PREDICTING THE CORPORATE FAILURE OF LISTED COMPANIES IN SRI LANKA

V.G.N. Sameera[1], R.W.M.K.M. Randika[2,*], and J.K. Hewage[2]

[1]*Department of Accountancy and Finance, Faculty of Management Studies, Rajarata University of Sri Lanka.*

[2]*Department of Management Studies, Faculty of Indigenous Social Sciences and Management Studies, Gampaha Wickramarachchi University of Indigenous Medicine.*

**Corresponding author: malithr@gwu.ac.lk*

Abstract

This study aims to investigate the ability of the corporate governance and financial variables to predict the corporate failure of listed companies in Sri Lanka and develop an accurate model for failure prediction with higher accuracy. Further, the study examined the applicability of the prediction model to all the listed companies, including the financial industry, using eighty-nine (for all industries) and sixty-two (except the financial industry) matched pairs of failed and non-failed companies listed in the Colombo Stock Exchange in Sri Lanka over the period from 2010 to 2022. A total of ten financial ratios and nine corporate governance variables were used as predictors of corporate failure. Binary logistic regression was employed to develop the prediction model and expectation-prediction evaluation to identify the prediction accuracy of the models. The results indicated that the model consisting of both corporate governance variables and financial variables had the highest prediction accuracy in both samples, with above 80 percent predictive accuracy in all three years prior to failure. It was further found that three financial variables, cash flow from operations to total assets, debt to asset ratio, revenue to asset ratio, and two corporate governance variables, CEO duality and director's remuneration, are significant variables in the failure prediction of listed firms except in the financial industry while five financial variables, cash flow from operations to net income, cash flow from operations to total assets, debt to asset ratio, return on assets, revenue to asset ratio, and three corporate governance variables, CEO duality, outside ownership, and board size, have more explanatory power to predict corporate failure in all listed companies in Sri Lanka. The results of this study assist investors, managers, shareholders, financial institutions, auditors, and regulatory agents in Sri Lanka and other countries in forecasting the corporate failure of listed companies in making decisions.

Keywords: Corporate failure, corporate governance, failure predictions, financial variables

Introduction

Corporate failure is a critical issue that can have significant negative impacts on companies, investors, and the economy as a whole. It emphasizes the significance of comprehending the variables influencing corporate failure. Financial variables and corporate governance are two critical factors that can impact a company's financial health and overall success. Corporate failure is an important topic in Sri Lanka and globally, particularly during economic crises. It underscores the need for robust corporate governance practices, effective risk management frameworks, and strong regulatory oversight to prevent corporate failures and promote sustainable economic growth (Jayamaha, 2008).

Rapid increase in sudden corporate failure motivates study about the prediction of corporate failure, and the importance of corporate failure prediction. According to the study conduct by Oduro and Asiedu (2017), there were several sudden corporate failures in Ghana, which led to an analysis and prediction of the corporate failure. These corporate failures highlight the need to develop an early warning system that can help prevent or avert corporate default (Vinh, 2015). This early warning system will help all the parties who are interested in the entity take immediate action to prevent losses. When companies do not take the necessary action at the initial stage of financial distress, it may lead to bankruptcy (Ahamed et al., 2018). As highlighted by Wijekoon and Azeez (2015), in Sri Lanka, the business industry also witnessed sudden corporate failures in the last decade, such as Vanik Incorporation Limited, Ferntea Ltd, Lanka Cement Limited, Associated Hotels Co. Ltd and Galadari Hotels (Lanka) Ltd.

Financial variables, such as liquidity, profitability, and solvency ratios, are widely used to analyze a company's financial health and performance. They provide insights into a company's ability to generate profits, manage its debt, and meet its financial obligations (Farawansyah, Rahayu, Gunawan, & Zhafiraah, 2024). Additionally, Corporate Governance plays a critical role in predicting potential corporate failure. It refers to the system of rules, practices, and processes that govern how a company is managed and controlled. Good corporate governance practices can help ensure that a company operates efficiently, effectively, and in the best interests of its stakeholders (Ministry of Finance, 2003). Most of the researchers focus on developing an early warning system by considering financial information. Financial variables can be used to predict financial distress, including the ratio of profitability, liquidity, solvency, leverage, and activity (Chairunesia, 2020). According to Amnedola et al. (2017), financial variables provide relevant of profitability, liquidity, solvency, and leverage, will enhance the prediction of corporate failure (Chairunesia, 2020). But the argument arises about the reliance on the financial variables, which is derived from the financial statements. On the other hand, criticism has occurred due to the sudden failure of the organization, which showed better financial performance in terms of financial variables.

The role of corporate governance in predicting corporate failure has been largely neglected and ignored by these researchers. Weakness in corporate governance is a major cause of financial distress for the entity (Oduro & Asiedu, 2017). According to Rajan and Zingales (1998) and Prowse (1998), poor corporate governance on top of a concentrated ownership structure paved the way for the financial crisis. Some researchers such as Lakshan and Wijekoon (2013), Destriwanti et al. (2022), Zulridah and Takiah (2012) indicated that poor corporate governance can cause sudden corporate failure even for firms with good financial performance. The corporate governance variables significantly improved the predictive power of the prediction model (Brédart, 2014). So most researchers try to predict corporate failure by using the corporate governance variables while ignoring the financial variables. But some researchers argued that ignoring the financial variables when predicting corporate failure may mislead the prediction. As a result of this, a few researchers such as Wijekoon and Azeez (2015), Balasubramanian et al. (2019) focused on predicting corporate failure by using both financial, non-financial and corporate governance variables.

This study intends to develop a new model that incorporates both financial and corporate governance characteristics to predict the corporate failure of the listed companies in Sri Lanka. For that purpose, researchers developed three models to test predictions using both financial and corporate governance characteristics. According to the authors' best knowledge, there are few research in developing countries that combine both corporate governance variables and financial variables to predict corporate failure. At the same time, researchers intend to use both financial and non-financial firms to assess the predictability of corporate failure, while empirical studies focus mostly on non-financial sector information. The most recent information available was used in this study's prediction of the corporate failure of Sri Lanka's listed firms. When considering the failure prediction, most researchers ignored the financial industry in their studies. The research focuses on identifying the applicability of the prediction model to all industries, including the financial industry, and excluding the financial industry. The study intent is to develop three failure prediction models (including corporate governance variables only, including financial variables only, and using both corporate governance variables and financial variables) for all listed companies and another three failure prediction models for listed companies except the financial industry. According to the researcher's best knowledge, there are no research considering the financial industry when developing the failure prediction in the Sri Lankan context. Therefore, the findings of the study aim to fill this gap by investigating the impact of financial variables and corporate governance factors on corporate failure prediction using all listed companies in Sri Lanka. Furthermore, the findings of the study will provide the most accurate failure prediction model in the Sri Lankan context. On the other hand, the findings of this research can provide valuable insights for investors, regulators, and policymakers to mitigate the risks of corporate failure and promote sustainable economic growth in Sri Lanka.

The remaining sections of the paper are structured in the following manner. The next section provides a literature review, which is followed by the research methodology and results and discussion sections. The last section provides the conclusions and implications of the study.

Literature Review

Theoretical Review

The prediction of corporate failure is a subject that has been extensively researched by numerous scholars, with a predominant focus on well-developed economies. The origins of corporate failure prediction studies can be traced back to the 1930s, when the first studies utilizing financial variables analysis as an indicator of bankruptcy were published. However, it was not until the mid-1960s that this topic gained significant importance and became one of the primary areas of research in the field of accounting & finance. The classification of failure forecasting models can be broadly categorized into two groups, as identified by Ooghe et al. (2009) market models and fundamental models. Market models incorporate market-derived information, specifically stock prices, while fundamental models rely on a combination of accounting models, macroeconomic models, and rating models. Accounting models, in particular, exhibit a substantial degree of prominence in terms of their predictive efficacy and ability to forecast the probability of corporate failure. This methodology is established on the utilization of accounting information, which facilitates the computation of financial variables that serve as indicative measures of the financial status of the firm (Agarwal & Taffler, 2008). Despite the potential for innovation in the selection of ratios utilized in this type of study, as the predictive efficacy of ratios may vary over time depending on the specific factors that contribute to bankruptcy, commonly employed indicators generally revolve around liquidity, profitability, or leverage, as highlighted by Tian and Yu (2017). On the other hand, the Association of Certified Chartered Accountants (2008) also classified corporate failure models into two distinct categories, namely quantitative models and qualitative models.

Quantitative Models

According to Argenti (2003), quantitative models are capable of determining financial variables that exhibit significant differences between companies that have survived and those that have failed. These variables can then be utilized to identify companies that display features similar to those of previously failed firms. These methods belong to the categories of univariate analysis and multiple discriminant analysis (MDA). In relation to univariate analysis, it is presumed that Fitzpatrick (1932) was the first author to use financial ratio analysis to predict corporate failure. Early explorations in this area were undertaken during the 1930s and 1940s, with notable contributions from Fitzpatrick (1932), Mervin and Wayne (1944), and Chudson (1945). These initial efforts involved the identification of financial indicators and their analysis through different selection methods. However, a significant surge in research activity in this field occurred during the 1960s, marking a period of rapid and extensive development. Subsequently, the utilization of corporate failure prediction models was pioneered by William Beaver in 1966. In his study, Beaver (1966) utilized univariate discriminant analysis (UDA) and discovered that the financial variables of non-failed companies exhibit dissimilarities from those of failed companies. This study expanded upon Patrick (1932) approach for ratio analysis and determined that this analytical approach may be advantageous in distinguishing between successful and unsuccessful companies. The initial utilization of Univariate analysis appeared beneficial; however, subsequent findings revealed its limitations. Enhanced outcomes were achieved by incorporating multiple ratios, resulting in a more resilient model with heightened predictive power. (Association of Certified Chartered Accountants, 2008). On the other hand, Altman (1968) proposed ‘multiple discriminant analysis’ (MDA) as a continuation of Beaver's study. Until the 1980s, this method was prevalent in the literature on models of corporate failure and is frequently employed as a standard for comparative studies (Association of Certified Chartered Accountants, 2008). Altman (1968) employed a set of five variables for financial analysis purposes. These variables comprise of working capital to total assets, which serves as a liquidity indicator; retained earnings to total assets, which is an indicator of firm ageing; earnings before interest and taxes to total assets, which is a measure of profitability; market value of equity to book value of total debt, which is a solvency indicator; and sales to total assets, which is an indicator of the volume of activity. However, all these studies such as Patrick, 1932; Mervin and Wayne, 1944; Chudson, 1945; Altman, 1968 were conducted within the context of developed economies and did not account for non-financial factors.

Qualitative Models

This classification of model is grounded on the underlying assumption that relying solely on financial measures to assess organizational performance is constrained in its effectiveness. Qualitative models, on the other hand, are built upon non-accounting or qualitative variables. In the field of corporate failure prediction, several techniques have been utilized to develop predictive models after the pioneering studies conducted by Beaver (1966) and Altman (1968) demonstrated the effectiveness of ratio analysis in this regard. Since the seminal studies conducted by Beaver (1966) and Altman (1968), which provided evidence of the predictive efficacy of ratio analysis, a diverse range of prediction techniques, including statistical and artificial intelligence methods, have been utilized in the development of corporate failure prediction models (Veganzones & Severin, 2020; Kumar & Ravi, 2007; Hasan & Hoque, 2023). Despite the availability of more advanced methods, researchers still commonly employ traditional statistical approaches, such as linear discriminant analysis and logistic regression, due to their simplicity and interpretability in handling the data. Additionally, in a comprehensive analysis of 89 studies conducted between 1968 and 2003, spanning ten different countries, Aziz and Dar (2006) observed that multi-variable models (Z-Score) and logit were widely employed in predicting corporate failure. Based on this established research direction, the current study employs the conventional logistic regression model as its chosen methodology.

Empirical Review

In the context of developing economies, Oduro and Asiedu (2017) has applied the logistic regression analysis and included non-financial indices to avoid the limitations of above techniques and the reliance on only financial variables in the Ghanaian setting. Empirical studies regarding failure prediction models signify inconsistent results. The study conducted by Wijekoon and Azeez (2015) in the Sri Lankan context stated that the model consisting of both corporate governance variables and financial variables has more prediction accuracy than the other models. Additionally, it implied that two financial ratios such as working capital to total asset and cash flow from operating activities and two corporate governance variables such as outside directors and company audit committee have significant explanatory power in the model. Even though the model with financial variables had lower prediction accuracy, it stated that working capital to total assets, cash flow from operating activities and debt ratio statistically significant in the model. Similar to that outside directors, CEO duality, company audit committee and directors' remuneration were statistically significant in the model consisting of corporate governance variables. Therefore, Wijekoon and Azeez (2015) highlighted that debt ratio, CEO duality and directors' remuneration became insignificant in model combining financial and corporate governance variables. Furthermore, a study conducted by Randika at al. (2019) examined the prediction accuracy of the model using only corporate governance variables, and they concluded that CEO duality, directors' remuneration, and outside directors have significant explanatory power in the model. Further Lakshan and Wijekoon (2012) stated that corporate governance variables such as CEO duality, directors' remuneration, outside directors, audit committee have significant prediction power in Sri Lankan context.

On the other hand, financial distress of Indonesian companies was significantly influenced by managerial ownership, institutional ownership, debt ratio, return on equity, retained earnings to total assets, earnings before interest tax to total assets, and return on asset (Destriwanti at al., 2022). Lee at al, (2003) found that debt ratio and return on assets were significant factors in corporate failure. Return on investment, return on equity, current ratio, and retention ratio have significant relationships with the financial distress of Indian companies (Balasubramanian at al., 2019). However the study conducted by Noor and Iskandar (2012) indicated that equity ownership is the only corporate governance factor that predict corporate failure in Malaysia while CEO duality, financial literacy, multiple directorships, and board activeness are insignificant in predicting corporate failure. Additionally, model consist of financial variables namely, profit, financial leverage, operating cash flow in not significantly applicable to the failure prediction in United Kingdom (Neophytou & Charalambous, 2000).

The analysis of previous research on corporate failures indicates that a significant limitation of these studies is their excessive dependence on financial variables as predictors of corporate failure. Therefore, it is rational to explore alternative sources of information beyond financial variables when developing early warning systems for corporate failures. Furthermore, it is observed that only a limited number of previous empirical studies have put forth a model that integrates the crucial factors of failure, specifically financial variables, and corporate governance, in order to predict corporate failures in firms based in Sri Lanka (Wijekoon & Azeez, 2015). This study has incorporated both quantitative and qualitative data, with the former consisting of financial variables such as return on assets (ROA), return on equity (ROE), debt-to-asset ratio, debt-to-equity ratio, current ratio, quick ratio, asset turnover ratio, and cash flow ratios. The latter includes qualitative variables such as board size, board diversity, financial expertise, CEO duality, outside directors, outside ownership, the presence of an audit committee, director remuneration, audit report, and firm age. Additionally, it has been noted that there is a lack of research utilizing up-to-date data ranging from 2010 to 2021 in the field of failure prediction in Sri Lanka. Furthermore, there is a dearth of studies that incorporate unique variables such as the 'financial acumen of company directors' in their models. Despite the significance of developing a robust failure prediction model with increased predictive accuracy within the Sri Lankan context, As per the best knowledge of the authors, there are no studies that have examined failure or non-failure in financial institutions, with most focusing on comparative evaluations of non-financial institutions. Thus, this study has directed its attention towards failure and non-failure in financial institutions.

Research Methodology

The research intends to develop failure prediction models that provide accurate predictions of corporate failure in Sri Lanka. Most previous researchers completely ignored the financial industry in their failure prediction model due to the changes in operations, nature of the business, mandatory governance mechanisms, etc. (Azeez, 2015; Lee et al., 2003, Neophytou, et al., 2000, Sood, 2008, Wijekoon & Azeez, 2015). So, this research intends to develop and analyze failure prediction models for a sample excluding and including the financial industry. In this study, failure prediction models are examined by using only financial variables, only corporate governance variables, and both financial and corporate governance variables to identify the most accurate model to predict corporate failure with the most significant variables for predicting the failures in each model.

Sample Selection and Data Collection

The present study selected samples from the listed companies on the Colombo Stock Exchange, Sri Lanka, that failed based on the conditions mentioned above during the period from 2010 to 2022. The study used a matching sample design for the analysis so that every failed company had a non-failed partner in the sample. Most researchers, such as Wijekoon and Azeez (2015), Lakshan and Wijekoon (2012), Altman (1968), Beaver (1968), and Charitou et al. (2004) used matching sample techniques in their prediction models. When deciding on the non-failed partner study, focus on criteria such as the same failure year and closest asset size. It is difficult to match the non-failure partners in the same industry due to the new industry classification of the Colombo Stock Exchange. According to the above-mentioned criteria, the present study identified 89 failed companies during the period (including those in the financial industry) and selected 89 non-failed companies as partners for the failed companies. Furthermore, research intends to develop models for failure prediction that exclude the financial industry. So, the research considered a sample by removing the companies in the financial industry from the failure prediction. For this purpose, the sample consists of 62 failed companies after removing the companies in the financial industry and 62 non-failed partners for each failed company as well. The study mainly relies on secondary data collected through the audited financial statements and published annual reports of the companies. So relevant data was collected through the annual reports of both failed and non-failed companies for the year before, two years before, and three years before failure.

Modelling Approach

The present study used the logistic regression as the analysis tool to develop the failure prediction models, which is powered by EViews version 09. Logistic regression is a statistical tool used to predict an event's probability of occurrence (Wijekoon & Azeez, 2015). Furthermore, binary logistic regression was used for analysis when the dependent variable is categorical, and the independent variables are both categorical and quantitative. The study developed three types of models, which consist of financial variables, corporate governance variables, and both financial and corporate governance variables. The study uses the one-year before failure data in each type of model to develop the failure prediction model of those three types of models. Further, to examine the prediction accuracy of each model to identify the most efficient model for failure prediction, two and three years before failure data are considered when checking the validation and accuracy of the developed model. The same method has been followed for the sample consisting of the financial industry and the sample that excludes the financial industry.
The following are the three logistic models developed for the study.

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

Model 1:- $1/ \{1+\exp [-(\beta_0 + \beta_1 BS + \beta_2 BD + \beta_3 FA + \beta_4 CD + \beta_5 OD + \beta_6 OO + \beta_7 PA + \beta_8 DR + \beta_9 AR)]\}$

Model 2:- $1/ \{1+\exp [-(\beta_0 + \beta_{10} RA + \beta_{11} RE + \beta_{12} EPS + \beta_{13} DAR + \beta_{14} DER + \beta_{15} CA + \beta_{16} QA + \beta_{17} RAR + \beta_{18} CFONI + \beta_{19} CFOTA)]\}$

Model 3:- $1/ \{1+ \exp [-([-(\beta_0 + \beta_1 BS + \beta_2 BD + \beta_3 FA + \beta_4 CD + \beta_5 OD + \beta_6 OO + \beta_7 PA + \beta_8 DR + \beta_9 AR + \beta_{10} RA + \beta_{11} RE + \beta_{12} EPS + \beta_{13} DAR + \beta_{14} DER + \beta_{15} CA + \beta_{16} QA + \beta_{17} RAR + \beta_{18} CFONI + \beta_{19} CFOTA)]\}$

Pi (Y = 1)	=	Probability of failure for firm i	AR	=	Audit report
exp	=	exponential function	RA	=	Return on assets
$\beta_1, \beta_2, \ldots$	=	slope coefficients	RE	=	Return on equity
BS	=	Board size	EPS	=	Earnings per share
BD	=	Board diversity	DAR	=	Debt to asset ratio
FA	=	Finance acumen	DER	=	Debt to equity ratio
CD	=	CEO duality	CA	=	Current ratio
OD	=	Outside directors	QA	=	Quick ratio
OO	=	Outside ownership	RAR	=	Revenue to asset ratio
PA	=	Presence of audit committee	CFONI	=	CF from operations to net income
DR	=	Director's remuneration	CFOTA	=	CF from operations to total asset

Operationalization

The study used corporate failure as the dependent variable in developing failure prediction models. Many researchers have defined corporate failure in different ways. El Sood, (2008) defined corporate failure as the result of company operations being unable to make a profit or earn enough revenue to cover company expenses. Additionally, numerous scholars define corporate failure as a situation for every organization that is not able to pay mature debt or expenses, involves liquidity problems, an insufficiency of equity to maintain the operations smoothly, default debts, and a lack of current assets (Huang, Tsai, Yen, & Cheng, 2008; Dias & Teixeira, 2017; Priego, Lizano, & Madrid, 2014; Lakshan & Wijekoon, 2016; Lee, Yeh, & Liu, 2003). The studies conducted by Lee et al, (2003), Wijekoon and Azeez (2015), Lakshan and Wijekoon (2012), Sood (2008) defined corporate failure using the following conditions: If one of the following conditions is satisfied, such an organization is considered to have failed.

- The companies which had been incurring losses for three years continuously or more
- The companies which had illustrated negative position in operating cash flow for three years continuously or more.

This study also used the above definition in order to determine corporate failure and considered it a categorical variable that indicated “1” for failure companies and “0” for non-failure companies. Table 1 shows the operationalization of financial and corporate governance variables used as the independent variables of the failure prediction models.

Table 1: Operationalization

Variable	Measurement
Corporate failure	Dummy variables (1= Failed, 0 = Non failed)
Corporate governance variables	
Board size	Total number of directors in the board
Board diversity	Presence of female director (Binary variable, 1= presence of female director and 0 = None)
Finance acumen	Dummy variable (1= Board has finance experts, 0 = Not available)
CEO duality	Dummy variable (1 = CEO duality, 0 = Otherwise)
Outside directors	Number of outside directors/ Total directors
Outside ownership	Dummy variable (1 = Shares for outside directors and 0= Otherwise)
Presence of audit committee	Dummy variable (1 = presence of audit committee and 0 = Otherwise)
Director’s remunerations	Director remuneration / Profit or loss
Audit report	Dummy variable (1 =report from big 04 audit firm, 0 = Otherwise)
Financial variables	
Return on assets	Net Income / Total assets
Return on equity	Net Income/ Shareholders equity
Earnings per share	Net profit (after tax) – preference dividend}/Average ordinary share holders’ equity.
Debt to asset ratio	Total debt / Total assets
Debt to Equity ratio	Total debt/ Total equity
Current ratio	Current Asset/ Current Liabilities
Quick ratio	(Current Assets- Inventories)/ Current Liabilities
Revenue to asset ratio	Revenue/ Total assets
CF from operations to net income	Cash flow from operations / Net income
CF from operations to total assets	Cash flow of operations/ Total assets

Empirical Results

The study used the initial logistic model to identify the significant variables of each model and developed the model based on the selected significant variables while dropping the insignificant variables. The logistic regression model provides coefficient values, the Z statistic, and McFadden's R squared of the model. Model fit can be tested through the log likelihood ratio of the model. Based on the logistic regression results, the study developed the regression function for each model.

Analysis Results Excluding Financial Industry

Results of Model I Consisting of Only Corporate Governance Variables

All corporate governance variables were first tested through the initial logit model to identify the significant variables and develop the regression model by dropping the insignificant variables. Table 2 presents the final selected variables relating to model I.

Table 2: Logistic Regression Results of Model I

Variable	Coefficient	Z-statistic	Prob.
Constant	2.836	2.194	0.028
CD	1.709**	3.436	0.000
DR	-4.274**	-3.007	0.002
FA	-3.560**	-2.718	0.006
McFadden R-squared	0.276		
LR statistic	47.542**		
Prob(LR statistic)	0.000		

Note: ** denotes significance at 1% level.

As shown in Table 2, CEO duality, director's remuneration, and financial acumen are found to be statistically significant at the 1% level. Furthermore, McFadden's R-squared is 27% and the log likelihood ratio is 47.54, which is statistically significant at the 1% level. The logistic regression function will be,

$$Z = 2.836 + 1.709CD - 4.274DR - 3.560FA$$

Results of Model II Consisting of Only Financial Variables

Table 3 shows the logistic regression analysis of financial variables that were found to be significant in the initial analysis. Both CF from operations to total assets and revenue to asset ratio are statistically significant at a 1% significant level, while debt to asset ratio is significant at a 5% significant level. McFadden R-squared is 59% and the log likelihood ratio is 146.77, and it is significant at the 1% level. The logistic function for the model consists of financial variables as follows:

$$Z = 0.747 - 19.111CFOTA + 2.174DAR - 2.335RAR$$

Table 3: Logistic Regression Results of Model II

Variable	Coefficient	Z-statistic	Prob.
Constant	0.747	1.587	0.112
CFOTA	-19.111**	-4.423	0.000
DAR	2.174*	2.213	0.026
RAR	-2.335**	-3.883	0.000
McFadden R-squared	0.594		
LR statistic	146.772**		
Prob(LR statistic)	0.000		

Note: ** and * denote significance at 1% level and 5% level respectively.

Results of Model III Consisting of Both Financial and Corporate Governance Variables

Table 4 presents the results of the model developed based on significant financial and corporate governance variables identified in the initial logit model. Initially, all the corporate and financial variables tested in the logit model identified the significant variables, and then the model was developed by dropping the insignificant variables. Among the significant variables, CF from operations to total assets, debt to asset ratio, and revenue to asset ratio are statistically significant at a 1% significant level, while CEO duality and director remuneration are statistically significant at a 5% significant level. The log likelihood ratio is 111.2863, and it is statistically significant at a 1% level. The logistic function for the model consists of both financial and corporate governance variables as follows:

$$Z= -1.376 +1.625CD -4.379DR- 27.726CFOTA +7.185DAR -1.823RAR$$

Table 4: Logistic Regression Results of Model III

Variable	Coefficient	Z-statistic	Prob.
C	-1.376	-2.224	0.026
CD	1.625*	2.073	0.038
DR	-4.379*	-2.361	0.018
CFOTA	-27.726**	-3.912	0.000
DAR	7.185**	3.906	0.000
RAR	-1.823**	-2.753	0.005
McFadden R-squared	0.647		
LR statistic	151.286**		
Prob(LR statistic)	0.000		

Note: ** and * denote significance at 1% level and 5% level respectively.

Goodness of Fit of the Models

In order to identify the most acceptable and appropriate model for failure prediction, the study used the log likelihood ratio (LR), McFadden R square, and Hosmer and Lemeshow tests. Usually, the log likelihood ratio indicates whether the selected variables in the model explain the significant amount of variability in the data. The log likelihood ratios of models I, II, and III are 47.54, 146.77, and 151.28 respectively, and they all are statistically significant at the 1% level. Further, the log likelihood ratio and McFadden R square in Model III are higher than those in Models I and II. In the Hosmer & Lemeshow test, a large value of Chi-squared (with a small p-value < 0.05) indicates poor fit, and small Chi-squared values (with a larger p-value closer to 1) indicate a good logistic regression model fit. As shown in Table 5, Model III has a p value greater than 0.05, which indicates the model fit. Based on the above tests, the study concluded that a model consisting of both corporate governance variables and financial variables (Model III) is more acceptable as a prediction model.

Table 5: Hosmer & Lemeshow Test Results

Model	HL statistic	P value
Model I	19.915	0.010
Model II	1.671	0.989
Model III	3.587	0.892

Note: P value >0.05 indicates that logistic regression model is a good fit.

Accuracy of the Prediction

The study tested the prediction accuracy of each model separately for failed and non-failed companies using the first year before failed data of the sample. In order to predict the accuracy of predictions, the study used expectation-prediction evaluation. In prediction evaluation, each company is classified as failed and non-failed based on a cutoff estimated probability of 0.5. If the probability estimation is higher than 0.5, it is considered failed, and if it is less than 0.5, it is considered a non-failed company. (Wijekoon & Azeez, 2015; Lee & Yeh, 2004; Gilbert, et al., 1990). As shown in Table 6, the model which consists of both corporate governance and financial variables appears to have a higher prediction accuracy than the other two models.

Table 6: Assessment of Prediction Accuracy

Model	Type of sample	Prediction accuracy
Model I	Failed	64.52%
	Non failed	87.10%
	Entire sample	75.81%
Model II	Failed	80.65%
	Non failed	90.32%
	Entire sample	85.48%
Model III	Failed	88.71%
	Non failed	91.94%
	Entire sample	90.32%

Validation of Models

The study further examined the validity of the model's prediction accuracy using the two and three years of the data set. The study considers that the model is valid since it can maintain higher prediction accuracy over a longer period of time (Wijekoon & Azeez, 2015). According to the results presented in Table 7, the Model III indicates higher prediction accuracy in the one year before failure, the two years before failure, and the three years before failure compared to the other two models.

Table 7: Assessment of Prediction Accuracy Over the Period

Model	One year before failure	Two years before failure	Three years before failure
Model I	75.81%	72.58%	69.35%
Model II	80.65%	81.45%	79.03%
Model III	90.32%	85.48%	80.65%

Analysis Results Including Financial Industry

Most past researchers have ignored the financial industry in their failure predictions. The study was intended to test whether results obtained by excluding the financial industry are significantly different from those obtained by including the financial industry.

Results of Model I Consisting of Only Corporate Governance Variables

Table 8 indicates the final selected variables and the logistic regression results of model I. Accordingly, CEO duality, director's remuneration, outside ownership, and board size are found to be statistically significant at the 1% level. Furthermore, McFadden's R-squared is 28%, the log likelihood ratio is 70.11, and it is statistically significant at the 1% level. The logistic regression function will be,

$$Z = 4.8659 + 2.1657CD - 5.3708DR + 1.3271FO - 2.9113BS$$

Table 8: Logistic Regression Results of Model I

Variable	Coefficient	Z-statistic	Prob.
Constant	4.865	3.007	0.002
CD	2.165**	4.834	0.000
DR	-5.370**	-3.570	0.000
OO	1.327**	3.292	0.001
BS	-2.911**	-3.659	0.000
McFadden R-squared	0.284		
LR statistic	70.118**		
Prob(LR statistic)	0.000		

Note: ** denotes significance at 1% level.

Results of Model II Consisting of Only Financial Variables

Table 9 shows the logistic regression analysis results of financial variables that were found to be significant in the. CF from operations to net income, CF from operations to total assets, return on asset, and revenue to asset ratio are statistically significant at a 1% level. Furthermore, the debt-to-asset ratio is also statistically significant at a 5% level. McFadden R-squared is 59%, the log likelihood ratio is 146.77, and it is significant at the 1% significant level. The logistic function for the model consists of financial variables as follows:

Z= 0.747 -0.249CFONI -19.111CFOTA +2.174DAR -24.413RA -2.335RAR

Table 9: Logistic Regression Results of Model II

Variable	Coefficient	Z-statistic	Prob.
Constant	0.747	1.587	0.112
CFONI	-0.249**	-3.258	0.001
CFOTA	-19.111**	-4.423	0.000
DAR	2.174*	2.213	0.026
RA	-24.413**	-4.075	0.000
RAR	-2.335**	-3.883	0.000
McFadden R-squared	0.594		
LR statistic	146.772**		
Prob(LR statistic)	0.000		

Note: ** and * denote significance at 1% level and 5% level respectively.

Results of Model III Consisting of Both Financial and Corporate Governance Variables

As given in Table 10, CEO duality, board size, CF from operations to total assets, CF from operations to net income, return of assets, and revenue to asset ratio are statistically significant at a 1% level. Outside ownership and the debt-to-asset ratio are statistically significant at the 5% level of significance. The log likelihood ratio is 172.87, and it is statistically significant at a 1% level. The logistic function for the model consists of both financial and corporate governance variables as follows:

Z = 7.219+2.715CD+1.384FO-3.747BS-0.215CFONI -19.200CFOTA +2.553DAR -25.622RA -2.789RAR

Table 10: Logistic Regression Results of Model III

Variable	Coefficient	Z-statistic	Prob.
Constant	7.219	2.419	0.015
CD	2.715**	3.453	0.000
OO	1.384*	2.049	0.040
BS	-3.747**	-2.616	0.008
CFONI	-0.215**	-2.588	0.009
CFOTA	-19.200**	-3.728	0.000
DAR	2.553*	2.306	0.021
RA	-25.622**	-3.444	0.000
RAR	-2.783**	-3.803	0.000
McFadden R-squared	0.700		
LR statistic	172.879		
Prob(LR statistic)	0.000		

Note: ** and * denote significance at 1% level and 5% level respectively.

Goodness of Fit of the Models

The study used the log likelihood ratio, McFadden R square, and Hosmer and Lemeshow test to identify the goodness of fit in each model. The log likelihood ratio of all models is statistically significant at the 1% level. Thus, the log likelihood ratio indicates the fitness of all the model, It is 70.11 for the model I and 146.77 for the model II. Further, it has been the highest (172.87) for the model III. In the Hosmer & Lemeshow test, as shown in Table 11, Model III has a p value greater than 0.05, which indicates the model fit. Based on the above tests, the study concluded that a model consisting of both corporate governance variables and financial variables (Model III) is more acceptable as a prediction model.

Table 11: Hosmer & Lemeshow Test Results

Model	HL statistic	P value
Model I	3.523	0.897
Model II	14.987	0.059
Model III	5.533	0.699

Note: P value >0.05 indicates that logistic regression model is a good fit.

Accuracy of the Prediction

As shown in Table 12, the model, which consists of both corporate governance and financial variables, shows a higher level of accuracy in prediction for both failed and non-failed companies. This result matched the result obtained from the data set, which excluded the financial industry.

Table 12: Assessment of Prediction Accuracy

Model	Type of sample	Prediction accuracy
Model I	Failed	74.16%
	Non failed	74.16%
	Entire sample	74.16%
Model II	Failed	87.64%
	Non failed	89.89%
	Entire sample	88.76%
Model III	Failed	91.01%
	Non failed	91.01%
	Entire sample	91.01%

Validation of Models

As per Table 13, model III indicates higher prediction accuracy one year before failure, two years before failure, and three years before failure compared to the other two models. This result complies with the result obtained from the data set, which excludes the financial industry.

Table 13: Assessment of Prediction Accuracy Over the Period

Model	One year before failure	Two years before failure	Three years before failure
Model I	74.16%	70.79%	68.54%
Model II	88.76%	84.27%	85.96%
Model III	91.01%	86.52%	88.20%

Discussion of Results

The study focused on examining the accuracy of the failure prediction models without considering the financial industry. Most researchers developed the failure prediction model while ignoring the financial industry due to their different financial and business nature (Gilbert et al., 1990). The study examined the prediction accuracy of the models consisting of corporate governance variables (Model I), financial variables (Model II), and both corporate governance and financial variables (Model III). As per the results, CEO duality, director's remuneration, and financial acumen are the significant corporate governance variables in model I. When predicting corporate failure using only financial variables, cash flow from operations to total assets, debt to asset ratio, and revenue to asset ratio are more critical. Model III indicates that CF from operations to total assets, debt to asset ratio, revenue to asset ratio, CEO duality, and director's remuneration are significant in failure prediction. Most importantly, financial acumen is insignificant when predicting failure using both financial and corporate governance variables. These findings are also consistent with Wijekoon and Azeez (2015) and Randika at al., (2019). Further research conduct by Lakshan and Wijekoon (2012) in Sri Lankan context also consistent with the findings of this study.

Research findings of Balasubramanian at al. (2019) and Destriwanti at al. (2022) also support the findings of this study in the other settings. When comparing the prediction accuracy of three models, model III shows the highest accuracy level in the entire sample as well as the failed sample. It shows 90.32% prediction accuracy for the entire sample while indicating 88.71% for the failed company. Validation of the model is also indicating that Model III is the failure prediction model that gives the highest prediction accuracy throughout the one year before failure (90.32%), two years before failure (85.48%), and three years before failure (80.65%). Model III shows higher and more stable prediction accuracy throughout the three years. Furthermore, while considering all three prediction models, cash flow from operations to total assets, debt to asset ratio, revenue to asset ratio, CEO duality and director's remuneration are significant variables in all the models in predicting firm failures in Sri Lanka.

When firms in the financial industry is incorporated into the analysis, the study indicates that prediction model III consisting of both financial and corporate governance variables are more accurate than prediction model I (consisting of corporate governance variables) and prediction model II (consisting of financial variables). According to the study there is a higher log likelihood ratio in prediction model III than in other models. It explains that model III has significant explanatory power for the corporate failure prediction of Sri Lankan listed companies. On the other hand, model III considers a significant number of variables from the fiancial and corporate governance, and most of them are statistically significant at the 1% level. It expresses that the combination of the finance and corporate governance variables in Model III provides better failure prediction than other models. Model III indicates that CEO duality, outside ownership, and board size are significant corporate governance variables, while cash flow from operations to net income, cash flow from operations to total assets, debt to asset ratio, return on assets, and revenue to asset ratio are significant financial variables. Altogether, all these variables provide 91.01% prediction accuracy in the failed, non-failed, and entire sample of the study. Furthermore study emphasized that directors' remuneration does not have significant predictive ability when combined with financial variables in model III. Model III indicates a prediction accuracy of 91.01%, 86.52%, and 88.20% in the one year before failure, the two years before failure, and the three years before failure, respectively. Overall, it is an acceptable prediction accuracy, which illustrates the validity of the model for failure prediction. The prediction accuracy of all three years for model III is higher than the models I and II. Furthermore, while considering all three prediction models, cash flow from operations to net income, cash flow from operations to total assets, debt to asset ratio, return on assets, revenue to asset ratio, CEO duality, Outside ownership, and board size are significant variables in the failure prediction of the firms in Sri Lanka.

Conclusions

This study indicates that the failure prediction model, which consists of both corporate governance and financial variables, is more accurate than the other models. It explains that failure of the organization can occur due to poor corporate governance variables as well as poor financial performance. On the other hand, it indicates that financial variables and corporate governance variables alone may not be good enough to predict corporate failure. Furthermore, it is applicable to organizations that operate in the financial industry. As per the results, CEO duality, director remuneration, cash flow of operations to total assets, debt to asset ratios, revenue to asset ratio and return on asset ratios are more significant in predicting failure. When the CEO and Chairman positions are held by the same person, it is more likely to occur frauds. Furthermore, increasing the director's remuneration will motivate the directors and reduce the incidence of fraud. Maintaining better cash flow from operations to total assets, debt to asset ratio, and return on asset ratio always leads to higher profitability and performance. Most failed companies were unable to generate sufficient liquidity, and they were inefficient in utilizing their assets to generate cash flows. So, cash flow from operations to total assets, return on asset and the revenue to asset ratio become more significant in failure prediction.

Some variables become more significant when developing the prediction model for listed firms in all industries than when developing the prediction model for listed firms in industries except the financial industry. When developing the prediction model for all industries, outside ownership and board size became significant, and when it came to the prediction model for the listed firms except the firms in the financial industry, those became insignificant in failure prediction. Same way, cash flow from operations to net income and return on assets ratios are the two financial variables that became insignificant when developing the failure prediction model for the listed firms except firms in the financial industry. Predicting corporate failure is essential to many parties, such as investors, auditors, government agencies, financial institutions, etc. Investors will be able to foresee the future performance of the organization and identify the undersirable investment. On the other hand, if the investor can make decisions related to the sale or purchase of company shares based on the information provided by the prediction model, auditors can obtain an idea of the going concern of the organization, and based on their prediction, they can prepare the audit report, including the going concern issue. On the other hand, financial institutions can use the prediction model to identify the going concern when it is essential to decide about the loan grant.

The study has some practical implications, which create gaps for future research. The study concerned only the organizations listed on the Colombo Stock Exchange, and it completely excluded private and other small enterprises. Further, sample selection was based on the temporary poor conditions during the period of the study concerned. So, these organizations may be able to earn a positive net operating cash flow even though they are considered failed organizations.

References

Abdullah, T. M., & Hussin, Z. (2010). Predicting corporate turnaround using logistic regression analysis: A research on Bursa Malaysia companies. *Journal of Management and Business, 9*(2). https://doi.org/10.24123/jmb.v9i2.166

Abou El Sood, H. S. (2011). The usefulness of accounting information, economic variables, and corporate governance measures to predict corporate failure. *Journal of Applied Business Research, 24*(4). https://doi.org/10.19030/jabr.v24i4.1326

Adnan Aziz, M., & Dar, H. A. (2006). Predicting corporate bankruptcy: Where we stand? Corporate Governance: *The International Journal of Business in Society, 6*(1), 18–33. https://doi.org/10.1108/14720700610649436

Ahmad, S. M., Ramakrishnan, S., Raza, H., Ahmad, H. (2018). Review of corporate governance practices and financial & distress prediction. *International Journal of Engineering & Technology, 7*(4.28), 30. https://doi.org/10.14419/ijet.v7i4.28.22385

Agarwal, V., & Taffler, R. (2008a). Comparing the performance of market-based and accounting-based bankruptcy prediction models. *Journal of Banking & Finance, 32*(8), 1541–1551. https://doi.org/10.1016/j.jbankfin.2007.07.014

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance, 23*(4), 589–609. https://doi.org/10.1111/j.1540-6261.1968.tb00843.x

Amendola, A., Giordano, F., Parrella, M. L., & Restaino, M. (2017). Variable selection in high-dimensional regression: A nonparametric procedure for business failure prediction. Applied Stochastic Models in Business and Industry.

Association of Certified Chartered Accountant. (2008). Business Failure: Prediction and Prevention. Association of Certified Chartered Accountant.

Azeez, Dr. A. (2015). Corporate governance and firm performance: Evidence from Sri Lanka. *Journal of Finance and Bank Management*, *3*(1). https://doi.org/10.15640/jfbm.v3n1a16

Balasubramanian, S. A., G.S., R., P., S., & Natarajan, T. (2019). Modeling corporate financial distress using financial and non-financial variables. International Journal of Law and Management, 61(3/4), 457–484. https://doi.org/10.1108/ijlma-04-2018-0078

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research, 4*, 71. https://doi.org/10.2307/2490171

Brédart, X. (2014). Financial distress and corporate governance: The Impact of Board Configuration. *International Business Research, 7*(3). https://doi.org/10.5539/ibr.v7n3p72

Chairunesia, W. (2020). Analysis of financial ratios and good corporate governance mechanisms in predicting financial distress. *International Journal of Management Studies and Social Science Research, 2*(4), 13.

Charitou, A., Neophytou, E., & Charalambous, C. (2004). Predicting corporate failure: Empirical evidence for the UK. *European Accounting Review, 13*(3), 465–497. https://doi.org/10.1080/0963818042000216811

Chudson, W. A., Paish, F. W., & Lutz, F. A. (1945). The pattern of corporate financial structure. A cross section of manufacturing, mining, trade and construction, 1937. *Economica*, *12*(47), 179. https://doi.org/10.2307/2550168

Destriwanti, O., Sintha, L., Bertuah, E., & Munandar, A. (2022). Analyzing the impact of Good Corporate Governance and Financial Performance on predicting Financial Distress using the modified Altman Z Score model. *American International Journal of Business Management, 5*(2), 10.

FitzPatrick, P. J. (1932). A Comparison of the Ratios of Successful Industrial Enterprises with Those of Failed Companies. Ohio: The Ohio State University.

Gilbert, L. R., Menon, K., & Schwartz, K. B. (1990). Predicting bankruptcy for firms in financial distress. *Journal of Business Finance & Accounting*, *17*(1), 161–171. https://doi.org/10.1111/j.1468-5957.1990.tb00555.x

Hasan, M., & Hoque, A. (2023). Fintech risk management and monitoring. *International Series in Operations Research & Management Science*, 3–16. https://doi.org/10.1007/978-3-031-18552-6_1

Hiau Abdullah, N., Halim , A., Ahmad, H., & Md. Rus, R. (2008). Predicting Corporate Failure of Malaysia's Listed Companies: Comparing Multiple Discriminant Analysis, Logistic Regression and the Hazard Model. *International Research Journal of Finance and Economics, 15*, 17.

Huang, S.-M., Tsai, C.-F., Yen, D. C., & Cheng, Y.-L. (2008). A hybrid financial analysis model for business failure prediction. *Expert Systems with Applications, 35*(3), 1034–1040. https://doi.org/10.1016/j.eswa.2007.08.040

Lakshan, A., & Wijekoon, N. (2013). The Use of Financial Ratios in Predicting Corporate Failure in Sri Lanka. *Journal on Business Review, 2*(4), 7

Lakshan, A. M. . I., & Wijekoon, W. M. H. N. (2012). Corporate governance and corporate failure. 2nd Annual International Conferences on Accounting and Finance (AF 2012). https://doi.org/10.5176/2251-1997_af90

NA, C., & M, F. (2016). Impact of financial performance and growth opportunities on success or failure of companies: Evidence from Tehran Stock Exchange. *Journal of Accounting & Marketing, 5*(2). https://doi.org/10.4172/2168-9601.1000166

Lee, T. S., Yeh, Y. H., & Liu, R. T. (2003). Can Corporate Governance Variables Enhance the Prediction Power of Accounting-Based Financial Distress Prediction Models? Center for Economic Institutions, 32

Lee, T.-S., & Yeh, Y.-H. (2004). Corporate governance and financial distress: Evidence from Taiwan. *Corporate Governance, 12*(3), 378–388. https://doi.org/10.1111/j.1467-8683.2004.00379.x

Lu, R., Lee, C.-J., & Chang, S.-L. (2008). Corporate governance, quality of financial information, and macroeconomic variables on the prediction power of financial distress of listed companies in Taiwan. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.1137046

Mervin, C. L. & Wynne, W. H., (1944). Financing small corporations in five manufacturing industries, 1926-36. *Journal of the American Statistical Association, 39*(225), 129. https://doi.org/10.2307/2280341

Mohd Noor, Z., & Mohd Iskandar, T. (2012). Corporate Governance and Corporate Failure: A Survival Analysis. Malaysia.

Oduro, R., & Asiedu, M. (2017). A model to predict corporate failure in the developing economies: A case of listed companies on the Ghana Stock Exchange. *Journal of Applied Finance & Banking, 7*(4), 15.

Ooghe, H., Christophe, S., & Pieter, V. (2009). Business Failure Prediction: Simple-Intuitive Models Versus Statistical Models. *IUP Journal of Business Strategy, 6*, 7-44.

Pervan, I., & Kuvek, T. (2013). The relative importance of financial rarios and nonfinancial variables in predicting of insolvency. *Croatian Operational Research Review, 4*, 12.

Ravi Kumar, P., & Ravi, V. (2007). Bankruptcy prediction in Banks and firms via statistical and Intelligent Techniques – A Review. *European Journal of Operational Research, 180*(1), 1–28. https://doi.org/10.1016/j.ejor.2006.08.043

Tian, S., & Yu, Y. (2017). Financial ratios and bankruptcy predictions: International evidence. International *Review of Economics & Finance, 51*, 510–526. https://doi.org/10.1016/j.iref.2017.07.025

Veganzones, D., & Severin, E. (2020). Corporate failure prediction models in the twenty-First Century: A Review. *European Business Review, 33*(2), 204–226. https://doi.org/10.1108/ebr-12-2018-0209

Vo Xuan, V. (2015). Using accounting ratios in predicting financial distress: An empirical investigation in the Vietnam Stock Market. *Journal of Economics and Development*, 41–49. https://doi.org/10.33301/2015.17.01.03

Wanyama, D. W., & Olweny, T. (2013). Effects of Corporate Governance on Financial Performance of Listed Insurance Firms in Kenya. *Public Policy and Administration Research, 3*(4), 26.

Wijekoon, N., & Azeez, A. (2015). An Integrated Model to Predict Corporate Failure of Listed Companies in Sri Lanka. *International Journal of Business and Social Research, 5*(7), 14.