION ACCURACY OF THE MODEL

[11] $Z_{CE} = (Z_A + Z_B)/2$

We have examined the advance prediction ability of the model for two years and three years before the financial distress of companies following the past studies (ex: Altman 1968; Beaver, 1966, Campbell et al., 2011, Yap et al., 2010 etc). According to the results the model has predicted the overall cases by 79.9% and 69.4% accurately for two years before the distress for three years before the distress respectively. Both percentages exceed the criterion of standard of chance and hence we can conclude in favor of the model with its advance predicting ability. The results are shown in Table 9 below.

Table 9: Classification results: Hit Ratio for two year and three year before distress

Year Before Failure		Predicted Group Membership					
				Number			Percentage
		0	1	Total	0	1	Total
Two*	0= Non-distress	50	17	67	74.6	25.4	100
	1=Distress	10	57	67	14.9	85.1	100
Three**	0= Non-distress	49	18	67	73.1	26.9	100
	1=Distress	23	44	67	34.3	65.7	100

*79.9% cases correctly classified
**69.4% cases correctly classified

The study has considered fourteen variables and concludes with a four variable model. The model consists with RETA, EBITINT, CFFOTD, and Firm size. RETA, which acts as the variable with highest discriminating ability in our first model (Nanayakkara & Azeez, 2013), is the only variable remains in our new model. The criticism over a model with purely accrual based accounting ratios has compensated with both cash flow based and market based variables in this model.

Among four predictors EBITINT provides the better discriminating power with highest discriminant loading and highest D^2 in the first step. CFFOTD, RETA and Firm Size become second, third and fourth better predictors respectively. All four variables in the model could be identified by the past studies also as variables with best discriminating ability. As the first study with a statistical face Beaver (1966) identifies the CFFOTD has the most ability of predicting bankruptcy. Further, studies like Deakin, (1972); Blum, (1974) and Yap et al., (2010) also recognize the importance of this variable in predicting bankruptcy or distress. Firm size is also identify by the literature as a best predictor in bankruptcy (ex: Beaver, 2005; Shumway, 2001), and according to Beaver (2005) the firm size will represent the declining of the value of the assets before they are not adequate to cover the present value of the debt payments. Further, smaller firms will not have enough ability to secure from the failure using temporary financings (Campbell et al., 2011). All these statements are increased the validity of the result of the study.

Further, this model is able to classify between distress and non-distress superiorly than the model results of original Altman's model which has tested in Sri Lanka by Samarakoon & Hasan (2003). However, Altman (1968) develops the original Z-score model with a 95% predicting accuracy based on the USA bankrupted manufacturing companies. Though it is a superior result over the model developed in this study the classification accuracy of Altman's model will decline when it applies in two year before the distress. That model provides 72% and 48% overall classification results two year and three year prior to the distress respectively. Since our model is able to classify the distressed companies by 79.9% and 69.4% in the two year and three year prior to distress it outperform the Altman's study in the aspect of advance classification accuracy.

Yap et al., (2010) test the applicability of the Z-score model in Malaysia with few new accounting variables that not suggested by Altman (1968) and conclude with better results in the context of Malaysia. According to them the model is able to predict the bankruptcy companies with high classification accuracy up to five years to the distress as 94%, 94%, 88%, 88%, 88%, and 90% respectively from first year to fifth year. Therefore they identified the Z-score model as a better distress prediction model for Malaysia. Though this model is able to predict the financial distress more accurately it has not address the criticism over accounting ratios.

Kosmidis, Venetaki, Stavropoulos, & Terzidiz (2011) test the applicability of the MDA model and logit model in predicting financial distress in Greek business. They identify that the both models are suitable for Greece and while logit model provides better results than MDA model in terms of correct classification and type I error. Bhunia, Khan & Mukhuti (2011) test the applicability of Z-score model in Indian context and develop a model which has a classification rate of 80%. Out of 64 accounting ratios two ratios identified as significant predictors in the model namely cash flow to sales and days sales in receivable. Hence, this study also proves the suitability of z-score model for emerging economies. But they have not tested the advance predicting ability of the model. And also it consists purely accounting ratios.

Further, our model has a greater canonical correlation (0.667) with high eigenvalue and a low Wilk's Lambda. In addition to that the model is able to provide a high chi-square with a significant p value. According to Yap et al., (2010) a function with a high eigenvalue, low Wilk's Lambda and a large significant Chi-Square will reflect better discriminating power of the discriminant function.

5.0 CONCLUDING REMARKS

The main objective of this study is to develop better financial distress prediction model for Sri Lankan quoted companies by advancing the existing Altman's Z-score model for a recent company sample with accounting, cash flow and market variables through Multivariate Discriminate Analysis. This study has used the accounting data from 2002 to 2011 in order to analyze the discriminant power of the variables.

Based on the results of the model in this study it has found that the developed model with accrual based, cash flow based and market variables as a better predictor of financial distress up to three years prior to distress. Since the model has a high advance predicting ability it is very useful to users of this model in their predictions.

Further this study revealed that Earnings before Interest and Taxes to Interest expense are able to predict firm's financial distress more accurately than the other variables. In addition to that Retained earnings to Total Assets, Cash Flow from Operations to Total debt, and Firm size also identified as better predictors for predicting distress.

Therefore, it can be concluded that our model which consists of earnings before interest and taxes to interest expense, cash flow from operations to total debts, retained earnings to total assets, and firm size is able to predict financial distress of Quoted public companies in Sri Lanka by 85.8% accurately while predicting distress firms by 91% accurately. Further, the model has the financial distress predicting ability of 79.9% and 69.4% for two year and three year before distress respectively. Hence our model can be identified as a better model that could be applied for advance prediction of firm's financial distress. In addition to that the study has revealed that the companies with negative (<0) cutoff score are in the zone of distress while companies with positive (>0) cutoff score are in the zone of safety.

Apart from that the study is able to mitigate the criticisms over existing z-score model in the world by developing the same with non-accrual based ratios. Testing the role of market data and cash flow data in assessing the financial distress under MDA the study has contributed to the existing knowledge of predicting financial distress. Additionally, the study has empirically developed context specific coefficients and a cutoff score which is more use full in the practice. Hence, our model can be used to assist investors, creditors, managers, auditors and regulatory bodies in Sri Lanka to predict the financial distress. With all the results it can be concluded that companies should pay attention not only on the accounting information in assessing the financial distress, but also on the cash flow and market data.

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APPENDIX A: SAMPLE

	Distressed Companies	Distressed year		Non-Distressed companies (Matched sample)
01	Coco Lanka Plc	2006/2007	68	Tea Smallholder Factories Plc
02	Convenience Foods (Lanka) Plc	2006/2007	69	Harischandra Mills Plc
03	Keells Food Products Plc	2010/2011	70	Cargills (Ceylon) Plc
04	Kotmale Holdings Plc	2006/2007	71	Lanka Milk Foods (Cwe) Plc
05	Lankem Ceylon Plc	2004/2005	72	CIC Holdings Plc
06	MTD Walkers Plc	2008/2009	73	Colombo Dockyard Plc
07	Carsons Cumberbatch Plc	2009/2010	74	Aitken Spence Plc
08	Dunamis Capital Plc	2008/2009	75	Sunshine Holdings Plc
09	Richard Pieris And Company Plc	2008/2009	76	The Colombo Fort Land & Building Company Plc
10	Asian Cotton Mills Ltd	2005/2006	77	Samson International Plc
11	Nawaloka Hospitals Plc	2008/2009	78	Ceylon Hospitals Plc (Durdans)
12	Associated Hotels Co. Ltd	2006/2007	79	Browns Beach Hotels Plc
13	Beruwala Walk Inn Plc	2008/2009	80	Hotel Services (Ceylon) Plc
14	Ceylon Hotels Corporation Plc	2007/2008	81	Asian Hotels & Properties Plc
15	Citrus Leisure Plc	2008/2009	82	Amaya Leisure Plc
16	Galadari Hotels (Lanka) Plc	2008/2009	83	John Keells Hotels Plc
17	Hotel Sigiriya Plc	2008/2009	84	Riverina Hotels Plc
18	Hunas Falls Hotels Plc	2008/2009	85	Kandy Hotels Company (1938) Plc
19	Mahaweli Reach Hotels Plc	2007/2008	86	Serendib Hotels Plc
20	Marawila Resorts Plc	2006/2007	87	Renuka City Hotel Plc
21	Miramar Beach Hotel Plc	2008/2009	88	Dolphin Hotels Plc
22	Pegasus Hotels Of Ceylon Plc	2008/2009	89	Royal Palms Beach Hotels Plc
23	Sigiriya Village Hotels Plc	2006/2007	90	The Lighthouse Hotel Plc
24	Taj Lanka Hotels Plc	2008/2009	91	Trans Asia Hotels Plc
25	The Fortress Resorts Plc	2008/2009	92	The Nuwara Eliya Hotels Company p
26	Ceylon Guardian Investment Trust Plc	2006/2007	93	Ceylon Investment Plc
27	Colombo Fort Investments Plc	2008/2009	94	Colombo Investment Trust Plc
28	Environmental Resources Investments Plc	2009/2010	95	Guardian Capital Partners Plc
29	Shaw Wallace & Hedges Plc	2008/2009	96	C T Land Development Plc
30	Colombo Land & Development Company Plc	2005/2006	97	Property Development Plc

31	East West Properties Plc	2005/2006	**98**	Seylan Developments Plc
32	Equity One Plc	2008/2009	**99**	Serendib Land Plc
33	Equity Two Plc	2005/2006	**100**	Commercial Development Co. Plc
34	Infrastructure Developers Plc	2006/2007	**101**	Cargo Boat Development Company Plc
35	Kelsey Developments Plc	2010/2011	**102**	Touchwood Investment Plc
36	Huejay International Investments Plc	2009/2010	**103**	York Arcade Holdings Plc
37	City Housing & Real Estate Co. Plc	2010/2011	**104**	On'ally Holdings Plc
38	Abans Electricals Plc	2007/2008	**105**	Acl Cables Plc
39	Acme Printing & Packaging Plc	2004/2005	**106**	Ceylon Grain Elevators Plc
40	Alufab Plc	2005/2006	**107**	Piramal Glass Ceylon Plc
41	Associated Electrical Cables	2005/2006	**108**	Kelani Cables Plc
42	Blue Diamonds Jewellery Worldwide Plc	2010/2011	**109**	Bogala Graphite Lanka Plc
43	Dankotuwa Porcelain Plc	2006/2007	**110**	Lanka Ceramic Plc
44	Hayleys Exports Plc	2006/2007	**111**	Acl Plastics Plc
45	Kelani Tyres Plc	2009/2010	**112**	Sierra Cables Plc
46	Lanka Aluminium Industries Plc	2006/2007	**113**	Central Industries Plc
47	Laxapana Batteries Plc	2005/2006	**114**	Chevron Lubricants Lanka Plc
48	Pelwatte Sugar Industries Plc	2009/2010	**115**	Dipped Products Plc
49	Regnis (Lanka) Plc	2005/2006	**116**	Printcare Plc
50	Richard Pieris Exports Plc	2007/2008	**117**	Lanka Floor Tiles Plc
51	Singer Industries (Ceylon) Plc	2008/2009	**118**	Lanka Wall Tiles Plc
52	Swadeshi Industrial Works Plc	2006/2007	**119**	Tokyo Cement Company (Lanka) Plc
53	Parquet(Ceylon) Plc	2007/2008	**120**	Royal Ceramics Lanka Plc
54	Diesel & Motor Engineering Plc	2005/2006	**121**	Sathosa Motors Plc
55	Lanka Ashok Leyland Plc	2006/2007	**122**	Colonial Motors Plc
56	United Motors Lanka Plc	2005/2006	**123**	The Autodrome Plc
57	Kahawatte Plantations Plc	2005/2006	**124**	Kegalle Plantations Plc
58	Madulsima Plantations Plc	2006/2007	**125**	Watawala Plantations Plc
59	Udapussellawa Plantations Plc	2004/2005	**126**	Talawakelle Tea Estates Plc
60	Ceylon Printers Plc	2004/2005	**127**	Kalamazoo Systems Plc
61	Lake House Printers and Publishers Plc	2009/2010	**128**	Mercantile Shipping Company Plc
62	Paragon Ceylon Plc	2006/2007	**129**	John Keells Plc
63	Gestetner Of Ceylon Plc	2006/2007	**130**	Colombo Pharmacy Company Plc
64	Ceylon & Foreign Trades Plc	2005/2006	**131**	Eastern Merchants Plc
65	Radiant Gems International Plc	2005/2006	**132**	C. W. Mackie Plc
66	Singer Sri Lanka Plc	2005/2006	**133**	Brown & Company Plc
67	Tess Agro Plc	2010/2011	**134**	Office Equipment Plc

APPENDIX B: CASE WISE RESULTS OF THE MODEL

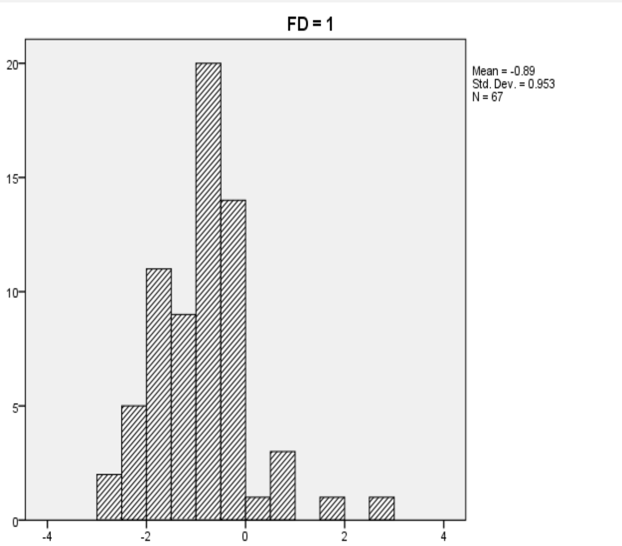
Company No	Actual Group	Predicted Group	Z-score	Company No	Actual Group	Predicted Group	Z-score
1	0	0	1.065	40	0	0	1.838
2	1	1	-1.504	41	0	0	.463
3	1	1	-.267	42	0	0	1.679
4	0	0	1.343	43	0	0	.530
5	1	1	-.376	44	1	0**	.574
6	1	1	-2.331	45	1	1	-.549

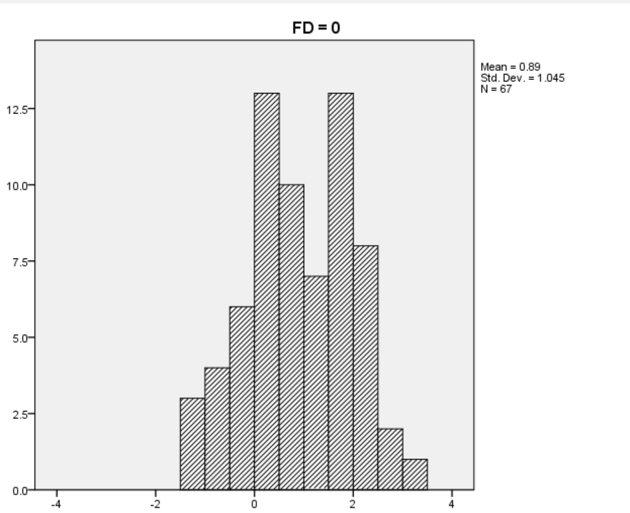
7	0	0	.306	46	1	1	-1.477
8	0	0	1.736	47	0	0	2.298
9	0	0	.238	48	0	0	1.710
10	1	1	-.885	49	0	0	2.240
11	1	1	-.766	50	1	0**	.655
12	0	0	2.397	51	0	0	1.122
13	0	0	.145	52	1	0**	1.809
14	1	0**	2.688	53	0	1**	-1.222
15	1	1	-.772	54	1	1	-1.617
16	1	0**	.186	55	0	0	2.528
17	0	0	.837	56	1	1	-.237
18	0	0	.610	57	0	0	1.644
19	1	1	-2.386	58	1	1	-.706
20	0	0	.192	59	1	1	-.447
21	1	1	-.118	60	1	1	-.207
22	0	1**	-.200	61	1	1	-.033
23	0	0	2.324	62	1	1	-.872
24	1	1	-1.098	63	1	1	-1.839
25	1	1	-2.156	64	1	1	-2.143
26	0	0	1.951	65	1	1	-.948
27	1	1	-.889	66	0	0	1.804
28	1	1	-.860	67	0	0	.239
29	0	0	1.131	68	0	0	1.746
30	1	1	-1.282	69	0	0	2.258
31	0	0	3.067	70	0	1**	-.422
32	1	1	-1.572	71	0	0	.170
33	1	1	-1.645	72	0	1**	-.048
34	0	0	.170	73	0	0	1.521
35	0	0	.023	74	1	1	-.847
36	1	1	-.084	75	0	1**	-.024
37	1	1	-1.414	76	0	0	1.698
38	1	1	-1.387	77	1	1	-1.280
39	1	1	-1.181	78	1	1	-2.986

Company No	Actual Group	Predicted Group	Z-score	Company No	Actual Group	Predicted Group	Z-score
79	1	0**	.908	107	0	0	1.549
80	1	1	-1.333	108	0	0	.038
81	0	0	.455	109	1	1	-.875
82	0	0	1.931	110	1	1	-.226
83	0	1**	-.890	111	0	0	.702
84	0	0	1.063	112	1	1	-.956
85	1	1	-1.614	113	1	1	-.895
86	0	0	.706	114	0	1**	-.145
87	1	1	-.730	115	1	1	-.819
88	0	0	2.064	116	0	0	.545
89	1	1	-1.442	117	1	1	-1.619
90	1	1	-.888	118	0	0	.100
91	0	0	.921	119	1	1	-.750
92	0	0	1.395	120	0	0	2.051
93	0	0	1.576	121	0	1**	-1.012
94	1	1	-1.600	122	1	1	-.472
95	1	1	-.854	123	0	1**	-1.268
96	0	0	2.715	124	1	1	-2.142
97	0	0	.307	125	0	1**	-.613
98	1	1	-1.516	126	1	1	-1.735
99	1	1	-.658	127	0	1**	-.079
100	0	0	.510	128	0	1**	-.673
101	0	0	.740	129	1	1	-.276
102	0	1**	-.685	130	0	0	.739
103	1	1	-.091	131	0	0	2.368
104	1	1	-.344	132	1	1	-2.658
105	0	0	1.235	133	1	1	-.315
106	1	1	-1.736	134	1	1	-.570

** Misclassified cases

APPENDIX C: DISCRIMINANT DISTRIBUTION





Note: FD- 1 = Distress group, FD- 0 =Non-distress group