A STUDY OF CORPORATE FINANCIAL DISTRESS PREDICTION OF SRI LANKA: AN APPLICATION OF LOGISTIC REGRESSION ANALYSIS AND MULTIPLE DISCRIMINANT ANALYSIS

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Degree of Master of Science

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DECLARATION

"I declare that this is my own work and this thesis/ dissertation does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other university or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text."

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The above candidate has carried out this research for the dissertation under my supervision.

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DEDICATION

This thesis is dedicated to my loving parents, my husband and the supervisor of my research, Dr SD Jayasooriya, Head of the Department of Quantity Surveying, General Sir John Kotalwala Defence University who always encouraged me to complete this research.

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ABSTRACT

A financial distressed situation means a company cannot settle its obligations, liabilities from the operating cash flows or value of total assets is lower than the aggregate value of the liabilities and equity. The probability of bankruptcy should be evaluated to reduce its' harmful effects. In such a situation, the firms should have to incur bankruptcy costs. It can be minimized through the evaluation of the possibility of financial distress. Up to now various types of models are generated to forecast bankruptcy. In this study, three models are evaluated to compare their distress prediction ability within the Sri Lankan Context. They are Altman's (1968) and Springate Model (1978) and Grover Model (2001). Therefore, the objective of this research is to identify the applicability of these models in forecasting the financial distress of listed companies in Sri Lanka. Those models are analyzed within the listed companies of the Colombo Stock Exchange. The relevant financial data is collected from the audited financial statements during the period of 2013/14-2017/18.

Descriptive Statistics and Regression Analysis are used to analyze collected data with Multivariate Discriminant Analysis (MDA) as the main method of analysis. The objective of this method is to identify groups of samples from a group of predictors by finding the relationship of the variables which maximize the deviance among the populations being studied.

The study findings reveal that Altman's model has a higher accuracy rate in predicting financial distress in a non-distressed sample rather than a distressed sample and can predict financial distress before one year to bankruptcy. Yet the Springate model has an excellent predicting ability both in distressed and non-distressed samples. And also, it can reveal a symptom of financial distress before three years to the bankruptcy. Therefore, it can be concluded that the Springate model is performed well than Altman's model within the Sri Lankan context.

Key Words: Financial Distress, Altman's Model, Springate Model, MDA

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LIST OF ABBREVIATIONS

Abbreviation	**Explanation**
CSE	Colombo Stock Exchange
MDA	Multivariate Discriminant Analysis
EBIT	Earnings Before Interest and Taxes
ROA	Return on Assets
RE	Retained Earnings
TA	Total Assets
WC	Working Capital
MVE	Market Value of Equity
TL	Total Liabilities
SE	Standard Error
CI	Confidence Interval
DF	Degree of Freedom
SD	Standard Deviation

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CHAPTER 01- INTRODUCTION

1.1 Background to the Study

A financial distressed situation means that a company cannot settle its obligations and trade liabilities from the operating cash flows (flow-based insolvency) or the worth of the total assets is lower than the aggregate worth of the total liabilities and equity (assets-based insolvency). The firms are vanished from the market due to various reasons. Examples: Liquidity problems, economic recessions, unrealistic performance goals, poor debt management, high operating expenses, depreciating local currency and high interest rates so on. They can create financial distress which leads to bankruptcy. The events that firms would have been faced before filing bankruptcy is called financial distress symptoms. Examples are,

i. Selling major assets
ii. Merging with another firm
iii. Exchanging assets with liabilities
iv. Reducing capital spending and research and development expenses
v. Issuing new securities
vi. Negotiating with banks and other creditors
vii. Exchanging debt for equity

The financial complications are affected by both in-house and outdoor factors. In-house factors begin from the monetary functioning and resources management of the companies. Outdoor factors can begin from the economic situation of the relevant industry. They can direct a corporation to default on an agreement, and it may comprise financial rearrangement among two organizations, its creditors, and its shareholders. The distress of the organization will create significant harm to all stakeholders of the firm (Deakin, 1972). Bankruptcy costs may be like legal fees, costs incurred from trading assets at a sale price lower than the market price, increased borrowing costs from loans obtained, and the departure of valuable human resources. If a company entered to a financial distress zone without identifying early it will cause to bankruptcy.

Predicting corporate distress or bankruptcy has become essential for any type of business. The occurrence of bankruptcy in Sri Lanka was apparent due to financial collapses such as ETI and Pramukha bank cases. In such cases, factors that project the possibility of bankruptcy can be seen in years before filing the bankruptcy.

The probability of bankruptcy should be evaluated in an organized way to reduce its' harmful effects. Due to the lower market value of distressed firms, the firms should have to incur huge bankruptcy costs. Through the evaluation of the possibility of bankruptcy is important in minimizing costs in the future. And also, stakeholders always try to find an appropriate method to forecast bankruptcy. Up to now various types of models are generated to forecast bankruptcy throughout the last sixty years.

In systematic research studies were commenced on financial distress with Univariate Discriminant Analysis (Beaver, 1966). Altman then introduced Multivariate Discriminant Analysis in 1968, with the use of accounting ratios as a turning point in distress prediction. The initial step is to distinct group categorization. There can be two or more original classes. Discriminant Analysis is referred as Multivariate Discriminant Analysis, when the number of classes is equal or greater than two. Data should be collected for the objects in the classification after classification has been made. MAD is trying to create a linear connection between features that distinguish well between categories. MDA will highlight discriminant coefficients if a specific firm has traits that can be quantified numerically for all of the sample units in the analysis. MDA's key benefit is to take into account all features of the respective companies. (Altman, Narayanan, 1977, and Haldeman).

Until now, many researchers evaluated the accuracy and applicability of Multivariate Discriminant Analysis in different economic situations (Samarakoon and Hasan, 2003; Balasundaram, 2009; Gunathilaka, 2014). Through the guidance of Altman's Z score model, some other modern techniques were also introduced. Examples: Springate Model, Zmijewski Model, Grover Model, Zeta Model, Artificial Neural Network, Linear Probability Model & Support Vector Machine etc.

All these prediction models can be categorized into mainly two parts. Accounting ratio-based models and market-based models are the two types. Models based on the accounting ratio are produced by many ratios drawn from the financial statement and their relative pesos. They are based on the selected samples of distressed and non-distressed firms (Abdullah, Ma'aji, and Khaw, 2016). The nature and composition of accounting ratios can be changed by the time (Chenchehene and Mensah, 2014). Examples of accounting ratio-based models are Altman's Z score model, Springate model, Ohlson O score model, and so on. Market-based models are the Black and Scholes model and the Merton model (Black and Scholes, 1973; Merton, 1974). This type of model can eliminate the limitations of accounting-based models with the following characteristics. 1) It supplies a fundamental fact for distressed firms. 2) In the share market, share market price can represent all relevant information that is not highlighted in the financial statements. 3) Expected future cash flows are included in the share market price (Agarwal and Taffler, 2008). Among other prediction models, Gorden Springate (1978) introduced a model to recognize the probability of failing. It is very popular since this method is also based on Discriminant Analysis. Zmijewski (1984) evaluated the liquidity of a firm with traditional ratios with the collected data from 40 distressed firms and 800 existing companies. Grover Model is another popular model among scholars. It is a result of the redesign of Altman's model. From all related models, the Zmijewski model has a stronger significance than Altman's model, the Springate model, and the Grover model (Husein and Pambekti, 2014).

Apart from those above, in the Sri Lankan context, the Company Act of 2007 outlines a requirement of solvency test before distributions to shareholders, the redemption of any shares, repurchase of shares, and amalgamation proposals. A company shall be deemed to be have satisfied the solvency test if it can pay its debts as they become due in the normal course of business and the value of the company's assets is greater than the value of its liabilities and the company's stated capital (Sri Lankan Government, 2010). As per sec 154 of the company act, every listed company of Colombo Stock Exchange must be audited by an independent professional auditor before publishing the annual reports of the firms to stakeholders. The nature of the audit opinion can reflect the probability of bankruptcy. An unqualified audit opinion shows the financial healthiness of the companies while a qualified opinion shows a problem in going concern most of the time.

Trading of the financial instruments under the Share Brokers Association was formed in 1896. However, in 1904 it was renamed as Colombo Brokers Association. After

Colombo Security Exchange was formed by merging Stock Brokers Association and Colombo Brokers and Stock Brokers. When considering the sampling unit, public companies incorporated in the Colombo Stock Exchange highlighting twenty industries will be used to conclude this study. There are 290 listed companies with a market capitalization of Rs. 2748.10 billion. They are incorporated according to rules and regulations of the Companies Act of No 07 of 2007 or the laws of the government. These listed companies can raise funds through debt issues or equity issues. For including to official listing and securing it will be impacted by the provisions of Security and Exchange Commission act No36 of 1987.

i. The 20 industries of CSE are as follows.
ii. Energy
iii. Health Care Equipment & Services
iv. Commercial & Professional Services
v. Transportation
vi. Automobiles & Components
vii. Consumer Durables & Apparel
viii. Consumer Services
ix. Retailing
x. Food & Staples Retailing
xi. Food, Beverage & Tobacco
xii. Household & Personal Products
xiii. Pharmaceuticals, Biotechnology & Life Science
xiv. Banks
xv. Diversified Financials
xvi. Insurance
xvii. Real Estate
xviii. Telecommunication Services
xix. Utilities
xx. Materials
xxi. Capital Goods

In this research study, all industries are considered except Banks, Diversified Financials, and Insurance Companies. The sample is selected by representing the above industries. Then the financial data of the selected sample was evaluated to do a comparative study regarding the applicability of financial distress prediction models within the Sri Lankan context by using Multivariate Discriminant Analysis.

1.2 Conceptual Framework

The following diagram depicts the conceptual framework of this investigation.

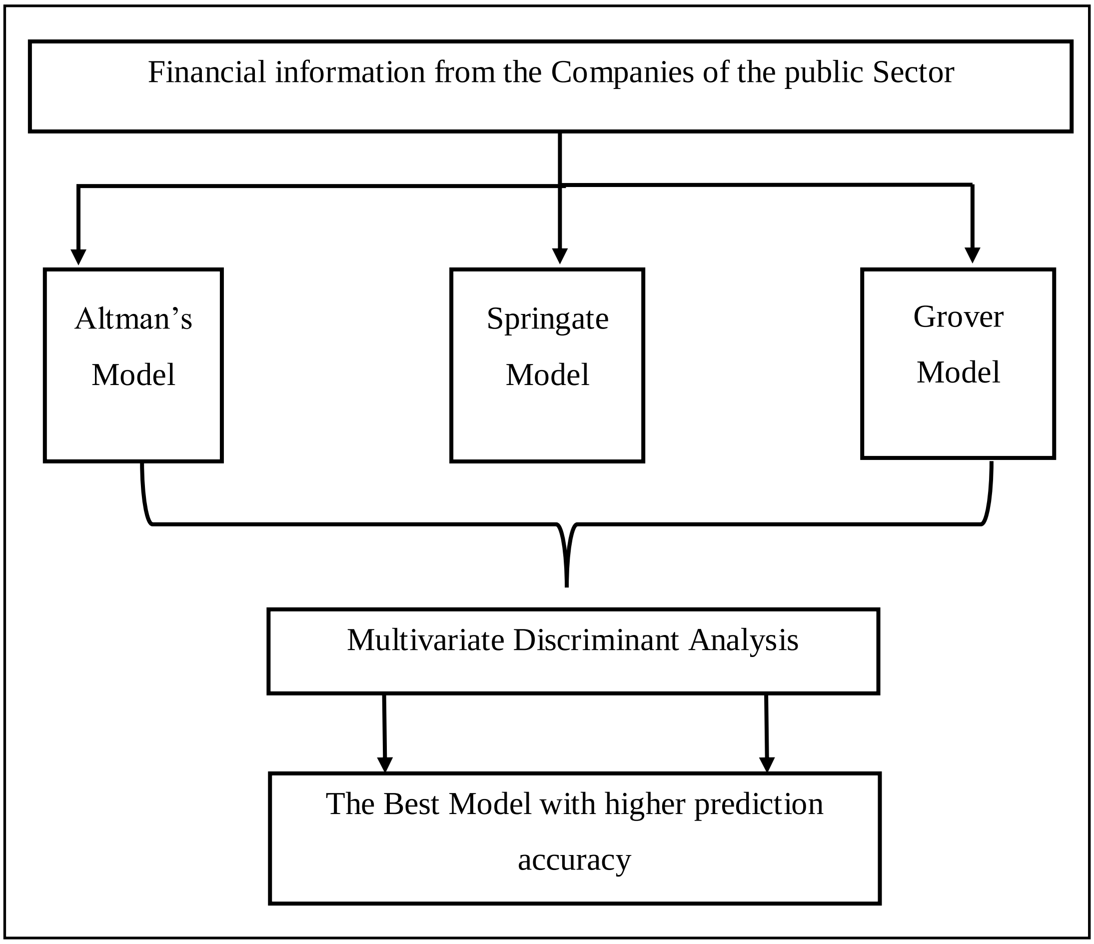

Figure 1.1: Conceptual Framework

This research study, it will be presented about corporate financial distress prediction models profoundly. The collected data relative to the listed companies in CSE from annual reports were analysed using three models; Altman's model, Springate model, and Grover model. The data was examined using Mini tab software for Multivariate

Discriminatory Analysis. The anticipated analysis is then compared to the actual financial performance of the selected organizations. The analysis resulted with a most accurate model which can use to predict financial distress in advance.

The most reliable bankruptcy prediction models which can indicate the chance of bankruptcy before few years was provided in this research study.

1.3 Problem Statement

Predicting the financial distress of a company is a major concern in order to sustain the financial condition of that company. Therefore stakeholders are always keen on the best models to predict the financial distress of a company and avoiding harmful effects. So, different models of distress prediction have been established with different approaches. The diverse researches have been carried out from 1966 to explore the factors affecting financial distress and invent prediction models using them. The univariate Approach (Beaver, 1966) used one variable to predict bankruptcy. It is not a judicious method. Most of the research studies have focused on one model or a mix of two or three models. A fewer amount of studies has considered more than three models of bankruptcy prediction. Multiple models mix can increase the accuracy of the predictive ability of distress in listed companies in China (Sun and Li, 2008). And also, it declines the variance of errors in forecasting distress. This type of multiple models' research study can't be seen in the Sri Lankan context also. For these reasons, three accounting-based prediction models Altman's model (1968), Springate Model (1978), and Grover Model (2001) have been taken into consideration in this research study.

As stated in the company act (2007) of Sri Lanka, the solvency test can analyze the actual financial situation before any distribution to its shareholders. It can be said that the least attention has been given to the comparability of Traditional Financial Distress Models and the actual financial healthiness by Sri Lankan researchers when looking at the recent researches. In Sri Lanka, very few research studies can be found regarding a mix of financial distress prediction models and the actual financial healthiness of the selected companies. The audited financial statements also can reflect the financial healthiness of the companies. Therefore, the main research problem of this research study is to identify how the above mentioned accounting-based bankruptcy prediction models of Altman (1968), Springate Model (1978), and Grover Model (2001) can apply to Public Listed Companies of Colombo Stock Exchange during 2013-2018 and compare the results with their actual financial healthiness.

1.4 Significance of the Study

The predominant aim of this study is to explore the comparability of various corporate bankruptcy models with the actual financial healthiness and their applicability within the Sri Lankan context. The final result will aim to identify the accurate prediction model and obtain more reliable information about the risk of bankruptcy of those companies. Thus, the purpose of this study can be summarized as follows. This research would support investors when evaluating the ability to repay debts of Sri Lankan Listed companies. They can create investment strategies based on the earlier forecasting of the financial healthiness of the companies which are not represented by the existing share price. Public listed companies are governed by the Security Exchange Commission and provisions of the Companies Act. Monitoring financial healthiness and the existence of the companies are the major tasks of Regulatory Bodies. They can evaluate and monitor policies that help in preventing financial distress from this study.

1.5 Research Questions

This investigation will look into the applicability of distress prediction inside the Sri Lankan environment, as well as a comparability of the above models with actual financial wellness. This study can summarize the problem discovered as follows.

i. Are the existing models of predicting bankruptcy applicable in Listed Companies of Sri Lanka?
ii. Which prediction models of financial distress are the most reliable in predicting financial distress in companies in the Sri Lankan context?

1.6 Research Objectives

The following are the primary goals of this research.

i. Investigate the applicability of traditional corporate bankruptcy models in the Sri Lankan Context.

ii. Identifying the most accurate corporate bankruptcy prediction model within the Sri Lankan Context.
iii. Identifying the most adequate financial ratios which assist to disclose the financial healthiness of a company.

1.7 Limitations of the Study

The dissertation will analyze five different accounting-based distress prediction models which we can see in the literature. Different financial ratios have been employed by these models. They can elucidate the accuracy of bankruptcy prediction at various levels even though no one can predict bankruptcy at 100% accuracy. (Kleinert, 2014)

No model has sufficient facts for the prediction of distress due to that all of the methods have pros and cons. The Market-based models perform well compared to accounting-based models since the macro-economic variables are employed in market-based models. The required data will be based on past information. The important feature of them is they can be influenced by future trends. But these trends can’t be presented in accounting-based models.

As well as, accounting values can be manipulated (Accounting Distortions) by covering the risks of bankruptcy from its stakeholders. It is also crucial when evaluating the accuracy of prediction models. Always a larger sample provides a clear conclusion about the applicability of distress prediction models. But this dissertation considers data from a limited sample due to time limitations to analyze.

1.8 Motivation behind the Research Study

This dissertation about forecasting distress was selected due to that it permits discussing the various stages of a firm that exist through the ending with the condition of bankruptcy. Financial Distress Prediction is a core area that has been attracted by researchers due to it is wide application. So, it emphasizes carrying out more researches is vital in the financial sector in this area.

This chosen area will be engaged in identifying whether accounting-based models can predict the probability of distress in the Sri Lankan context. The scope of the study is confined by focusing only on the Listed companies in CSE in Sri Lanka without moving into companies in other countries. It can be found only a few studies related to the applicability of mixed models among the studies carried out in the Sri Lankan context. It can be observed that one or two models have been involved by most of the researchers in their studies.

This study will analyze three financial distress prediction models like Altman's Z Score Model, Springate Model and Grover model and how they can apply in Sri Lankan Context. Therefore, this becomes a multi-model study.

1.9 An Outline of the Research Study

The be named units of the expositions are arranged in the thesis as mentioned below.

1.9.1 Chapter 01: Introduction

Chapter one acquaints the basal layer of the study concisely and shown the research context. The problem assertion and purpose of the study scoup-out based on that problem statement. Chapter will also stress the significance of the study as well as the limits of the research..

1.9.2 Chapter 02: Literature review

Second Chapter contains several sections of the review conjoining to the factual literature. It can be classified as a general outline, axiomatic determinants, and definitions. In chapter, primary points are summarized in a comprehensive manner in order to organize the previous studies in an systematic manner from the reviewed literature.

1.9.3 Chapter 03: Research methodology

Third chapter includes the methods and techniques used in the research study. It covers study design, sampling design, data sources and collection, data analyzing techniques, and model specification. Further, the definitions and measurements of the variables were annotated in this chapter explicitly.

1.9.4 Chapter 04: Data presentation and analysis

Chapter four combine the results of the statistical data analyzing part and the discussion drawn from the outputs. It shows the flow to the ultimate outcomes of the study starting from the part of the descriptive statistics. Also, it summarized the prediction accuracy comparing the major results of financial healthiness given by the statistical models used.

1.9.5 Chapter 05: Conclusion & recommendations

The fifth chapter condenses the outcomes of the research, conclusions, and recommended suggestions which can be given rely on the end result of the research concisely.

CHAPTER 2 - LITERATURE REVIEW

This section will reveal out the indispensable concepts that follow in this dissertation which is the theory of bankruptcy. Since this dissertation compacts with models of distress prediction, an explanation of this theory will be provided to comprehend that what does the term of bankruptcy reveals and how it is implemented within the context of Sri Lanka.

2.1 Bankruptcy, Financial Distress, Insolvency

The inability to its paying obligations, trade payable, tax liabilities and short term bank loans of a firm can be identified as financial distress. Financial distress can be divided into economic failure, business breakdown, technical insolvency, insolvency in bankruptcy, and legal bankruptcy. (Brigham & Gapenski,1997)

When a company has an operating cash flow greater than its obligations, the company will have enough capital to settle the total liabilities. It is the main fact in recognizing whether the company is going financially distressed or not. So financial distress means a situation where the company has net income from operations for more than a year and no dividend payments (Almila & Kristijadi,2003). It cannot be concluded that all the companies will bankrupt which face financial distress since it is not the only reason for bankruptcy.

The models of financial distress prediction should be developed since it is expected to take corrective actions to conditions that lead to bankruptcy. Examples: liquidating assets of the company to settle the liabilities, evaluating the funds of the working capital, issuing share capital, borrowing funds from outsiders etc. Then the harmful effects of financial distress can be avoided by the companies themselves.

Among the remaining literature, various terms can be found regarding corporate failure. (McKee, 2003) brings out this fact as “while there is abundant literature describing prediction models of corporate bankruptcy, few research efforts have sought to predict corporate financial distress.”

There are other definitions for explaining corporate failure. In the basic terms of economic theories, failure can be explained as the actual rate of return on invested capital is lower than the existing return of investments. Inadequate income to cover costs and lower return of investments than the cost of capital of the firm are the causes of this failure. (Altman and Laitinen, 2014). As well as many firms fail within a short period due to the failures of their corporate strategies. Due to that company can't face the market demand properly to earn profit. Sometimes corporate failures may happen without the knowledge of the stakeholders of the company as a result of the window dressing. If a firm has to face a lower or negative return continuously, that firm has no opportunity to expand while facing huge liquidity problems. The next term is insolvency and can be explained as the inability to serve its current liabilities due to the less position of liquidity and finally, it leads to the legal bankruptcy process. The term default happens when a borrower is difficult to repay the lender.

Yet the term of distress or bankruptcy is difficult to explain since there is no clear definition for the term financial distress because researchers have used various meanings and circumstances to define so. "Financial distress is the final stage of business failure which indicate the results of bankruptcy. (Piatt and Piatt, 2002). Corporate failures can be affected by several facts such as 1) Managerial inefficiency 2) Socio-cultural factors 3) Economic instability 4) Public Policy. (Mbat and Eyo, 2013). When evaluating articles regarding the chosen models of bankruptcy prediction, it is clear that various circumstances were used to outline a firm as distressed and non-distressed.

The financial situation of a corporation is a key factor in assessing the effectiveness of the operation activities. Therefore, a model of financial distress forecasting is a systematic way that we used to evaluate when a company will be bankrupted or not with the use of financial ratios or some other fact based on the performance of the relevant company. They can provide an overall idea about the performance of the company. For that many bankruptcies, predictions models have developed.

2.2 Models of Bankruptcy Prediction

Among the literature, It can be seen the the names of two models have been highlighted used in predicting bankruptcy Accounting-based models and Market-based models. These models of distress prediction depend on market base information and accounting-based information. It can be identified that the market information such as exchange rates, gross domestic production, interest rate, and share prices. etc are scraped by these Market-based models. But the Accounting based models depend on data obtained from the financial statements. Accordingly, these methods predict the potential possibilities from past data. According to (Penman, 1997) The facts regarding investment through assessing the value of the firm can be identified by analyzing of financial statements which are considered as a benefit. It can be observed that these methods are used by developed countries like the USA and Australia according to the previous studies.

The accounting-based models was begun to use for grouping firms as bankruptcy prediction models in the period of 1930. Univariate analysis which was based on accounting data were used by Beaver to predict financial distress 1966 for the first time. Since then this corporate financial distress forecasting has become a most captivated research topic in the field. The majority of these models are based on accounting-based ratios. There are some well-known prediction models used like Zmijewski model, Altman Z score model, Springate model etc. thirteen ratios which can be suspected as factors and can be determined the financial healthiness of a company from distress and non-distress firms were identified by Beaver. Also, he specified the best predictors among them like net income/total assets, total assets/ total liabilities and cash flow / total debt ratios. It can be identified that the various statistical techniques have been used by the researchers when analyzing data using accounting-based models.

2.2.1 Altman model (1968)

Multivariate Discriminant Analysis was introduced by Altman in 1968 by extending the used ratios in the Beavers Univariate Analysis. Univariate analysis means the simplest form of evaluating collected data. “Uni” means data has only one variable. It never argues with reasons or relationships (unlike regression) and its main objective is to describe and summarize the collected data and get an idea of the patterns in the data. The Univariate Analysis was further disapproved by Altman’s model. The companies may be bankrupted when the profitability and solvency ratios are getting weak. But when liquidity position is above the average liquidity, that situation is not harmful. The z score model can measure the stability of the corporations and the accurate prediction of distress.

Altman used a mix of accounting ratios to forecast the bankruptcy level. Finally, he ended up with the most suitable financial ratios at the best level. In his investigation, he used 66 sample listed companies in the USA from 1946 to 1965. When selecting the listed companies relatively large and small companies were neglected since they can affect the accuracy of the conclusions. He used the essential ratios to check whether they can predict the financial healthiness accurately and categorized them into the relevant group using various types of tests. The vital facet of the Altman model is the Multivariate Discriminant Analysis.

It is a statistical technique used to categorize an observation into one observation's features. It can help forecast financial status incorporate failure (Altman, 1968) Multiple Discriminant Analysis (MDA) is a formal approach for reducing the ratio in order to improve the representativeness of the selected financial ratios as variables. This analytical model may be used to forecast the company's bankruptcy, analyze the company's prospects, and examine the feasibility and rationality of an organizational strategy while choosing on alternatives.

MDA prediction models derived from Altman's Model are as follows.

$$Z\ Score = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5 \qquad (1)$$

Where,

$a = Intercept$

$b = Coefficient$

$X_1 = Working\ Capital\ to\ Total\ Assets$

$X_2 = Retained\ Earnings\ to\ Total\ Assets$

$X_3 = Earnings\ before\ Interest\ and\ Taxes\ to\ Total\ Assets$

$X_4 = Market\ Value\ of\ Equity\ to\ Total\ Liabilites$

$X_5 = Sales\ to\ Total\ Assets$

Alman's (1968) model for publicly traded firms is as follows.

$$Z\ Score = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5 \qquad (2)$$

Where,

$X_1 = Working\ Capital\ to\ Total\ Assets$

$X_2 = Retained\ Earnings\ to\ Total\ Assets$

$X_3 = Earnings\ before\ Interest\ and\ Taxes\ to\ Total\ Assets$

$X_4 = Market\ Value\ of\ Equity\ to\ Total\ Liabilties$

$X_5 = Sales\ to\ Total\ Assets$

X1 means the liquidity ratio which has higher importance on both univariate and multivariate approaches. X2 will be got a less amount by newly established companies due to the inability of improving the retained earnings. X3 means that EBIT (earnings before interest and taxes) considers only operation profit. X4 reflects the ratio of market capitalization and total debt. X5 is used to present the total assets turnover of the company which is highly sensitive to the type of the company.

Altman (1968) chose a cut-off point (z-score) of 2.99. A greater z-score than the cut-off value reveals that the firm is not bankrupt, but a z-value lower than the cut-off value indicates that the company is bankrupt, and values between the above two values are regarded to be in the grey region.

2.2.2 Altman’s model (1983)

Altman's 1983 model is created by replacing the market price of equity with the book value of equity. The reason is the previous model can be used in only publicly traded companies. The new model revised in 1983 can be used in all private firms.

$$Z\ Score = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5 \qquad (3)$$

Where,

$X_1 = Working\ Capital\ to\ Total\ Assets$

$X_2 = Retained\ Earnings\ to\ Total\ Assets$

$X_3 = Earnings\ before\ Interest\ and\ Taxes\ to\ Total\ Assets$

$X_4 = Market\ Value\ of\ Equity\ to\ Total\ Liabilties$

$X_5 = Sales\ to\ Total\ Assets$

When focusing on the range of discrimination, the firm is not in bankruptcy if the Altman’s Z score value is higher than 2.9. The firm is in the grey area if the Z value is greater than 1.23 and less than 2.9. It categorized the firm into the risk area when the z score value is less than 1.23.

2.2.3 Altman's model (1993)

But there is a limitation of the above two models. It is the use of total assets turnover. It is an industry sensitive ratio. So, this industry effect should be minimized in a good model. Altman re-revised the Z core model as follows.

$$Z = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \qquad (4)$$

Where,

$X_1 = Working\ Capital\ to\ Total\ Assets$

$X_2 = Retained\ Earnings\ to\ Total\ Assets$

$X_3 = Earnings\ before\ Interest\ and\ Taxes\ to\ Total\ Assets$

$X_4 = Book\ Value\ of\ Equity\ to\ Total\ Liabilities$

In this model, it categorized the firms into three groups like healthy, grey and distress. These regions were separated by the values 1.1 and 2.6. If the z value is less than 1.1 the firm is in the risk region. If the z value is in between 1.1 and 2.6 and greater than 2.6 the firm falls into grey and safe region respectively.

(Frydman, Altman and Kao, 1985) identified that the "MDA approach (1968) is one of the most appropriate models for detecting bankruptcy since it includes a wide range of financial ratios." Later bankruptcy models have been created on the Altman z-score model (1968) (Ooghe and Balcaen, 2004) such as Springate Model (1978), Deakin (1972), Taffler model (1983) and Zmijewski model (1984), etc.

Throughout the past periods, It has been used these methods in different contexts and periods. (Gunathilaka, 2014) expressed that Altman's and Springate's Z core models have similar predictability. Altman's Z score model can be used to detect the distressed companies at least one year before they bankruptcy since it offers a greater discriminant ability. According to (Balasundaram, 2009), The Altman model reveals the soundness of the selected manufacturing businesses, it may be said. The financial condition should be re-engineered to save them from going bankrupt. Altman's model can predict distress in terms of percentage for four years before the bankruptcy (Mahalakshmi, 2015). In this case, Altman's model gives moderate support for predicting the bankruptcy of the selected sample of 30 sick and 30 non-sick companies from the official website of the Board for Industrial and Financial Reconstruction. According to the results of the research done by Samarakoon &

Hassan (2003) Altman's models are more accurate at anticipating bankruptcy based on data from the year preceding the bankruptcy. (Soni, 2019) It has been noticed that the probability of bankruptcy in Ruchi Soya Industries Limited can be predicted by Altman’s model. Further, it has been discovered that the two ratios the firm’s market value and assets turnover ratio are relevant in the Z score model. When the general model is applied in different countries, country-specific measures can be used to improve the accuracy of the model, (Altman *et al.*, 2014).

Altman’s model and Zavgren model were compared and reveal that there is a meaningful variation among Altman’s adjusted model and Zavgren’s model in bankruptcy prediction. It means that there is a meaningful difference between Altman's adjusted model and Zavgren's model in accepted companies’ bankruptcy anticipation and also is the indicator of the lack of confirmation, it reveals that Zavgren accuracy model in accepted companies’ bankruptcy anticipation in Tehran Stock Exchange is more than Altman's adjusted model.

(Grice and Ingram, 2001) also have been used Altman’s model to forecast the financial distress of sample firms and they suggested the interpretation should be done cautiously. The model's capacity to properly categorize companies as financially distressed is likely to differ significantly from that expected by individuals using the model. It can be seen that the different researchers have obtained different results and conclusions. Based on the findings of the study of (Imelda and Alodia, 2017) concluded that Ohlson’s Model is more reliable than Altman’s Model in forecasting financial distress on manufacturing companies listed on the Indonesian Stock Exchange in 2010-2014.

2.2.4 Springate model (1978)

Springate model (1978) can be introduced as the first model of Gorden LV Springate. It is a kind of a developed model of multiple discriminant analysis. Although this model considered 19 common ratios as its variables finally it end up with only four financial ratios. Moreover, this model can be predicted the financial healthiness of a company with a 92.5% accuracy rate.

$$Z = 1.03X_1 + 3.07X_2 + 0.66X_3 + 0.4X_4 \qquad (5)$$

Where,

$X_1 = Working\ Capital\ over\ Total\ Assets$

$X_2 = Net\ Profit\ bfore\ Interest\ and\ Taxes\ over\ Total\ Assets$

$X_3 = Net\ Profit\ before\ Taxes\ over\ Current\ liabilities$

$X_4 = Sales\ over\ Total\ Assets$

This method divides the firms' healthiness into two parts like distress and healthy. The region will be separated by 0.862. If the score is less than 0.862 the firm is in the risk area and if it is greater than 0.862, The firm is expected to run into financial difficulties in the future.

A study was carried out by (Gepp and Kumar, 2015) to describe the financial distress prediction using the Springate model for the foods and beverage sector in Indonesia stock exchange using the data from 2006 to 2010. Based on the final output of this study it can be concluded that The Springate model may be used to analyze an organization's performance as an early warning system for insolvency. (Gunathilaka, 2014) stated that Altman's model and Springate model have the similar predictive ability as a result of the research carried out using 15 distress and 67 non-distress companies. He has used t-test to the significance of the two samples and the prediction ability of models has been analysed by using Multiple Discriminant analyses. His results show the ability of Altman's model in forecasting financial healthiness of distress companies if higher at least one year before

Financial distress prediction plays a vital role in the financial market since it can be forecasted the probability of bankruptcy before it happens and avoid the harmful effects to the firms by protecting the stability of the financial market. Another study conducted by Talebina et al. (2016) found Springate model is the better model when compare to the accuracy of other forecasting models. The research has been done using the data available in Iran's Exchange market. Further, it concluded that the Springate model and other perdition models should be ameliorated and restated to get more convergent to the actual situation. It can be said that various researches have been terminated with different results.

In pursue of the views of, (Türk and Kurklu, 2017) the Altman Z score model and Springate Z score model disclosed tantamount verdicts in recognizing the failure of business from the data collected from seven sectors.

But still, the success rate of Altman's and Springate models are 69% and 57% according to the analysis of the year based average. Based on these values it can be agreed with the conclusion the financial failure forecasting models gave similar results.

It was found from the analysis done by (Sinarti and Sembiring, 2015) There is no significant difference between Altman's Z score model and the Springate model. Further, it elaborates the results saying that Altman's model is impacted by the sales data of the firm while the Springate model does not include a component of the results to say that the affects the results of prediction.

According to the findings of (Primasari, 2018), it has been revealed that the Springate model is better than the Grover model to use when forecasting the financial distress of the firm.

It can be proven that the Springate model and Z score model have similar characteristics when comparing the capability of predicting the financial healthiness of a firm.

Kleinert (2014) considered German and Bulgarian Listed companies during 2008 and 2013 with the models of Altman's model, Ohlson model, Zmijewski model to value the accuracy rate of the distress prediction models. Because the data on German listed businesses has a lower accuracy ratio than the sample on Belgian listed companies, this model stated that the Zmijewski model is acute in forecasting.

The Z score of the Springate model is significantly reliable than the Z score of the Zmijewski model. Thus, he had concluded that the model is significantly higher than the Z score of the Zmijewski model. Springate's z core is more conservative than Zmijewski's Z score in the textile and pharmaceutical firms in the Tehran stock exchange.

According to (Husein and Pambekti, 2014) Zmijewski model is the most appropriate and accurate model for predicting the financial distress of a company since it has the highest level of significance compared to the other model. It is also stated that the

Zmijewski model is utilized to place a greater focus on the leverage ratio as a signal of financial crisis.

"According to the results obtained from the determination of Altman, Springate, Zmijewski, and Grover bankruptcy coefficients, which are 92%, 84%, 9%, and 98% respectively, the ability to predict financial crises at the highest level and, consequently, the Altman model and the Springate model, and the lowest ability to Zmijewski model, are allocated to the ability to predict bankruptcy in Tehran Stock Exchange" (Pakdaman, 2018).

2.3.5 Grover model (2001)

Altman's model is a recreation of the Grover model. The model was improved by taking Working Capital to Total Assets and Earnings before Interest and Taxes to Total Assets by adding the profitability ratio with ROA(return on assets). According to the research carried out by Ni Made et al. (2013) it has been found that the Grover model is the most applicable method model to forecast the distress in the food and beverage sector. In this study, they have compared four models and conducted a model comparison using the food and beverage sector in the Indonesian stock exchange. Further, the results of the model accuracies of the four models Grover model, Altman's model, Springate model, and Zmijewski model are respectively 100%, 80%, 90% and 90%.

The equation of the Grover model is as follows:

$$\text{Score} = 1.650X_1 + 3.404X_2 - 0.016ROA + 0.057 \qquad (6)$$

Where,

$X_1 = Working\ Capital\ over\ Total\ Assets$

$X_2 = Earnings\ before\ Interest\ and\ Taxes\ over\ Toal\ Assets$

$ROA = Net\ Income\ over\ Total\ Assets$

This model has only three variables and discriminates into three regions as risk, grey and healthy areas. These regions were divided by the values -0.02 and 0.01. If the score is less than -0.02 the firm has a risk of bankruptcy if the score is between -0.02 and 0.01 the firm is in the grey area and if it is greater than 0.01 the firm does not have a risk of bankruptcy.

Based on the outputs of the study done by (Pakdaman, 2018), the Grover model has a higher predictor ability of financial healthiness than Zmijewski and Springate model. The first place acquired by the Grover model with a 78% accuracy rate when ordering the compared three models. Springate model has a 67% accuracy rate (Hungan and Sawitri, 2018). According to (Gunawan, Pamungkas and Susilawati, 2017) the Grover model can be used to predict financial distress and the financial ratios in the Grover model can reveal the financial healthiness of a firm.

(Rahimipoor, 2013) has concluded in the study carried out using data of 90 firms listed in Tehran Stock Exchange using Taffler model and Fulmer’s model, Fulmer's model acts more conservatively in predicting firms' bankruptcy. The results of frequencies of being bankrupted or not being bankrupted among the firms are 27 and 63. The Wilcockson test has been used to test the disparity between the outcomes of the two models. It has shown a substantial difference between the two models’ outcomes. Also, the results of other studies carried out in this area showed that Fulmer’s model acts more accurately in forecasting predicting insolvency of the firm than the Taffler model. Finally, we can see by using these models, helps us to identify the current status of a firm and also to avoid bankruptcy by investigating financial statements.

2.3 Summary

The result of the literature study is that the financial crisis of companies can be predicted by using several models. When some of them are evaluated, a few models stand out as the most widely used prediction models. The models include Altman S score, Springate, Zmijewski and Grover models. Multivariate Discriminant Analysis can be used to test all of these models. In diverse economic conditions, most researchers have measured their level of precision. Come studies on these concepts can also be found in the Sri Lankan setting. The model of Altman is regarded as the cornerstone for all these other literacy models. Hence, several of the models have been chosen to be evaluated within the consumer industry in Sri Lanka.

CHAPTER 3 - METHODOLOGY

A quantitative research approach is selected to continue the research. This includes the collection of quantitative data that is put into deep quantitative analysis. Experimental, Inferential and Simulation methodologies are also included in this approach. The relevant data to the variables collected from the annual reports and multivariate analysis technique was used to analyze the data to obtain expected results as the research objective.

3.1 Research Design

Before delving into the sample selection and statistical procedures that will be employed in this study, it is necessary to assess their key methodological ideas. The chapters that follow will examine the accuracy rates of three accounting-based bankruptcy models used by Sri Lankan businesses.

This quantitative study evaluates the bankruptcy models in listed companies in the Colombo Stock Exchange. Further proportional sampling will be used to reduce the choice-based sample biases. Because prior research has shown that test samples did not correspond to real-world bankruptcy rates. Another reason for selecting proportional sampling is the usefulness in describing efficiently the sample variations. A multi-dimensional technique called Multivariate Discriminant Analysis (MDA) was applied in these bankruptcy models. This method evaluates the impact of different variables to identify financial healthiness. Thus, more than one independent variable was used to explain the nature of financial healthiness. “According to (Rencher, 2002), Multivariate Analysis is an appropriate method due to the mathematical accuracy and flexibility of usage although there are some criticisms of MDA”. This will create a lower understanding of the data since group differences are reported in linear form. As well as this method confides in specific rules and assumptions. But the accuracy of the result of MDA is greater than Univariate Analysis, MDA is selected as the data analysis technique of this research.

3.2 Research Model and Operationalization

In this dissertation, the dependent variable is the bankruptcy or financial healthiness or status of the bankruptcy of selected companies. The independent variables are the various accounting base ratios used by the selected prediction models which are Altman's model, Springate Model, and Grover Model.

Altman's Model (1968)

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$$

Springate Model (1978)

$$Z = 1.03X_1 + 3.07X_2 + 0.66X_3 + 0.4X_4$$

Grover Model (2001)

$$G = 1.650X_1 + 3.404X_2 - 0.016X_3 + 0.057$$

3.2.1 Independent variables

Table 3.1: Independent variables of the selected models

Altman's model uses five variables. They are Working Capital / Total Assets - X_1, Retained Earnings / Total Assets – X_2, Earnings before Interest and Taxes / Total Assets – X_3, Market value equity/book value of total debt – X_4 and Sales / Total Assets – X_5. The Springate model uses four variables, Working Capital / Total Assets - X_1, Net Profit before Taxes / Current Liabilities – X_3, Net Profit before Taxes / Current Liabilities – X_3 and Sales / Total Assets – X_4. The Grover model is the one that uses the least number of factors among these. Working capital / Total assets - X_1, Earnings before Interest and Taxes / Total Assets – X_2 and After-tax earnings /total assets (ROA) - $X_{3.}$

The nature of the selected independent variables will be detailed in the following portion of the chapter.

i. **Working Capital to Total Assets**

The working capital of a company assesses the ability to pay its current liabilities with the current assets. Particularly, it is represented by the gap between a company's current assets and current liabilities. The company's short-term financial health and capacity to pay its obligations are emphasized by it. A positive working capital indicates that the firm can meet its short-term financial obligations while also generating funds to speculate in various investment portfolios and grow. If a corporation has negative working capital, it is unable to satisfy its short-term financial commitments caused by a lack of current assets. As a result, it is a warning indicator that the company is on the verge of going bankrupt.

ii. **Retained Earnings / Total Assets**

A company's preserved earning or losses are represented by the retained earnings/total assets ratio. If the retained earnings to total assets ratio are low, it suggests that the corporation is spending borrowed cash rather than its own retained earnings. It raises the possibility of a company going bankruptcy shortly. A greater retained earning value to total assets ratio implies that the corporation invests its retained earnings. The company will thus be able to attain profitability over a long period without having to depend on borrowed funds.

iii. **Earnings Before Interest and Tax/ Total Assets.**

EBIT stands for a company's ability to generate profits solely from its activities. The EBIT/Total Assets ratio measures a company's ability to generate enough revenue to stay profitable, fund ongoing operations, and clear debts.

iv. Market Value of Equity/ Total Liabilities

In this context, market value refers to the market capitalization of a relevant company, which shows the worth of that company's equity. It is determined by increasing the number of shares in that company by the current share price. The Market Value of Equity/ Total Liabilities ratio indicates how much the company market value would fall if declared bankruptcy before the value of its liabilities exceeded the value of its assets. A larger value of equity compared to total obligations gives stalwart investors' faith in the company's financial health.

v. Sales/ Total Assets

This variable demonstrates how effectively management uses assets to generate revenue to compete. A greater value indicates that the management needs a modest investment to develop sales, which contributes to boosting the profit of the company. The management will need additional resources to create sales in order to maintain profitability if this ratio is low.

vi. EBT / Total Debt

The ratio assesses a company's ability to repay its present debt. A high ratio indicates that the corporation has a significant present liability to pay. Credit rating firms utilize this information to determine the likelihood of debtors failing to repay their outstanding debts. Firms having a high EBIT/Dept ratio may be unable to pay their debts on time, resulting in a poorer credit rating.

vii. After-tax Earnings / Total Assets

The return on assets evaluates how profitable a company's assets are in terms of revenue generation. ROA can be calculated as follows: This ratio shows what the firm can accomplish with what it has, i.e. how much revenue it creates for every rupee of assets it has.

The main issue to evaluate when presenting accounting-based models is if there is a considerable deviation between the outcomes of the accounting-based bankruptcy prediction models of Altman (1968), Springate (1978), and Grover model (2001). The components included, as well as the outcomes of each model, were thoroughly evaluated in a study of the literature. However, because the environment is constantly changing, it is intriguing to see how such models behave in various economic conditions and industrial levels. (Grice and Dugan, 2003) reviewed Altman, Ohlson, and Zmijewski's models in the context of numerous bankrupt and non-bankrupt enterprises from various times and industries rather than those employed in original studies. The nature of the relationship between the status of the financial situation and the accounting ratio changes throughout time.

According to the literature, the accuracy rate of those models is high, and all models function equally by displaying accuracy rates that are close to each other. "Despite minor variations in the performance of the accuracy rates in the selected models. (Ingram, 2001) discovered that the accuracy rate of Altman's model diminishes over time". This is because the nature of the relationship between financial distress and financial ratios has shifted. Because it was developed for the manufacturing business, the MDA model is sensitive to industry classification. As a result, it is suggested that the Z score model be appraised by the coefficients. Another explanation for Altman's model's diminishing accuracy is the underestimate of type I error and overestimation of type II error caused by a non-proportional sample of companies. When the null hypothesis is true, type I error occurs, and when the null hypothesis is incorrect, type II error occurs. In this research type, I would make the mistake of classifying distressed enterprises as non-distressed firms.

Accounting-based models, according to some experts, perform differently because they are based on different accounting ratios. Researchers have researched how the above-mentioned models behave differently when applied to one country, however, it is not clear whether there is a variation inside the country. This dissertation looks into the corporations that are listed on the Colombo Stock Exchange. It tries to determine whether or not there are differences in the accuracy rates of the selected models. According to Kleinert (2014), the Altman model's accuracy rate decreases over the course of the study, according to a popular conclusion.

3.3 Procedures

3.3.1 Population and sample

Corporate distress is defined as companies that have been losing money, having a negative cash flow, and having three years or longer negative net worth. The dependent variable has considered as a dichotomous variable financially distress firm or not. The companies which show the above symptoms are identified as distress companies.

As of December 31, 2019, the Colombo Stock Exchange-listed 20 industries and 290 firms. Banking, finance, and insurance industries were excluded from the list of companies since they have different characteristics and capital structures when identifying the population. After removing them from the population, 61 distress companies that show the symptoms of distress were selected out of the remaining 216 quoted public companies. Companies that did not have previous records were neglected when selecting the distressed companies. Similarly, 61 non-distress companies also were selected. This research study drew on a sample of 122 CSE-listed firms. The matched sample consists of 122 enterprises, 61 distressed and 61 non-distressed. Financial and insurance industries, as well as small businesses, were overlooked. The rejection of insurance companies is due to the differing financial structures.

3.3.2 Data collection method

Required secondary data were gathered using the proportional sampling technique in order to achieve the objectives of the study from the Colombo Stock Exchange. All pertinent information, such as the firms' financial situation, size, and name, etc., was gathered. To find the values for the target variables, data of the accounting ratios were collected from the annual reports of the firms. The time and money can be saved since the data are recorded in the annual reports and open tractability by third parties is also another advantage of these reports. The Minitab software was used to calculate different financial ratios and to conduct the data analyzing part.

According to Altman (1968), the bankruptcy status does not appear within a single year. Using the same assumption, the most current data from 2015 to 2019 were chosen. There will not be enough time to take corrective actions if the time period is too short. The chance of forecasting will not be identified if the data time period is too long.

3.3.3 Mode of analysis

Multivariate Discriminant Analysis (MDA) was used as the main data analyzing technique in this research study. MDA is a statistical technique that can be adopted to identify potential investments when there are several variables taken into account. This method classifies data into different groups while screening for several variables. It will provide the relationship between the dependent and independent variables as a linear function that perfectly categorizes the data into various clusters. These clusters have different characteristics different from one to another. Discriminant Analysis is more powerful than Logistic regression. But it is conjectured certain restrictive assumptions. The assumptions which are expected to be followed by Discriminant Analysis are multivariate normality and independent of explanatory variables. These statistical techniques which are built on these consequential assumptions are more powerful than other methods which accomplish the same job.

3.3.4 Regression analysis

Regression analysis is a statistical analysis used to elucidate a linear relationship between a dependent variable and one or more independent variables. There are varieties of regression models that can be differentiated based on the types of the variables assumptions. The simple linear regression model is the basic model which has only one independent and one dependent variable in it. If there are two or more independent variables it is considered as a multiple regression model. In a binomial (probit) logistic regression model there are two possible outcomes in the dependent variable. If there are three or more possible outcomes, an ordinal logistic regression model should be used. In this study, there are three possible outcomes of Altman and Springate models which are distressed, non-distressed, and grey areas of financial status. Therefore, in Altman's model and the Springate model, the ordinal logistic regression model will be used to analyze the relationship of the selected ratios as independent variables and the financial status of the selected sample.

3.3.4.1 Ordinal logistic regression analysis

$$\boldsymbol{logit(p) = a_k + b_1 x_1 + b_2 x_2 + \cdots b_n x_n} \qquad \textbf{(7)}$$

Where,

$$p = \frac{e^{logit}}{(1 + e^{logit})}$$

$$a = Constant$$

$$b = Coefficient$$

$$x = Independent\ Variable$$

Simply put, ordinal logistic regression is the modelling of the connection between predictors and response with three or more ordinal outcomes. An ordinal outcome has three or more outcomes that have an order. To confirm the results of the ordinal logistic regression model are valid, there are some guidelines to follow in collecting, analyzing, and interpreting.

a. The independent variables may be discrete or continuous categorical.
   A continuous variable has an infinite number of figures. The categorical variable has a finite number of groups or categories. A discrete variable can be measured yet has a limited number of values.
b. The dependent variable must be ordinal.

The ordinal variable has three or more outcomes and the order or the rank of the data are meaningful. Ordinal logistic regression can be used if there are three or more categories or groups in the variable.

c. Best practices in collecting data.

   Data should represent the population of interest. Sufficient data should be provided to obtain the required precision. The collected data should be recorded in the order that is collected.

d. The multicollinearity should not be severe.

   The multicollinearity means the correlation among the predictors. This value should not be severe. Correlation within the predictors reflects multicollinearity.

e. The fitted model should have the following properties.

   i) The probability value of the goodness of fit test should be greater than the level of significance. This reveals that there is insufficient evidence to ensure that the model doesn't fit the collected data.

   ii) The findings of the association measures must meet or surpass the predictive ability standards.

When doing the ordinal logistic regression in Minitab, there are three link functions which are logit, normal and gompit. The inverse of the cumulative logistic distribution function is the logit. The Gompit is the inverse of the Gompertz distribution function, while the Normit is the inverse of the cumulative normal distribution function.

$$g(X\ k) = \theta_k + x^1 + \beta_1, k = 1, \ldots., K - 1 \qquad (8)$$

The links function and their respective distribution patterns can be summarized as follows.

Table 3.2: Link functions of ordinal logistics analysis

Name	Link function	Distribution
Logit	$g(X) = log_e\left(X^1(1 - X)\right)$	Logistic

Normit	$g(X) = \emptyset^{-1}(X)$	Normal
Gompit	$g(x) = log_e\big(-log_e(1 - X)\big)$	Gompertz

Where,

$K = Numer\ of\ distinct\ categories\ of\ the\ response$

$X\ k = Cumulative\ probablity\ up\ to\ an\ including\ category$

$g(X\ k) = Vector\ of\ predictor\ variable$

$\theta_k = Constant\ associated\ with\ the\ k^{th}\ distinct\ response\ category$

$x = A\ vector\ of\ predictor\ variables$

$\beta = A\ vector\ of\ coefficients\ associated\ with\ the\ predictors$

3.3.4.1.1 Factor or covariate pattern

It explains the values of a single set of groups in a data collection. For each factor/covariate pattern, event probability, residuals, and other metrics may be computed.

$Event\ Probability = \pi_k\ for\ k = 1,2, \dots, k$

$$P(y \leq k) = \pi_1 + \pi_2 + \cdots + \pi_k = \frac{\exp(\theta_k + x\beta)}{1 + \exp(\theta_k + x\beta)} \qquad (9)$$

Where,

$k = Equals\ 1, \dots \dots K - 1$

$\theta_k = Constant$

$\beta = Vector\ of\ coefficients\ from\ the\ logit\ equation$

3.3.4.1.2 Cumulative event probability

For each potential k, it denotes the likelihood that the dependent variable falls into the incorrect category.

$$P(y \leq k) = p_1 + \cdots + p\ k, k = 1, \dots \dots, k \qquad (10)$$

These are the responses of a model with k response groups in sequence. The total number of probabilities equals one.

$$P(y \leq 1) < P(y \leq 2) \leq \cdots \leq P(y \leq K) = 1 \qquad (11)$$

The results of the ordinal logistic regression analysis of Minitab software, proportional odds model is used for a vector of predictors. One coefficient is calculated for each predictor. The coefficient represents the change in the response when the predictor is at 1 level.

A constant for each K-1 category is calculated. It measures the probabilities for each category which is the cumulative probability.

$$P(y \leq k) = \frac{\exp(\theta_k + x\beta)}{1 + \exp(\theta_k + x\beta)} \qquad (12)$$

3.3.4.1.3 Standard error

The accuracy of the calculated coefficient is shown by the standard error. A smaller standard error indicates a more accurate estimate. The Z value can be used to determine if the predictor is connected to the independent variable in a meaningful way. Z values greater than one indicate a substantial connection. The Z value's P-value indicates where it sits within the normal distribution.

Equation 1

$$Z = \frac{\beta_i}{Standard\ Error} \qquad (13)$$

The p-value should be evaluated in Ordinal Logistics Analysis to assess whether there is a relationship between the dependent and independent variables and to check whether the model is statistically significant. Here 0.05 is treated as the significance level. It indicates that there's a 5% chance of concluding that there's a link between the variables when there isn't one.

When the p-value is less than or equal to the significance level, the null hypothesis should be rejected. It can be finalized that the relationship among the independent variables and dependent variable statistically significant. If the p-value is greater than the significance level, the null hypothesis can be accepted. It can be finalized as there is no statistically significant relationship among the variables.

3.3.4.1.4 Odds ratio

The odds ratio examines the chances of two possible outcomes. The odds of an occurrence are the chances that it will happen divided by the chances that it will not happen. Only when the logit link function is used in the model can Minitab generate odds ratios. The odds ratio can be used to figure out how much an independent variable matter. It makes use of the odds ratio to determine the impact of a predictor. The odds ratio can be interpreted differently depending on whether the predictor is a categorical or continuous variable.

3.3.4.1.5 Confidence intervals

These confidence intervals (CI) are value ranges that are most likely to include the real odds ratio values. The normal distribution is used to calculate the confidence intervals. If the sample size is high enough, the distribution of the sample odds ratios follows a normal distribution, the confidence interval is accurate.

Confidence interval for β is,

$$\beta_i + Z_{\alpha 12} * SE \qquad (14)$$

3.3.4.1.6 Log-likelihood

The log-likelihood may be used to compare two models that estimate the coefficients using the same data. Because their values are negative, the value that is closer to 0 is better, and the model matches the data. It is derived from the probability density functions individually. It is maximized to obtain the best value of β. It cannot be used to compare samples since it is dependent on sample size.

$$L(\pi; Y) = \varepsilon_i L(\pi_i; Y_i) \qquad (15)$$

3.3.4.1.7 Variance-covariance matrix

It denotes a square matrix of dimensions p + K – 1. Each coefficient's variance is in the diagonal cell, and each pair's covariance is in the corresponding off-diagonal cell. The variance is the square of the standard error of the coefficient.

Where,

$p = Number\ of\ Predictors$

$K = Number\ of\ categories\ in\ the\ response$K

3.3.4.1.8 Goodness of fit tests

a) Pearson Goodness of Fit Test

It calculates the difference between the current model and the complete model. Pearson is ineffective when the number of different covariate values is near to or equal to the number of observations, but it is effective when there are repeated observations at the same covariate level. Higher 2 test statistics and lower p-values indicate that the model may not well match the data.

$$X^2 = \varepsilon_j \frac{r_j^2}{m\pi_0} \qquad (16)$$

Where,

$r = Pearson\ Residuals$

$m = Number\ of trials\ in\ the\ j^{th}\ factor$

$\pi_0 = Hypothesized\ value\ of\ the\ proportion$

b) Deviance Goodness of Fit Test

It employs goodness-of-fit tests to assess if the anticipated and observed probability differs in ways that the multinomial distribution does not predict. The test is useless when the number of unique values equals the number of observations, but it is beneficial when there are numerous observations with the same predictor values. If the p-value for the goodness-of-fit test is less than the specified significance threshold, the predicted and observed probability varies.

$$D = 2\varepsilon Y_{ik} log P_{ik} - 2\varepsilon Y_{ik} log \pi_{ik} \qquad (17)$$

Where,

$\pi_{ik} = Pobability\ of\ the\ i^{th} observations\ for\ the\ k^{th} category$

3.3.4.1.9 Measures of association

Minitab calculates the following measures to test how the model fits the data.

$$Somers'D = \frac{nc-nd}{nc+nd+nt} \qquad (18)$$

$$Goodman - Kruksal\ Gamma = \frac{nc-nd}{nc+nd} \qquad (19)$$

$$Kendall's\ Tau - a = \frac{nc-nd}{5*N*(N-1)} \qquad (20)$$

Where,

$nc = Number\ of\ concordant\ pairs$

$nd = Number\ of\ discordant\ pairs$

$nt = Number\ of\ tied\ pairs$

$N = Total\ Number\ of\ observations$

3.3.4.2 Binomial logistic regression analysis

$$\boldsymbol{Y} = b_0 + b_1X_1 + b_2X_2 + \cdots + b_kX_k + e \quad (21)$$

A binomial logistic regression can be used to forecast a binary dependent variable based on one or more independent variables. In the Springate model, there are only two outcomes which are distress or non-distress. This is the most common type of logistic regression analysis. Binomial logistic regression is a type of multiple linear regression, but the difference is binomial logistic regression is done for a dichotomous variable, not for a continuous variable.

When running binary logistic regression, there are several assumptions to meet.

i) The dependent variable should have consisted of two categorical outcomes. These two groups need to be mutually exclusive and exhaustive.

ii) There are one or more independent variables that may be continuous or nominal.

iii) There should not be a relationship among the observations.

iv) The value of multicollinearity should be zero. It occurs when two or more independent variables are highly correlated.

v) The relationship between any continuous independent variable and the logit transformation of the response variable should be linear.

vi) The outliers should not have existed.

There are two major results of a binary logistic regression.

a) The model summary and the goodness of fit tests measure how the overall model fits the data. Hosmer-Lemeshow test is one of the most popular measures and it has appeared in the last row of the Goodness of Fits Data.

b) The coefficients and the measures of the statistical significance are represented in the coefficients table. Those can be used to measure whether the model is statistically significant. It is denoted by p-value.

CHAPTER 4 - DATA PRESENTATION AND ANALYSIS

4.1 Introduction

This chapter discusses the data analysis and interpretation of results. The applicability of the distress prediction models such as Altman's (1968) model, Springate (1978) model & Grover (2001) model in forecasting the financial healthiness of companies listed in the Colombo Stock Exchange is evaluated which reach the objective of this study. Statistical Package known as Minitab 19 was used to analyze quantitative data and this chapter comprised the findings and it will be represented as follows.

4.2 Analysis of Altman's model

4.2.1 Descriptive statistics

When considering descriptive statistics, collecting, processing, and presenting data of the relevant observations should be done. From that, the nature and the features of such data can be easily understood. The crucial fact of this descriptive statistics is the homogeneity and heterogeneity and normal distribution of the data.

The Skewness of a data set measures symmetricity and Kurtosis represent whether the data distribution is a heavy-tailed or light-tailed distribution. Skewness is a measure to identify the degree of inclination of a frequency distribution of a set of data. A perfect data has a value of skewness closer to 0, called as it is a perfectly normal distribution. If the skeweness is positive, it implies that most of the observations are below the mean. Negative skeweness implies that most of the observations are above the mean.

Kurtosis can be used to measure to check whether a given distribution is too peak. Distributions can be divided into three categories based on the Kurtosis value. When it is fewer than 3 it's called a tapered distribution. When it is 3, it can be identified as a blunt distribution. If the Kurtosis value is greater than 3, it has heavier tails than a normal distribution.

The standard deviation provides more information than the range or the IQR. It measures the deviation of each observation from the mean of the data distribution simply can say it measures the spread ness of the data set. It uses all the observations in the data set while Range and IQR use only a few values of the distribution. However, the standard deviation can be sensitive to the extreme values of the distribution. Comparatively smaller values of standard deviation are better than larger values.

Table 4.1: Descriptive statistics of the sample of non-distressed listed companies

Variable	Mean	SD	Minimum	Maximum	Skewness	Kurtosis
X1	0.1865	0.2085	-0.3858	0.7930	0.49	0.56
X2	0.2998	0.2690	-0.9002	1.0890	-0.77	2.86
X3	0.1208	0.2093	-1.9071	1.4023	-0.25	4.13
X4	0.1750	0.9725	0.0112	1.4823	5.77	3.48
X5	0.7667	0.9224	0.0010	5.7029	3.07	1.48
Score	2.4601	4.5615	-4.6023	8.4221	5.73	2.46

Zones of discrimination:

Z>2.99 - Safe Zone, 2.99>Z<1.8 - Grey Zone, Z<1.8 - Distress Zone

According to the results of Table 4.1 average of the dependent variable (Z) is 2.4601 standard deviation is 4.5615 from 305 observations gained from 61 non-distressed listed companies in the period of 2013/2014 to 2017/2018. The mean and standard deviation of the X1 variable are 0.1865 and 0.2085 respectively and the values of X1 spreads from a minimum of -0.3858 to a maximum of 0.7930. the expected value of the variable X2 is 0.2998 and the standard deviation is 0.2690. Minimum and maximum of X2 variable have given in the descriptive analysis as -0.9002 and maximum of 1.0890. The independent variable X3 has mean of 0.1208 and a standard deviation of 0.2093 also the minimum and maximum values are recorded as -1.9071 and 1.4023. The of the variable X4 range from minimum 0.0112 to maximum 1.4823 while the mean and standard deviation are recorded as 0.1750 and 0.9725. The mean, the standard deviation, minimum and maximum of the variable X5 are 0.7667, 0.9224, 0.0010 and 5.7029. The skewness of the X1, X2, X3, X4 and X5 explanatory variables are 0.49, -0.77, -0.25, 5.77 and 3.07 consequently. As it has been explained earlier positive skewness values tell that the distribution is overhung.

X4 and X5 variables have heavier tails. X1, X2 and X3 have tapered distribution since their values are lower than 3.

Table 4.2: Descriptive statistics of the sample of distressed listed companies

Variable	**Mean**	**SD**	**Minimum**	**Maximum**	**Skewness**	**Kurtosis**
X1	0.0236	0.2212	-0.8648	0.7217	0.76	1.67
X2	0.1376	0.3378	-1.3064	0.8855	-1.03	2.19
X3	0.0429	0.0949	-0.4512	0.7399	0.86	2.69
X4	3.7885	3.8324	0.0297	5.1291	4.94	2.09
X5	0.5695	0.5084	0.0008	3.9587	2.57	1.70
Z Score	3.2054	2.4747	-2.5051	4.4654	4.62	2.45

Zones of discrimination:

Z >2.99- Safe Zone, 2.99>Z>1.8- Grey Zone, Z <1.8- Distress Zone

According to the results of Table 4.2 average of the dependent variable (Z) is 3.2054 and the standard deviation is 2.4747 from 305 data obtained from 61 distressed listed firms in the period of 2013/2014 to 2017/2018. The mean and standard deviation of the X1 variable are 0.0236 and 0.2212 respectively and the values of X1 spreads from a minimum of -0.8648 to a maximum of 0.7217 expected value of the variable X2 is 0.1376 and the standard deviation is 0.3378 Minimum and maximum of X2 variable have given in the descriptive analysis as -1.3064 and maximum of 0.8855. The independent variable X3 has a mean of 0.0429 and a standard deviation of 0.0949 also the minimum and maximum values are recorded as -0.4512 and 0.7399. The of the variable X4 range from minimum 0.0297 to maximum 5.1291 while the mean and standard deviation are recorded as 3.7885 and 3.8324. The mean, the standard deviation, minimum and maximum of the variable X5 are 0.5695, 0.5084, 0.0008 and 3.9587. The skewness of X1, X2, X3, X4 and X5 the explanatory variables are 0.76, -1.03, 0.86, 4.94 and 2.57 consequently. As it has been explained earlier positive skewness values tell that the distribution is overhung. X4 variable has heavier tails. X1, X2, X3 and X4 have tapered distribution since their values are lower than 3.

4.2.2 Implication of Altman's model to the sample

Table 4.3: Altman Z score for non-distressed listed companies

Status	Year				
	2014	2015	2016	2017	2018
Non-Distress	50	49	44	45	43
Distress	1	1	2	1	2
Grey	10	11	15	15	16
Total	61	61	61	61	61

Table 4.4: Accuracy of the Altman model on non-distressed listed companies

Classification	Frequency	Percentage
Distress	7	2.29%
Non-Distress	231	75.74%
Grey	67	21.97%
Total	305	100%

Altman's model discriminates 75.74% of the listed companies as non-distress precisely, but 2.29% as in the distress zone and 21.97% are in the grey zone. (See Appendix II)

Table 4.5: Altman Z score for distressed listed companies

Status	Year				
	2014	2015	2016	2017	2018
Non-Distress	19	18	14	14	10
Distress	23	23	32	35	35
Grey	19	20	15	12	16
Total	61	61	61	61	61

Table 4.6: Accuracy of the Altman model on distressed listed companies

Classification	Frequency	Percentage
Distress	148	48.52%
Non- Distress	75	24.59%
Grey	82	26.89%
Total	305	100.00%

Table 4.6 shows that 48.52 percent of the distressed firms examined were correctly identified, while 24.59 % were classified as non-distressed, and 26.89 % were difficult to assess. (See Appendix III for more information.)

4.2.3 Analysis of predicting ability of Altman's model

The table below provides a summary of the coefficients of Multivariate Discriminant Analysis of Altman's model (MDA) (1968). To classify the dependent variable's sub factors and independent quantitative variables, this statistical technique MDA can be used. This research study, it has considered the dependent variable as the financial healthiness of the firm which has categories like distress or non-distress and the five financial ratios as the independent variables. One estimate model was built for each year of investigation. Estimation models 1, 2 and 3 represent bankruptcy within 1 year, 2 years and within 3 years respectively.

Table 4.7: Coefficients of Multivariate Discriminant Analysis

	Estimation Model 1	Estimation Model 2	Estimation Model 3
Constant	-1.6727	-1.4134	-1.2329
X1	2.1702	1.8673	2.0595
X2	2.9623	2.7173	2.3006
X3	0.7319	0.9496	0.8707
X4	0.0295	0.0189	0.0135
X5	1.5895	1.4515	1.3620
Accuracy Rate	72.10%	69.30%	64.80%

When the years inside the bankruptcy prediction diminish, the coefficient for X3 (EBIT/TA) drops from 0.8707 to 0.7319. During the three years of research, this financial ratio becomes a less accurate predictor of bankruptcy likelihood. In contrast, the estimated coefficient of X2 (RE/TA) and X3 (WC/TA) has risen in performance. Therefore, those predictors for the likelihood of distress when investigation years decline. The financial ratio X4 (MVE/TL) is not a good predictor of the likelihood of distress since it does not vary much over the inquiry period. In terms of overall performance, estimating model 1 excels with an accuracy rating of 72.10 percent. This helps to conclude that Altman's model can give higher prediction ability within 1 year before.

4.2.4 Regression analysis

Link Function: Logit

Table 4.8: Response information of regression analysis for the Altman Z score model

Confusion Matrix and Statistics		
Predicted	0	1
0	182	71
1	62	173

488 data out of the total observations of 610 was used as training data and obtained from the used sample of distressed and non-distressed listed companies, 182 observations are categorized as non-distressed status, 173 observations are categorized as distressed status and 133 observations are categorized wrongly.

Table 4.9: Logistic Regression table for the Altman Z score model

glm(formula = Y ~ X1 + X3 + X4 + X5, family = "binomial", data = training_data)				
	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-0.931814	0.149072	-6.251	4.08e-10
X1	3.317094	0.508874	6.519	7.10e-11
X3	6.210747	1.200214	5.175	2.28e-07
X4	0.020097	0.008582	2.342	0.0192
Null deviance: 676.51 on 487 degrees of freedom Residual deviance: 529.50 on 483 degrees of freedom AIC: 571.78 Number of Fisher Scoring iterations: 6				

The maximum likelihood estimates of the constant term and the coefficients of independent variables occupied in Altman's model are -0.931814, 3.317094, 6.210747 and 0.020097 respectively. From the step wise logistic regression it has shown that the X2 and X5 are not significant is not significant to the model. The estimated logit function is given by the equation,

$$\log\left(\frac{p}{1-p}\right) = -0.931814 + \ 3.317094X_1 + 6.210747X_3 + \ 0.020097X_4$$

Three additional columns are present in the table contains the estimates of the standard errors of the estimated coefficients, the next column shows the ratios of estimated coefficients to their estimated standard errors and the last column displays the p-values. From the p-values it can be seen that the coefficients of the variables X_2 and X_5 are not significant. Coefficients reflect that the probability of an outcome changes when the independent variables change. The forecasted coefficient for an independent variable shows the change in the link function for each unit change in the independent variable with the assumption that other variables are remaining constant. All independent variables have positive coefficients exceptX_5. It means that it makes the non-distress are more likely as those variables are increased. Larger coefficients values highlight the important of the independent variables comparatively than the smaller coefficients values.

Another major statistic ratio is the odds ratio. It compares the odds of two events. The odds of an event are the possibilities that the event occurs divided by the possibilities that the event doesn't occur. If it is greater than 1 highlight that the first event and the events closer to the first event are more likely. Odds ratios that are less than 1 indicate that the last event and the events that are closer to it are more likely.

In the above analysis, the odds ratio for variables except X2 is greater than 1. The first event of this study is the Non-Distress status of a company. Its odds ratio implies that when all predictors increase, a company is more likely to go for a non-distress situation.

Confidence Intervals for the odds ratio (95% CI) means the ranges of values that are likely to contain the true values of the odds ratio. The confidence interval is accurate if the sample size is large and the distribution of the odds ratio has a normal distribution. Under the 95% confidence level, it can be concluded that the confidence interval includes all values of the odds ratio for the population.

Log-Likelihood = -51.141

Log-likelihood can be used to compare two models that use the same data to estimate the coefficients. Since this value is negative and closer to 0, the model fits the data in a better way.

Table 4.10: Confusion Matrix and Statistics of The logistic regression model

```
Confusion Matrix and Statistics

          Actual
Pedicted   0  1
         0 45 19
         1 16 42
```

Table 4.10 shows the Confusion matrix for the testing data set. 122 observations used as testing data (20%) of the data. 45 non-distress companies and 42 distress companies have been correctly categorized according to the confusion matrix.

Table 4.11: Measures of Association

```
               Accuracy : 0.7295
                 95% CI : (0.6416, 0.8059)
    No Information Rate : 0.5
    P-Value [Acc > NIR] : 2.02e-07

                  Kappa : 0.459

 Mcnemar's Test P-Value : 0.1637

            Sensitivity : 0.8033
            Specificity : 0.6557
         Pos Pred Value : 0.7000
         Neg Pred Value : 0.7692
             Prevalence : 0.5000
         Detection Rate : 0.4016
   Detection Prevalence : 0.5738
      Balanced Accuracy : 0.7295

       'Positive' Class : 0
```

Sensitivity and Specificity measures the performance of a binary classification. Sensitivity 80.33% means it has identified the 80.33% of the non-distress companies have been correctly. Specificity percentage 65.57% means it has identified the distress companies 65.57% correctly. According to that measure predictability of Altman's model is higher.

4.3 Springate Model

4.3.1 Descriptive statistics

Table 4.12: Descriptive statistics of the sample of non-distressed listed companies

Variable	Mean	SD	Minimum	Maximum	Skewness	Kurtosis
X1	0.1865	0.2085	-0.3858	0.7930	0.55	4.21
X2	0.1208	0.2093	-1.9071	1.4023	-0.78	3.97
X3	2.2130	4.6870	-4.7174	30.682	3.50	3.67
X4	0.7667	0.9224	0.0010	5.7029	2.67	4.07
Score	**2.3304**	**3.3770**	**-8.7177**	**20.964**	**3.06**	**3.33**

Zones of discrimination

Z>0.862 – Non-Distress; Z<0.862 – Distress

According to the results of Table 4.12 average of the dependent variable (Z) is 2.3304 and the standard deviation 3.3770 from 305 data obtained from 61 distressed listed companies in the period of 2013/2014 to 2017/2018. The mean and standard deviation of the X1 variable are 0.1865 and 0.2085 respectively and the values of X1 spreads from a minimum of -0.3858 to a maximum of 0.7930. The expected value of the variable X2 is 0.1208 and the standard deviation is 0.2093 minimum and maximum of X2 variable have given in the descriptive analysis as -1.9071 and maximum of 1.4023. The independent variable X3 has mean 2.2130 and a standard deviation 4.6870 also the minimum and maximum values are recorded as -4.7174 and 30.682. The of the variable X4 range from minimum 0.0010 to maximum 5.7029 while the mean and standard deviation are recorded as 0.7667 and 0.9224. The skewness of the explanatory variables X1, X2, X3 and X4 are 0.55, -0.78, 3.50 and

2.67 consequently. X3 variable has heavier tails since the skewness is greater than 3. X1, X2 and X4 have tapered distribution since their values are lower than 3.

Table 4.13: Descriptive statistics of the sample of distressed listed companies

Variable	Mean	SD	Minimum	Maximum	Skewness	Kurtosis
X1	0.023	0.221	-0.8648	0.7217	0.76	3.67
X2	0.042	0.094	-0.4512	0.7399	0.86	3.69
X3	0.156	1.116	-7.4624	13.356	4.87	4.64
X4	0.569	0.508	0.0008	3.9587	2.57	5.70
Score	**0.487**	**1.015**	**-4.9755**	**9.6235**	**2.54**	**6.09**

Zones of Discrimination:

Z>0.862 – "Non-Distress"; Z<0.862 – "Distress"

According to the results of Table 4.13 average of the dependent variable (Z) is 0.487 and the standard deviation 1.015 from 305 data obtained from 61 listed distressed companies in the period of 2013/2014 to 2017/2018. The mean and standard deviation of the X1 variable are 0.023 and 0.221 respectively and the values of X1 spreads from a minimum of -0.8648 to a maximum of 0.7217 expected value of the variable X2 is 0.042 and the standard deviation is 0.094 minimum and maximum of X2 variable have given in the descriptive analysis as -0.4512 and maximum of 1.4023. The independent variable X3 has mean 0.156 and a standard deviation 1.116 also the minimum and maximum values are recorded as -7.4624 and 13.356. The of the variable X4 range from a minimum 0.0008 to a maximum 3.9587 while the mean and standard deviation are recorded as 0.569 and 0.508. The skewness of the explanatory factors X1, X2, X3 and X4 are 0.76, 0.86, 4.87 and 2.57 consequently. X3 variable has heavier tails since the skewness is greater than 3. X1, X2 and X4 have tapered distribution since their values are lower than 3.

4.3.2 Implication of Springate (1978) Score for the samples

Table 4.14: Springate model for non-distressed listed companies

Status	**Year**				
	2014	**2015**	**2016**	**2017**	**2018**

Non-Distress	39	46	46	38	41
Distress	22	15	15	23	20
Total	61	61	61	61	61

Table 4.14 shows the results of applying the Springate Model to the sample of Non-Distressed Companies. (See Appendix IV)

Table 4.15: Accuracy of Springate model on the non-distressed listed companies

Classification	**Frequency**	**Percentage**
Non-Distress	210	68.85%
Distress	95	31.15%
Total	305	100%

According to table 17, the model accurately classified 68.85 percent of the observed non-distressed listed companies, whereas 31.15 percent were labelled as distressed.

Table 4.16: Springate model for distressed listed companies

Status	**Year**				
	2014	**2015**	**2016**	**2017**	**2018**
Non-Distress	16	10	9	15	15
Distress	45	51	52	46	46
Total	61	61	61	61	61

Table 4.17: Accuracy of Springate model for the distressed listed companies

Classification	**Frequency**	**Percentage**
Non-Distress	65	21.31%
Distress	240	78.69%
Total	305	100%

It can be noted that from the total observations of 305 from 61 distressed listed companies of CSE, 78.89% are accurately classified as distressed companies while 21.31% are categorized as non-distressed companies. (See Appendix V)

4.3.3 Analysis of predicting ability of Springate's model

Table 4.18: Coefficients of Multivariate Discriminant Analysis

	Estimation Model 1	Estimation Model 2	Estimation Model 3
Constant	-1.05610	-1.21605	-1.25870
X1	1.72765	2.36845	2.92355
X2	0.13150	0.09680	0.70730
X3	0.16580	0.18925	0.18290
X4	1.55475	1.59430	1.56825
Accuracy Rates	82.8%	84.8%	84.7%

The coefficient for X1 (WC/TA) decreases from 2.92355 to 1.72765, X2 decreases from 0.7073 to 0.1315, X3 decreases from 0.1829 to 0.1658 and X4 decreases from 1.56825 to 1.55475 when the years within the prediction of the bankruptcy decline. This implies that during the one-year examination, this financial ratio becomes a less accurate predictor of bankruptcy probability. As a result, as the number of investigation years increases, so do the predictors of discomfort. Coming to the overall performance, with an accuracy rating of 84.7 percent, estimating model 3 outperforms all others. It means that Springate's S Score model can give higher prediction ability within 3 years before.

4.3.4 Regression analysis

Since there are two possible outcomes of this model, Binary Logistic Model can be run to test the fitness of this model.

Table 4.19: Response information of regression analysis on Springate model

Variable	Value	Count
Status	1	336
	0	274
	Total	**610**

Out of the total observations of 610 from the distressed and non-distressed listed companies,336 observations are categorized as distressed and 274 observations are categorized as non-distressed**.**

Table 4.20: Coefficients of regression analysis

Term	**Coef**	**SE Coef**	**VIF**
Constant	4.30	7.31	
X1	4.66	8.37	2.50
X2	1.61	2.74	8.48
X3	3.51	5.71	3.89
X4	1.49	3.50	6.18

$$Y = 4.30 + 4.66X_1 + 1.61X_2 + 3.51X_3 + 1.49X_4 \qquad (22)$$

The coefficients of binomial regression analysis, the size and the direction of the relationship among the predictor and the response variable. It can be used to determine whether a change in a predictor variable makes the event more likely or less likely. The positive coefficients of the Springate Model indicate that the event (non -distress) becomes more likely.

The Standard error measures the precision of the estimate. VIF measures the multicollinearity among the selected variables. It means that variables are highly correlated or not. As a rule, the VIF value should be less than 10. In this study, all VIF values are less than 10. It reflects that the estimation is more precise.

Table 4.21: Model summary

Deviance R-Sq	**Deviance R-Sq(adj)**	**AIC**
99.15%	98.67%	1.16

Deviance R^2 can be considered as the proportion of the deviance in the response variable that the selected model explains. Normally higher R2 represents the fitness of the data to the model. The Deviance R2 for this model is 99.15%. Therefore, the Collected from the Sri Lankan companies are suitable for this model. This measure can be used to compare the suitability of some other selected models.

Adjusted deviance R2 is the proportion of deviance in the response that is explained by the model which is adjusted for the number of predictors in the model relative to the number of observations. It will be increased when the number of predictors ae increased.

Akaike Information Criterion (AIC) is a measure that shows a measure of the relative quality of a model that included the fit and the number of the terms in the model. The Smaller AIC represents that the better model to fit the data. To confirm that conclusion the Goodness of Fit Test can be used.

4.4 Grover Model

4.4.1 Descriptive Statistics

Table 4.22: Descriptive statistics of the sample of non-distressed listed companies

Variable	Mean	SD	Minimum	Maximum	Skewness	Kurtosis
x1	0.1865	0.2085	-0.3858	0.7930	0.55	0.21
x2	0.1208	0.2093	-1.9071	1.4023	-0.78	2.97
x3	0.1291	0.3123	-1.8976	2.9377	3.99	1.28
Score	0.7737	0.8202	-6.6608	5.5501	-0.79	2.22

According to the results of Table 4.22 average of the dependent variable (Z) is 0.7737 and the standard deviation 0.8202 from 305 data obtained from 61 listed distressed companies from 2013/2014 to 2017/2018. The mean and standard deviation of the X1 variable are 0.1865 and 0.2085 respectively and the values of X1 spreads from a minimum of -0.3858 to a maximum of 0.7930. The expected value of the variable X2 is 0.1208 and the standard deviation is 0.2093 minimum and maximum of X2 variable have given in the descriptive analysis as -1.9071 and maximum of 1.4023. The independent variable X3 has mean 0.1291 and a standard deviation 0.3123 also the minimum and maximum values are recorded as -1.8976 and 2.9377. The skewness of the independent variables X1, X2 and X3 are 0.55, -0.78 and 3.99 consequently. X3 variable has heavier tails since the skewness is greater than 3. X1 and X2 have tapered distribution since their values are lower than 3.

Table 4.23: Descriptive statistics of the sample of distressed listed companies

Variable	Mean	SD	Minimum	Maximum	Skewness	Kurtosis
X1	0.0236	0.2212	-0.8648	0.7217	0.76	1.67
X2	0.0429	0.09490	-0.4512	0.7399	0.86	1.69
X3	0.0038	0.1987	-3.0708	0.7220	-1.19	1.18
Score	0.2422	0.4810	-1.9130	2.3981	0.60	2.34

According to the results of Table 4.23 average of the dependent variable (Z) is 0.2422 and the standard deviation 0.4810 from 305 data obtained from 61 listed distressed firms from 2013/2014 to 2017/2018. The Mean and the standard deviation of the X1 variable are 0.0236 and 0.2212 respectively and the values of X1 spreads from a minimum of -0.8648 to a maximum of 0.7217. The expected value of the variable X2 is 0.0429 and the standard deviation is 0.0949 minimum and maximum of X2 variable have given in the descriptive analysis as -0.4512 and maximum of 0.7399. The independent variable X3 has mean 0.0038 and the standard deviation 0.1987 also the minimum and maximum values are recorded as 3.0708 and 0.7220. The skewness of the explanatory factors X1, X2 and X3 are 0.76, 0.86 and -1.19 consequently. All X1, X2 and X3 have tapered distribution since their values are lower than 3.

4.4.2 Implication of Grover model for the sample

Table 4.24: Grover model for non-distressed listed companies

Status	Year				
	2014	2015	2016	2017	2018
Non-Distress	60	57	60	58	58
Distress	1	2	1	2	1
Grey	0	2	0	1	2
Total	61	61	61	61	61

Table 4.25: Accuracy of Grover model for non-distressed listed companies

Classification	Frequency	Percentage
Non-Distress	293	96.06%
Distress	7	2.29%
Grey	5	1.65%
Total	305	100%

Grover Model accurately classify 293 observations out of 305 observations from non-distressed companies with a percentage of 96.06%. 7 observations are categorized as distress and 5 observations as grey. Therefore, the Grover model has an accuracy rate of 96.06% for the non-distress sample of listed companies. (See Appendix VI)

Table 4.26: Grover model for distressed listed companies

Status	Years				
	2014	2015	2016	2017	2018
Non-Distress	51	45	44	40	37
Distress	10	15	15	20	22
Grey	0	1	2	1	2
Total	61	61	61	61	61

Table 4.27: Classification accuracy of Grover model on distressed listed companies

Classification	Frequency	Percentage
Non-Distress	217	71.15%
Distress	82	26.88%
Grey	6	1.97%
Total	305	100%

From the total observations of 305 from 61 Distressed listed companies, only 82 companies are correctly categorized as Distressed companies with a 26.88%. 217 companies are categorized as Non-Distressed with 71.15% even though they are in the distress sample. 6 companies are categorized as Grey area with a 1.97%. (See Appendix VII)

4.4.3 Analysis of Predicting ability of Grover model

Table 4.28: Coefficients of Multivariate Discriminant Analysis

	Within 1 Year	**Within 2 Years**	**within 3 Years**
Constant	-0.3435	-0.3130	-0.3486
X1	0.8506	0.8241	0.8638
X2	2.0967	1.4816	1.7299
X3	1.1313	0.0011	0.0189
Accuracy Rate	72.1%	70.87%	70.50%

When the years inside the bankruptcy prediction decrease, the coefficients for all factors increase. This suggests that after a year of research, these financial measures become a less accurate predictor of bankruptcy risk. When it comes to total performance estimation, model 1 performs the best. The rate of accuracy is 72.1 percent. It may be claimed that the Grover Model draws fewer exact differences between bankrupt and non-bankrupt firms, and hence the categorization rate in inquiry years 2 and 3 is nearly identical.

4.4.4 Regression Analysis

Link Function: Logit

Table 4.29: Response information on Grover model

Variable	**Value**	**Count**
Status	0	511
	1	89
	2	10
	Total	610

Out of the total observations of 610 obtained from both sample distressed and non-distressed listed companies, 511 observations are categorized as non-distressed status,89 observations are categorized as distressed status and 10 observations are categorized as firms that are in the grey area.

Table 4.30: Logistic Regression Table

						95% CI	
Predictor	**Coef**	**SE Coef**	**Z**	**P**	**Odds Ratio**	**Lower**	**Upper**
Const(1)	1.17572	0.170516	6.90	0.000			
Const(2)	5.12910	0.484918	10.58	0.000			
x1	10.7864	1.158570	9.31	0.000	3.59	2.48	5.86
x2	14.7873	2.554780	5.79	0.000	7.09	6.77	9.55
x3	**0.15198**	**1.192880**	**1.13**	**0.049**	**1.16**	**0.11**	**12.06**

$logit(P) = 1.18 + 10.78X_1 + 14.78X_2 + 0.15X_3$

$logit(P) = 5..13 + 10.78X_1 + 14.78X_2 + 0.15X_3$

The coefficients for all predictor variables are positive values. It reflects the first event (Non-Distress) and the events that are closer to the first event are more likely when the independent variables of the Grover Model are increased.

As a measure of the precision of the estimations of the coefficients, they are smaller values 1.158570, 2.554780 and 1.192880. They indicate that the estimate of coefficients for the Grover model is precise. The Z values are sufficiently distant from zero, indicating that the coefficient estimate is both big and exact. The Grover model's p values are smaller than the significance level, indicating that there is a statistically significant link between the dependent and independent variables. Because the odds ratios are larger than one, the first event and occurrences around it become more likely as the predictor rises. All of the odds ratios are within the 95 percent confidence range. Then we may infer that there is a 95% chance that the confidence interval contains the population's odds ratio value. This research study's practical importance grows as a result.

Log-Likelihood = -69.505

The value of log-likelihood is negative and a little bit closer to 0. Therefore, the Grover model fits the data in a better way.

Table 4.31: Test of all slopes to zero

DF	**G**	**P-Value**

3	266.812	0.000

The number of predictors in the Grover model equals the degree of freedom. Because the p-value is smaller than the significance level, it may be concluded that the dependent and independent variables have a statistically significant connection.

Table 4.32: Measures of Association

Pairs	**Number**	**Percent**	**Summary Measures**	**Value**
Concordant	50323	97.8	Somers' D	0.96
Discordant	1094	2.1	Goodman-Kruskal Gamma	0.96
Ties	62	0.1	Kendall's Tau-a	0.27

Somers' D and Goodman-Kruskal Gamma can be between -1 and 1. The results show a value of 0.96. It is closer to 1. It indicates that the Grover Model has a higher predictive ability. The value of Kendall's tau-a is 0.57. it is closer to 0.6667. It is also an indicator to highlight that the Grover Model has a good predictive ability.

4.5 Summary

The following results were given by the findings and analysis from this research study. According to the results it can be shown that the Altman's, Springate and Grover models can be used to forecast financial distress in the future. Nonetheless, it can be said that the Springate model has a stronger significance for both distress and non-distress samples than the other models. For that reason, It can be articulated the Springate model has a higher tendency and it is the most ideal model used for financial distress forecasting is Springate Model. This beckon that the most advisable set of variables are in Springate model to predict financial healthiness.

Table 4.33: Summary of accuracy rates of the models

Accuracy Rates						
	Altman's Model		**Springate Model**		**Grover Model**	
Status	**Non - distress sample**	**Distress sample**	**Non - distress sample**	**Distress sample**	**Non - distress sample**	**Distress sample**
Non-Distress	75.54%	24.59%	68.85%	21.31%	96.06%	71.15%

Distress	2.29%	48.52%	31.15%	78.69%	2.29%	26.88%
Grey Area	21.97%	26.89%	-	-	1.65%	1.97%

Altman's model can be ordered in the second place after the Springate model based on the accuracy of the classification into distress and non-distress classes. It has perfectly classified the non-distress sample by 75.54% accuracy but in the distress sample by 48.52%. When comparing with the other two models the Grover Model achieves the third position based on predicting accuracy.

Table 4.34: Summary of predictive power

Predictability Power			
	Within 1 Year	**Within 2 Years**	**Within 3 Years**
Altman's Model	72.10%	69.30%	64.80%
Springate Model	82.80%	84.80%	84.70%
Grover Model	72.10%	70.87%	70.50%

When comparing the predictability power of considered models, Altman's model has the ability to forecast the financial distress 1 year before with an accuracy rate of 72.10%. But Springate model can predict financial distress within 3 years before. with an accuracy rate of 84.70%. Grover model can predict distress within 1 year before with an accuracy rate of 72.10%. This summary also highlights that within the Sri Lankan context, the Springate model takes a higher place than Altman's model and Grover model.

CHAPTER 5 - CONCLUSION AND RECOMMENDATION

5.1 Introduction

The chapter summarizes the important findings, draws judgments, and makes suggestions for future research investigations.

5.2 Summary of Findings and Discussions

The goal of this research study was to identify the applicability of Altman's model, the Springate model and Grover model in prognosticating financial distress of listed firms in the Colombo Stock Exchange. Quantitative secondary data was collected from the audited financial statements within the period of 2013/2014-2017/2018. The model was applied to the selected paired sample of 61 distress and 61 non-distressed samples obtained from the CSE. Those data were analyzed using Minitab19 software.

The study findings highlight that Altman's Z Score model correctly classified 75.54% of the non-distressed Listed Companies, 2.29% were categorized in the distress Zone while 21.97% were classified in the Grey Zone. Similarly, for distressed Listed companies, Altman's model correctly classified 48.52% of them, 24.59% were classified in the safe area and 26.89% were classified in the grey area. X3 (EBIT/TA) becomes a less good predictor for estimating bankruptcy probability during the three years of investigation. X2 (RE/TA) and X3 (WC/TA) the estimated coefficient is increased. Therefore, those predictors for the likelihood of distress when investigation years decline. The financial ratio X5 (MVE/TL) is not a good predictor for the probability of distress because it does not show considerable changes within the investigation period. Altman's model can give a higher prediction ability within 1 year before.

The Springate model correctly classified 68.85% of the non-distressed Listed Companies, 31.15% were categorized as distressed. As well as 78.69% were correctly categorized as distressed from the distressed sample and 21.31% were classified as non-distressed. X1 (WC/TA), X2(EBIT/TA), X3(NBT/CL) and X4(Sales/ TA) become good predictors for estimating bankruptcy probability when the prediction years are increased. The Springate model can give a higher prediction ability within 3 years before.

The Grover model correctly classified 96.06% as non-distress from the non-distressed sample, 2.29% as distressed while 1.65% as grey area. From the distressed sample 26.88% correctly classified as distress, 71.15% as non-distress, and 1.97% as in the grey area. When the years inside the bankruptcy prediction decrease, the coefficients for all factors increase. This shows that these financial measures become a less accurate predictor of bankruptcy risk after a year. It can provide better forecasting abilities within one year of forecasting.

5.3 Conclusion

This chapter examines the performance of three accounting-based bankruptcy prediction models, notably Altman's (1968), Springate Model, and Grover Model, on Sri Lankan companies. The major summary shows vividly that the Springate model performed most accurately between 2013 and 2018: that is, the selected financial ratios of the Springate model are most accurate in forecasting bankruptcy.

The accounting-based bankruptcy prediction models function as expected in the common literature in a rather different manner concerning their accuracy. Grice (2001) explains that Altman’s model accuracy rate decreases during the period of the time of the investigation, as shown in the literature. It can be endorsed by the results of this research, Hayes et al. identified that Altman’s model is trustworthy in small scale firms as illustrated in the literature. As a result, Grice (2001) and Agarwal (2008) argue that the problem can be overcome by re-estimating the model’s coefficients using a sample of firms that is close to the proportion of distressed and non-distressed companies in the population. Altman’s Z score and Springate models both have a similar predictive capability, according to Chandana Gunathilake (2014), however Altman’s Z Score model has a stronger power to discriminate to recognize distressed companies at least a year in advance. However, the results of this study revealed a difference in accuracy between the Altman model and the Springate model. Furthermore, the Apringate model has a higher discriminant power in recognizing distressed firms three years earlier. Samarakoon and Hassan (2003) concluded that Altman’s model has a greater level of correctness in predicting bankruptcy relying on information from the previous year. This study adds more evidence for it. According to the findings of Grice and Ingram (2001), the conclusions of recent studies that used Altman’s model to evaluate the financial distress of sample firms should be viewed with caution. It is able to ascertain the model’s capacity to appropriately designate firms as financially distressed is likely to vary. The Altman’s Z score model and a the Springate score model showed similar results in determining a business failure, according to the conclusions of Turk and Kurklu (2017). Yet, the precision of Altman’s model differs from that of the Springate model in the Sri Lankan context. The Springate model works better than the Altman model for both distressed and non-distresses samples. The Springate model outperforms Altman’s model for both distresses and non-distressed samples. The Grover model’s capacity to predict financial distress is more strong than the Zmijewski and Springate models, according to the findings acquired from Pakdaman (2018). Although the companies mentioned in Sri Lanka demonstrate that the model Springate is superior to the Grover model. It could be because of the disparity in Sri Lankan financial ratios.

5.4 Implications

In this research study, the accuracy rates of three bankruptcy prediction models are evaluated within the Sri Lankan context. Those can be used to measure the financial soundness of a rational investor. As well as potential stock return and investment strategies can be designed through these findings.

As well as Current stakeholders can take their decisions by looking at the future distress probabilities. It will affect the decisions of whether to buy further shares of that company or sell the current portion before going bankrupt. Then the government can take policy decisions if there is a symptom of distress of a relevant company to prevent bankruptcy.

5.5 Limitations

This study examined three accounting-based financial distress prediction models that are often utilized in the literature. Because they are all derived from distinct factors, they depict precision at varying degrees and phases, despite the fact that none of the chosen models can identify bankruptcy with 100 percent accuracy. Based on the literature, one may infer that neither model is a perfect model, since they all have advantages and limitations. When compared to other bankruptcy prediction models, market-based bankruptcy prediction models perform better since they take into account macroeconomic indicators.

All the data are based on historical information and they are affected by future trends. Those trends are not considered in accounting-based prediction models. Therefore, they are limited from the scope. But a company's performance is largely affected by macroeconomic variables. Since they are crucial in determining financial distress.

Another common limitation of accounting-based financial distress prediction is that most of the accounting information can be manipulated through the depreciation method, going concern principle etc. They should be considered in measuring bankruptcy. Data of this study was obtained from a small database and therefore this study is comprised of a limitation of some data availability. Data availability from a large sample will assist in concluding a clear picture of bankruptcy prediction models.

The impact on the reporting season from 2019/ 2020 could be significant due to the global outbreak of the COVID 19 pandemic. This widespread effect severely on financial markets and add significant uncertainties in investor communication. Therefore data has been collected up to 2019.

The results of Logistic regression analysis is more accurate than Multivariate Discriminant Analysis in this research since some independent variables do not satisfy Normality assumptions in the prediction as expected.

5.6 Outlook for Future Research

The performance of three prediction models was examined in this study to determine the possibility of distress for shareholders and other stakeholders such as potential investors. However, this research included some gaps for future researches. Firstly, as the discussions of the literature review, market-based bankruptcy prediction models are well-performing over accounting-based bankruptcy prediction models. But this is not considered in this study. Since it can be concluded as a suggestion that a future study can be conducted by comparing accounting-based distress prediction models with market-based distress prediction models. This will create value to the existing literature. As well as a further suggestion can be given to evaluate the study into different economic periods to identify how the models perform in various time intervals and different environments. The study of cash flow factors as a forewarning of potential financial troubles might then be a significant contribution to this research. Because if a firm has any difficulty in cash flow availability, its probability of going for a distress situation is higher. This can be beneficial in the study of financial ratio evaluation. Since future research can be undertaken with an analysis of cash flow variables to identify bankruptcy likelihood with logit, probit, and hazard models.

As well as the researches regarding financial distress should be done on the categories of state corporations such as public universities, training and research corporations, etc. since most studies have been done regarding public listed companies and private companies. Further, although the Discriminant Analysis has been used as the primary method, the new methods have tended to logit analysis, Machine Learning, Deep Learning and Neural Networks. In this research such kind of methods have not used except logit method. Therefore, future researches can compose Machine Learning Algorithms can be employed in financial distress prediction models to obtain better models using available data and make better trade decisions. With the rapid development of modern information technology, machine learning and deep learning are being used in various fields including the financial sector. The evolvement of information technology these techniques can be used in bankruptcy models including the classical machine learning models such as Multivariate Discriminant Analysis (MDA), Logistic Regression, and Neural Network.

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APPENDICES

Appendix I: Review of Literature

Serial Number	Published Year	Author	Topic	Findings	Remarks
1	1968	Edward I Altman	Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy.	Multiple Discriminant Analysis is introduced with Altman's Z score model for addressing the shortcomings of traditional ratio analysis. Its statistical	Only public listed companies are used to elaborate the model, Altman's Z core model. Used an initial sample of sixty-six firms to establish the function. Another secondary sample is used to examine the
2	1972	Edward B. Deakin	A Discriminant Analysis of Predictors of Business Failure	Discriminant analysis can be used to predict business failure from accounting data as far as three years in advance	The model was derived from a small population and results are on a cross-validation sample. He was accurately classified 78% of his sample of firms five
3	1972	Edward I. Altman	Predicting Financial Distress of Companies: Revisiting the Z-Score and ZETA® Models	The ZETA model for assessing bankruptcy risk of corporations demonstrates improved accuracy over the existing failure classification model (Z-Score) and, perhaps more importantly, is based on data more	Z Score models and Zeta models are considered. Two samples of firms consist of 53 bankrupt firms and a matched sample of 58 non-bankrupt entities
4	1973	Fischer Black, Myron scholes	The Pricing Options and Corporate Liabilities	These tests indicate that the actual prices at which options are bought and sold deviate in certain systematic ways from the values predicted by the	Black Scholes model can predict the financial distress using market information
5	1974	Robert C Merton	On the Pricing of Corporate Debt: The Risk Structure of Interest Rates	It is developed a method for pricing corporate liabilities which is grounded in solid economic analysis, requires inputs which are on the whole observable; can be used to price almost any type of financial instrument. The method was applied to risky discount	The model forecast bankruptcy by features of financial instruments

6	1977	Edward I. ALTMAN Robert G. HALDEMAN P. NARAYANAN	ZETA TM* ANALYSIS A new model to identify bankruptcy risk of corporations	ZETA is effective in classifying bankrupt companies up to five years before failure on a sample of corporations consisting of manufacturers and retailers. New ZETA model for bankruptcy classification appears to be quite accurate for up to five years before failure with the successful	Two samples of firms consist of 53 bankrupt firms and a matched sample of 58 non-bankrupt entities. Bankruptcy classification is attempted via the use of a multivariate statistical technique known as discriminant analysis. The ZETA model for assessing the bankruptcy risk of corporations developed in this paper demonstrates significantly improved accuracy
7	1980	James A Ohlson	Financial Ratios and the Probabilistic Prediction of Bankruptcy	The predictive power of any model depends upon when the information (financial report) is assumed to be available. The predictive powers of linear transforms of a vector of ratios seem to be robust across (large sample) estimation	The methodology is based on likelihood estimation (Conditional Logit Model). It avoids the problems of MDA.
8	1984	Mark E Zmijewski	Methodological Issues Related to the Estimation of Financial Distress Prediction Models	The two issues examined in this paper arise because of sample selection/data collection constraints typically faced by financial distress researchers. The first constraint is the extremely low-frequency rate of firms exhibiting financial distress	Population: all firms listed on the American and New York Stock Exchanges during the period 1972 through 1978 which have industry (SIC) codes of less than 6000.5. The bivariate probit model consists of two probit equations, the financial distress equation and the complete data equation.
9	1988	Christine V. Zavgren and George E. Friedman	Are Bankruptcy Prediction Models Worthwhile? An Application in Securities Analysis	The selected bankruptcy model can be fairly easily used to predict a firm's likelihood of failure and to pinpoint specific financial or operating areas that	Logistic regression analysis was selected to develop the model
10	1996	Stephen H. Penman	The Articulation of Price-Earnings Ratios and Market-to-Book Ratios and the Evaluation of Growth	The PIE ratio indicates future growth in earnings which is positively related to expected future return on equity and negatively related to the current return on equity. The P/B ratio reflects only	The articulation of PIE and PIB follows from the dividend discount formula and the clean-surplus accounting relation. GAAP provides descriptions of the PIE and P/B ratios and their

11	2001	John Stephen Grice, Robert W. Ingram	Test of the Generalizability of Altman's Bankruptcy Prediction Model	The accuracy of Altman's model is declined when it is applied to another sample. Its coefficients were changed dramatically with changing over time. The overall accuracy of the Altman's model was higher when	There is an underestimation of type 1 error and overestimation of type 2 error in applying the Altman's model. It can be addressed by changing the coefficients of the model with a sample of distressed and non-distressed firms.
12	2001	John Stephen Grice, Robert W. Ingram	Tests of the generalizability of Altman's bankruptcy prediction model	Altman's model was sensitive to industry classifications in the sample used in this study. The overall accuracy of the model was significantly higher for manufacturing firms (69.1%) than for the entire sample (57.8%) that included non-manufacturing firms.	(1) Is Altman's original model useful for predicting bankruptcy in recent periods as it was for the periods in which it was developed and tested by Altman? (2) Is the model useful for predicting bankruptcy of non-manufacturing firms as it is for predicting bankruptcy of manufacturing firms? (3) Is the model useful for predicting
13	2003	Lalith P. Samarakoon Tanweer Hasan	Altman's Z core Models of Predicting Corporate Distress: Evidence from the	The Altman; s models have a higher level of accuracy in forecasting bankruptcy from the information in the year before the	Three versions of Altman's model are considered. Sample: Firms listed between 1986 and 1997 in the Colombo stock exchange
14	2005	Julio Pindado, Luis Rodrigues	Determination of Financial distress Cost	Distress costs are negatively related to liquid assets; hence, their benefits more than offset their opportunity costs.	Direct financial distress costs, which are the administrative and legal costs associated with the bankruptcy process.
15	2003	Thomas E. Mackie	Rough Sets Bankruptcy Prediction Models versus Auditor Signaling Rates	Rough sets theory does provide a useful way to determine a bankruptcy prediction decision model. Model accuracy might increase if additional non-financial variables were included in the analysis.	The samples used in this research were matched for asset size and industry. The model accuracy rate in this study was significantly lower than several previous studies employing both rough sets theory and other methodologies.

16	2005	Yu-Chiang Hu, Jake Ansel	Developing Financial Distress Prediction Models A Study of US, Europe and Japan Retail Performance	SMO is the better performing model amongst the three models, closely followed by the neural network model. Logistic regression model shows the lowest performance in terms of similarity with	Naïve Bayes, Logistic Regression, Recursive Partitioning, Artificial Neural Network, and Sequential Minimal Optimization (SMO)
17	2006	Jie Sun, Hui Li	Data mining method for listed companies' financial distress prediction	The empirical experiment involving 35 financial ratios and 135 pairs of listed companies got a satisfactory result, which means the application of the proposed data mining method to listed companies' financial	Existing financial distress prediction methods have problems such as lacking dynamic learning ability and difficulty to understand
18	2006	Yang Hwae Huo	Bankruptcy Situation Model in Small Business: The Case of Restaurant Firms	It was found that Altman's model for the non-manufacturing industry provided the most accurate bankruptcy prediction	Among financial data, working capital, retained earnings, and EBIT are the most critical factors that contribute to bankruptcy.
19	2007	Vineet Agarwal, Richard Taffler	Comparing the Performance of Market-based accounting Bankruptcy Prediction Models	Two approaches are found which are capture different aspects of bankruptcy risk, and while there is little difference in their predictive ability in the UK, the z-score approach leads to significantly greater bank profitability in conditions of differential decision error costs	This paper compares the performance of two alternative formulations of market-based models for the prediction of corporate bankruptcy with a well-established UK-based score model. there is little difference between the market-based and accounting models
20	2009	Tzong-Huei Lin	A cross model study of corporate financial distress prediction in Taiwan: Multiple discriminant analysis, logit, probit, and	predictive accuracy of the three most commonly used financial distress prediction models is lower with Taiwan data	Multiple discriminate analysis, logit, probit, and artificial neural networks methodology were employed to a dataset of matched samples of failed and non-failed Taiwan public industrial firms from 1998–2005.

21	2009	Nikolaos Gerantonis, Konstantinos Vergos, Apostolos G. Christopoulos	"Can Altman Z-score Models Predict Business Failures in Greece?"	A high percentage of failure makes the investigation and prediction of company failures a useful tool for both financial managers and analysts, since the ability to predict these failures is valuable. model is useful in identifying financially troubled companies that may fail up to 2 years	Examines all listed in the Athens Exchange companies. It is investigated whether Z-score models can predict bankruptcies for a period up to three years earlier.
22	2009	Nimalathasan Balasundaram	An Investigation of Financial Soundness of Listed Manufacturing Companies in Sri Lanka: An application of	The soundness of the selected manufacturing companies are revealed by the Altman model. To save them from the bankruptcy position, the financial position should be re-engineered.	Selected samples from listed manufacturing companies for over 5 years. Their soundness is tested by the Altman's Z core model
23	2009	Erol Muzir, Nazan Caglar	The Accuracy of Financial Distress Prediction Models in Turkey: A comparative Investigation with Simple Model Proposal.	Findings show that none of the existing prediction models could achieve a satisfactory level of prediction performance. The best model among the existing financial distress prediction models is Ohlson's O-Score Model. New	Dependent Variable: Company's Financial Situation Independent Variable: Financial Ratios. Statistical Analysis: Linear Discriminant, Logit, Multiple Discriminant Analysis, Probit techniques. Population: Publicly held corporations on the Istanbul Stock
24	2010	William H Beaver	Financial Ratios as Predictors of Failure	several different ratios and/or rates of change in ratios over time, would predict even better than the single ratios	Used Univariate Analysis, Multivariate Analysis used. The best predictor of failure can't be found rather than predictive ability was studies.
25	2011	William H. Beaver, Maria Correia, and Maureen F. McNichols	Financial Statement Analysis and the Prediction of Financial Distress	Market-value based variables also have significant explanatory power. The accounting characteristics, raising the possibility that the characteristics are proxies for unspecified underlying economic differences	The presence of restatements, discretionary accruals, research and development intensity, and disparities between the market value and accounting book value can cause a reduction in predictive power.

26	2011	Peyman Imanzadeh, Mehdi Maran-Jouri, Petro Sepehri	A Study of the Application of Springate and Zmijewski Bankruptcy Prediction Models in Firms Accepted in Tehran Stock Exchange	The Z-score of the Springate model is significantly higher than the Z-score of the Zmijewski model. Thus, we can conclude that Springate's Z-score is more conservative than Zmijewski's Z-score. The result of this hypothesis is that the Springate model is more efficient than the Zmijewski model in	Dependent Variable: There is one dependent variable in the present research with two conditions: firms' financial conditions which are either bankrupt or successful. Independent Variable: The independent variables in the present research involves financial ratios. Since two models are used, first the Springate
27	2012	Mihail Diakomihalis	The accuracy of Altman's models in predicting hotel bankruptcy	Five- and three-star hotels show a higher bankruptcy risk than 4-star hotels, while the smaller risk is depicted in 2-star hotels. The general conclusion that can be drawn from the results is that the Altman model can be applied with considerable success (i.e., a high degree of reliability and accuracy) to forecasting the	The objective of this study was to evaluate Altman's three models on the private hotels in Greece, examining the possibility of forecasting bankruptcy and determining the precise percentage of enterprises for which accurate predictions could be made. The three versions of Altman's model have been applied to evaluate the bankruptcy prediction and its accuracy
28	2013	Jeroen Oude Avenhuise	Testing the Generalizability of the Bankruptcy Prediction Models of Altman, Ohlson and Zmijewski for Dutch Listed and Large Non-listed Firms	There is a difference between the predictive power of Altman's model, Ohlson model, Zmijewski model. Zmijewski model has the highest predictive ability. But is not able to discriminate against the bankrupt and non-bankrupt firms. The accuracy rate for the Altman's model is lower than the	Population: All listed and non-listed companies in Netherland. H10: There is no difference in the predictive power between the models of Altman (1968), H20: There is no difference in the predictive power between the models of Altman (1968) Dependent Variable: Bankruptcy Independent
29	2013	David O. Mbat, Eyo I. Eyo	Corporate Failure: Causes and Remedies	An effective way of averting corporate failure is to consider the relative influence of management, board of directors, employees, external auditors, regulatory bodies, government, etc. on the operating performance of a firm and see how they	Corporate failure could be caused by several factors, such as; 1) Managerial inefficiency and ineffectiveness 2) Socio-cultural factors. 3) Economic instability. 4) Public policy.
30	2013	Jiří Omelka, Michaela Beranová, Jakub Tabas	Comparison of the models of Financial Distress Prediction	Sales to asset ratio was identified ed as the most frequent ratio applied. Among statistically signify cantly indicators, the ration of return on sales was	Define a set of basic indicators that indicate a potential threat to financial distress in a business entity

31	2014	Chandana Gunathilake	Financial Distress Prediction: A comparative study of Solvency Test and Z core Models with Reference to Sri Lanka	Altman's and Springate's Z core models have similar predictive ability. Altman's Z core model has a higher discriminant power to identify distressed firms at least 1 year before.	Models Tested: Altman's Z score model and Springate Model and Solvency Test. Significance of the group differences are tested sample t-test and predictions of models are analyzed by MDA
32	2014	Edward I Altman Malgorzata Iwanicz-Drozodowska Erkki K. Laitinen	Distressed Firm and Bankruptcy Prediction in an International Context: A Review and Empirical Analysis of Altman's Z core Model	Original Z core model can be predicted successfully in the international context also. The classification accuracy of the general model can be improved with country-specific estimation when applying to different countries.	Used common Altman's z core model which can be used for both private and listed manufacturing companies and non-manufacturing companies. Logistic Regression analysis is used as the methodology of this research because the selected
33	2014	Mareike Kira Kleinert	Comparison of Accounting-based Bankruptcy Prediction Models of Altman (1968), Ohlson (1980), and Zmijewski (1984) to German and Belgian Listed Companies during 2008 -	The Zmijewski model (1984) is sensitive since the estimated coefficient of financial ratios is not stable because the sample on German listed companies has a low ratio of bankruptcy to non-bankrupt companies. The models perform less accurately than on Belgian listed companies.	Consider German and Bulgarian listed companies (2008-2013) Models: Altman's Model, Ohlson Model, Zmijewski model. Measure the accuracy rate of the distress prediction models.
34	2014	M. Fakhri Husein, Galuh Tri Pambekti	Precision of the Models of Altman, Springate, Zmijewski, and Grover for Predicting the Financial distress	The model of Zmijewski is the most appropriate model to be used for predicting financial distress because it has the highest level of significance compared to the other models. Zmijewski model is used for having more	A non-participant observation was applied for collecting the data. Models: Altman's Z score model, Springate model, Zmijewski model, Grover model
35	2014	Reza Jamshedi, Aftekhar Sadegh Khani, Zahra Noori, Fatemah Sher Gholami	A Survey of the Capability of Zavgren Bankruptcy Prediction in Determining the Bankruptcy Condition of the Companies Listed in TSE	Zavgren model for the successful companies in 100% and bankrupt companies in 60% correct answers were given. There is a significant relationship between financial ratios based on the Zavgren model and continuance of the activities of companies listed in TSE.	The hypothesis is as: There is a significant association between financial ratios based on the Zavgren model with the bankruptcy of the companies listed in TSE. Logit regression analysis is applied. The Independent variable in the study based on the Zavgren model is including the financial ratios applied in this model. The dependent quality variable is activity continuance showing the bankrupt and nonbankrupt condition

36	2014	Chenchehene, Kingsford Menash	Corporate Survival: Analysis of Financial Distress and Corporate Turnaround of the UK Retail Industry.	The model has 65% and 80% classification accuracies for failed and recovered companies respectively. The results for the descriptive statistics obtained through a bivariate analysis indicate that corporate turnaround is dependent on company size and management turnover.	A multiple discriminant model is developed. Samples for the study are 20 companies with two or more consecutive losses which have ceased to operate classified as failed companies; and 20. The companies with two consecutive losses followed by profits, also classified as recovered companies.
37	2015	Mahalakshmi	Validity of Altman's Z core Model in Determining Corporate Sickness of Indian Companies.	The Altman's model can predict distress in terms of percentage for four years before the bankruptcy. Misclassification errors also there.	Altman's model gives moderate support to predict the financial distress of the selected sample of 30 sick and 30 non-sick companies from the official website of the Board for Industrial and Financial Reconstruction. Type 1 error and type 2 error can
38	2015	Judy Ramage Lawrence, Surapol Pongsatat,	The Use Of Ohlson's O-Score For Bankruptcy Prediction In Thailand	Losses could have been avoided with a suitable early warning system that identified weaknesses and allowed the constituents to make adequate plans and	Logit Regression Analysis is used. Selected 60 failed and 60 non failed firms. The probit model of the Ohlson O score model is considered.
39	2015	Adrian Gepp, Kuldeep Kumar	Predicting Financial Distress: A Comparison of Survival Analysis and Decision Tree Techniques	survival analysis and decision tree techniques in financial distress warning systems that are useful to most entities in the financial markets.	CART decision – tree technique and the Cox survival analysis technique were used.
40	2015	Sinarti, Tia Maria Sembiring	Bankruptcy Prediction Analysis of Manufacturing Companies Listed in Indonesia Stock Exchange	The conclusions of the three models showed a significant difference to the approach of Z-Score with Zmijewski and Springate with Zmijewski, but there is no significant difference between the approach of the Z-Score with Springate.	As for the prediction model has four components Zmijewski calculations significantly affect the results of the calculation of the prediction, there is profit after tax, total assets, total debt, and current debt, it indicates any change in each of these components will affect the predicted outcome significantly

41	2015	Hanieh Shahdoust, Mohammad Reza Karimi pouya, Behzad Parvizi	A Study of Bankruptcy prediction accuracy of Altman Adjusted and Zavgren models in firms accepted in Tehran stock exchange. (based on Altman adjusted model by Kordestani and colleagues)	There is a meaningful difference between Altman's adjusted model and Zavgren's model in bankruptcy anticipation in each year except 2009. There is a meaningful difference between Altman's adjusted model and Zavgren's model in accepted companies' bankruptcy anticipation and also is the indicator of the lack of confirmation.	The dependent variable is the indicator of the companies' financial situation. Independent variables (X) are all ratios used to anticipate companies' bankruptcy at Altman and Zavgren adjusted models
42	2016	Ghodratollah Talebnia, Fatemeh Karmozi, Samira Rahimi	Evaluating and comparing the ability to predict the bankruptcy prediction models of Zavgren and Springate in companies accepted in Tehran Stock Exchange	The adjusted Springate Model was more efficient than other models in the bankruptcy year.	Population: the companies accepted in Tehran Stock Exchange. Information Sources: The data has been collected through the library method to study the theoretical foundations, literature, and background of the research. Moreover, different tools have been conducted like Excel spreadsheet software. To analyze the data and test the hypotheses, SPSS
43	2016	Safiye Mohammadi	Studying the Efficiency and the Power of Predicting Bankruptcy of Firms Listed on the Stock Exchange using Springate, Fulmer, and Zavgren Models	The overall accuracy of Fulmer Model (within the year, one year, and two years before financial distress) is more than Zavgren Model. The overall accuracy of Springate model (within the year, one year and two years before financial distress)	This study has been done during 2007-2012 within the scope of firms listed on the Tehran Stock Exchange. The proper model for the estimation of the regression model was created by the use of Chow and Hausman Tests.
44	2016	Abdullah, Ma'aji and Lee-Hewi Khaw	The Value of Governance Variables in Predicting Financial Distress among Small and Medium Sized Enterprises in Malaysia.	The prediction models perform relatively well especially Model 3 that incorporates governance, financial and nonfinancial variables, with an overall accuracy rate of 93.6% and 91.2% in the estimated sample and holdout sample respectively. This	The study develops distress prediction models combining financial, non-financial, and governance particularly ownership and board structures, on the likelihood of financial distress by using the logit model. The final sample for the estimation model consists of 172 companies with 50% non-failed cases

45	2017	Prof. Dr. Zeynep TURK.Erdem KURKLU	Financial Failure Estimated in BIST Companies with Altman (Z-score) and Springate Model.	Altman model shows that 115 (%69) out of 166 companies are not under financial stress while the Springate model demonstrates that 95 (%57) companies. Both of the models indicate	Yearly based averages analyzed in the Altman Z model showed that approximately 69% of the companies were successful whereas the Springate S model showed that the level of success reached 57%
46	2017	Edward I. Altman, Małgorzata Iwanicz-Drozdowska,Erkki K. Laitinen,Arto Suvas	Financial Distress Prediction in an International Context: A Review and Empirical Analysis of Altman's Z-Score Model	original Z"-Score model performs well in an international context. But, more efficient country model for most European countries and non-European countries using the four original variables	Considering practical applications, it is obvious that while a general international model works reasonably well, for most countries,
47	2017	Elsa Imelda and Clara Ignacia Alodia	The Analysis of Altman Model and Ohlson Model in Predicting Financial Distress of Manufacturing Companies in the Indonesia Stock	Ohlson's model is more accurate than the Altman's model in predicting financial distress. Logit Analysis has a greater accuracy than the Multiple Discriminant Analysis.	Sample: 40 listed manufacturing companies in the Indonesian Stock Exchange. Considered Altman's Z score model and Ohlson O score model Analyzed data from Multivariate Discriminant Analysis and Logit Regression Analysis.
48	2018	Binh Pham Vo Ninh, Trung Do Thanh, Duc Vo Hong	Financial Distress and Bankruptcy Prediction: An Appropriate Model for Listed Firms in Vietnam	Accounting, market, and macro-economic variables affect the likelihood of financial distress at Vietnams firms during the period of research. Higher financial liquidity, productivity of assets, solvency, and	Consider accounting-based, market-based, and macro-economic factors that are affected by the finance distress. Sample: 800 listed firms on the Hanoi Stock Exchange and Ho Chi Minh Stock Exchange for the period 2003-2016. Macro-economic data were gathered from the world bank reports.
49	2018	Hasan Pakdamnan	Investigating the Ability of Altman and Springate and Zmijewski and Grover Bankruptcy Prediction Models in Tehran Stock Exchange	Grover model is the best model for forecasting financial crises in Tehran Stock Exchange.	A correlation test was used to examine the significance of each Altman, Springate, Zmijewski, and Grover models, and multiple linear regression methods were used to find the research model for panel data.

Grover method is the most accurate method for predicting financial distress in the coal company with a value of 78% accuracy rate and an error rate of 22%, in the second position is occupied by Springate method to value an accuracy rate of 67% and an error rate of 33%.
Zmijewski (1984) model selected ratios that reflect the firm’s performance, leverage, and liquidity If the Score is negative (X-Score <0), then the company is classified in a healthy condition. Contrariwise, if the X-score is positive (X-Score ≥ 0) then the company can
The study covers the three mobile telecommunications companies that are listed on Boursa Kuwait during the period 2013–2017
Models: D score model of Blums, Logit model of Ohlson, Hazard model of Shumway, Altman's Z score model, Probit model of Zmijewski. The study was done prior, during, and after the financial crisis.
This is a case study method research that satisfies the use of Z score model to identify the bankruptcy of the company. The secondary data for the assessment were obtained from the financial statement of the company.

50	2018	Agnes Gracia Devina Hungan,Ni Nyoman Sawitri	Analysis of Financial Distress with Springate and Method of Grover in Coal In BEI 2012 - 2016	Grover method is the most appropriate method in predicting financial distress.
51	2018	Musaed S. AlAli et al.	The use of Zmijewski Model in Examining the Financial Soundness of Oil and Gas Companies Listed at Kuwait Stock Exchange	Companies working in that sector tend to have a healthy financial position and they are on the safe side when it comes to bankruptcy risk. The study also observed that companies facing declining X-score
52	2018	Musaed S. AlAlia, Ahmad Y. Bashb, Eman O. AlForaihc, Aldana M. AlSabahd, Abdulaziz S.	The Adaptation of Zmijewski Model in Appraising the Financial Distress of Mobile Telecommunications Companies Listed at Boursa Kuwait	All Kuwaiti telecommunications companies showed a safe and healthy financial position. Despite being the last company to enter the mobile telecommunications market in Kuwait, Viva managed to outperform its
53	2019	Sumaira Ashraf ,Elisabete G. S. Félix and Zélia Serrasqueiro	Do Traditional Financial Distress Prediction Models Predict the Early Warning Signs of Financial Distress?	The selected models can be applied to the Pakistan share market. But the accuracy of the predictability is declined through the passage of the time. D score model, logit model of Ohlson, and hazard model are not
54	2019	Rashmi Soni	Application of Discriminant Analysis to Diagnose the Financial Distress	It is recognized that the Altman's model can be used in Ruchi soya Industries Limited to forecast the possibility of bankruptcy. The market value of the firm and the assets turnover ratio is significant in the z score

Appendix II: Results of Altman (1968) Z Score for Non-Distressed Listed Companies

Company	**2014**	**2015**	**2016**	**2017**	**2018**
Abans Electricals Plc	Non-Distress	Non-Distress	Grey	Grey	Grey
Access Engineering Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
ACL Plastics Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Agstar Plc	Grey	Gray	Distress	Grey	Grey
Alumex Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Grey
Amaya Leisure Plc	Non-Distress	Distress	Distress	Distress	Grey
Cargo Boat	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress

Development Company Plc					
Central Industries Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Ceylon Cold Stores Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Ceylon Tobacco Company Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Chevron Lubricants Lanka Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Colombo City Holdings Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Colombo Land & Development Company Plc	Grey	Grey	Grey	Grey	Distress
Commercial Development Company Plc	Non-Distress	Grey	Grey	Grey	Grey
Dankotuwa Porcelain Plc	Non-Distress	Non-Distress	Grey	Grey	Non-Distress
Dialog Axiata Plc	Grey	Grey	Grey	Grey	Non-Distress
Dilmah Ceylon Tea Company Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Asia Siaka Commodities Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Asiri Surgical Hospital Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Bairaha Farms Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Bansei Royal Resorts Hikkaduwa Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Bukit Darah Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
C M Holdings Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
C T Holdings Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
C. W. Mackie Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Dolphin Hotels Plc	Grey	Grey	Grey	Grey	Grey
Galadari Hotels (Lanka) Plc	Non-Distress	Non-Distress	Non-Distress	Grey	Non-Distress
Gestetner Of Ceylon Plc	Non-Distress	Non-Distress	Non-Distress	Grey	Non-Distress
Harischandra Mills Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Hayleys Plc	Grey	Grey	Grey	Grey	Non-Distress
Hemas Holdings Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Hotel Sigiriya Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress

Hunas Falls Hotels Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Hunters & Company Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
John Keells Holdings Plc	Grey	Grey	Grey	Grey	Non-Distress
Keells Food Products Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
John Keells Hotels Plc	Non-Distress	Non-Distress	Non-Distress	Grey	Grey
Kegalle Plantations Plc	Grey	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Kelani Cables Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Grey
Kelani Tyres Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Grey
Kotmale Holdings Plc	Non-Distress	Grey	Grey	Non-Distress	Non-Distress
Lake House Printers and Publishers Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lanka Aluminum Industries Plc	Non-Distress	Grey	Grey	Grey	Grey
Lanka Ashok Leyland Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lanka Ceramic Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Grey
Lanka IOC Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lanka Milk Foods (CWE) Plc	Grey	Non-Distress	Grey	Non-Distress	Distress
Lanka Tiles Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Laugfs Gas Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Laxapana Batteries Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lee Hedges Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lion Brewery Ceylon Plc	Non-Distress	Non-Distress	Non-Distress	Grey	Grey
Lotus Hydro Power Plc	Grey	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Mahaweli Reach Hotels Plc	Grey	Grey	Grey	Non-Distress	Non-Distress
Mercantile Shipping Company Plc	Non-Distress	Non-Distress	Grey	Non-Distress	Grey
Millennium Housing Developers Plc	Distress	Non-Distress	Grey	Non-Distress	Grey
Morison Plc	Non-Distress	Non-Distress	Non-Distress	Grey	Grey
Muller And Phipps (Ceylon) Plc	Non-Distress	Non-Distress	Grey	Non-Distress	Non-Distress
Nestle Lanka Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Panasian Power Plc	Non-Distress	Grey	Non-Distress	Non-Distress	Non-Distress
Pegasus Hotels of	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Grey

Ceylon Plc					

Appendix III: Result of Altman Z Score Model on Distressed Listed Companies

Company	2014	2015	2016	2017	2018
ACL Cables Plc	Grey	Grey	Grey	Non-Distress	Grey
Acme Printing & Packaging Plc	Distress	Distress	Distress	Distress	Distress
Cargills Ceylon Plc	Grey	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Carson Cumberbatch Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Ceylon Beverage Holdings Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Ceylon Hospitals Plc (Durdans)	Grey	Grey	Grey	Distress	Distress
Ceylon Hotels Corporation Plc	Distress	Grey	Grey	Non-Distress	Distress
Ceylon Printers Plc	Non-Distress	Non-Distress	Distress	Distress	Distress
Ceylon Tea Brokers Plc	Distress	Distress	Distress	Distress	Distress
Chemanex Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
CIC Holdings Plc	Distress	Grey	Grey	Distress	Distress
Citrus Leisure Plc	Distress	Distress	Distress	Distress	Distress
City Housing & Real Estate Co. Plc	Distress	Distress	Distress	Distress	Distress
Colombo Dockyard Plc	Distress	Grey	Distress	Grey	Grey
Convenience Foods (Lanka) Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Diesel & Motor Engineering Plc	Grey	Grey	Grey	Grey	Grey
Dipped Products Plc	Non-Distress	Grey	Grey	Grey	Grey
Distilleries Company of Sri Lanka Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Asiri Hospital Holdings Plc	Non-Distress	Distress	Grey	Grey	Grey
Anilana Hotels and Properties Plc	Distress	Distress	Distress	Distress	Distress
Beruwala Resorts Plc	Grey	Grey	Grey	Distress	Distress
Blue Diamonds Jewellery Worldwide Plc	Non-Distress	Non-Distress	Non-Distress	Distress	Distress
Bogawantalawa Tea Estates Plc	Distress	Distress	Distress	Distress	Distress
Brown & Company Plc	Grey	Grey	Distress	Distress	Distress
E B Creasy & Company Plc	Grey	Grey	Grey	Grey	Grey
Eden Hotel Lanka Plc	Distress	Distress	Distress	Distress	Distress
Elpitiya Plantations Plc	Grey	Distress	Distress	Grey	Grey
Expolanka Holdings Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Hapugastenne Plantations Plc	Distress	Distress	Distress	Distress	Distress
Haycarb Plc	Non-Distress	Non-Distress	Grey	Grey	Grey
Hayleys Fibre Plc	Grey	Grey	Non-Distress	Non-Distress	Non-Distress

Hikkaduwa Beach Resort Plc	Grey	Non-Distress	Distress	Distress	Distress
Horana Plantations Plc	Distress	Distress	Distress	Distress	Distress
HVA Foods Plc	Distress	Distress	Distress	Distress	Distress
Industrial Asphalts (Ceylon) Plc	Non-Distress	Non-Distress	Distress	Distress	Non-Distress
Kahawatte Plantations Plc	Distress	Distress	Distress	Distress	Distress
Kelani Valley Plantations Plc	Grey	Grey	Distress	Distress	Grey
Lanka Walltiles Plc	Grey	Grey	Non-Distress	Non-Distress	Grey
Lankem Ceylon Plc	Distress	Distress	Distress	Distress	Distress
Lucky Lanka Milk Processing Company Plc	Grey	Grey	Distress	Distress	Distress
Mackwoods Energy Plc	Non-Distress	Non-Distress	Non-Distress	Grey	Grey
Madulsima Plantations Plc	Distress	Distress	Distress	Distress	Distress
Malwatte Valley Plantations Plc	Distress	Distress	Distress	Distress	Distress
Marawila Resorts Plc	Distress	Distress	Distress	Distress	Distress
Maskeliya Plantations Plc	Distress	Distress	Distress	Distress	Distress
MTD Walkers Plc	Non-Distress	Non-Distress	Distress	Distress	Distress
Namunukula Plantations Plc	Non-Distress	Grey	Distress	Grey	Grey
Nawaloka Hospitals Plc	Grey	Distress	Distress	Distress	Distress
Odel Plc	Non-Distress	Grey	Grey	Distress	Distress
Palm Garden Hotels Plc	Distress	Non-Distress	Grey	Distress	Distress
Paragon Ceylon Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Royal Ceramics Lanka Plc	Grey	Grey	Grey	Grey	Distress
Sigiriya Village Hotels Plc	Grey	Grey	Grey	Distress	Distress
Sri Lanka Telecom Plc	Distress	Distress	Distress	Distress	Distress
Swadeshi Industrial Works Plc	Non-Distress	Non-Distress	Non-Distress	Grey	Grey
Swisstek (Ceylon) Plc	Grey	Non-Distress	Non-Distress	Non-Distress	Grey
Tal Lanka Hotels Plc	Distress	Distress	Distress	Distress	Distress
Talawakelle Tea Estates Plc	Grey	Grey	Distress	Grey	Grey
Tess Agro Plc	Grey	Distress	Distress	Distress	Distress
Singhe Hospitals Plc	Distress	Distress	Distress	Distress	Distress
Tokyo Cement Company (Lanka) Plc	Non-Distress	Grey	Grey	Non-Distress	Grey

Appendix IV: Results of Springate Model on Non-Distressed Listed Companies

Company	2014	2015	2016	2017	2018
Abans Electricals Plc	Non-Distress	Non-Distress	Non-Distress	Distress	Non-Distress
Access Engineering Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Distress
ACL Plastics Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Agstar Plc	Distress	Non-Distress	Distress	Distress	Distress

Alumex Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Distress
Amaya Leisure Plc	Non-Distress	Distress	Distress	Distress	Non-Distress
Cargo Boat Development Company Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Central Industries Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Ceylon Cold Stores Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Ceylon Tobacco Company Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Chevron Lubricants Lanka Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Colombo City Holdings Plc	Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Colombo Land & Development Company Plc	Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Commercial Development Company Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Dankotuwa Porcelain Plc	Distress	Distress	Distress	Distress	Distress
Dialog Axiata Plc	Distress	Distress	Distress	Distress	Distress
Dilmah Ceylon Tea Company Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Asia Siaka Commodities Plc	Non-Distress	Distress	Distress	Distress	Distress
Asiri Surgical Hospital Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Bairaha Farms Plc	Distress	Distress	Non-Distress	Non-Distress	Non-Distress
Bansei Royal Resorts Hikkaduwa Plc	Distress	Distress	Non-Distress	Distress	Distress
Bukit Darah Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
C M Holdings Plc	Distress	Non-Distress	Non-Distress	Distress	Distress
C T Holdings Plc	Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
C. W. Mackie Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Dolphin Hotels Plc	Distress	Non-Distress	Non-Distress	Distress	Non-Distress
Galadari Hotels (Lanka) Plc	Distress	Distress	Distress	Distress	Distress
Gestetner Of Ceylon Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Harischandra Mills Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Hayleys Plc	Distress	Distress	Distress	Distress	Distress
Hemas Holdings Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Hotel Sigiriya Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Hunas Falls Hotels Plc	Distress	Distress	Distress	Distress	Distress
Hunters & Company Plc	Distress	Distress	Distress	Distress	Distress
John Keells Holdings Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Keells Food Products Plc	Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
John Keells Hotels Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Kegalle Plantations Plc	Non-Distress	Distress	Distress	Distress	Distress
Kelani Cables Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Kelani Tyres Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress

Kotmale Holdings Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lake House Printers and Publishers Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lanka Aluminum Industries Plc	Distress	Non-Distress	Distress	Distress	Non-Distress
Lanka Ashok Leyland Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lanka Ceramic Plc	Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lanka IOC Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lanka Milk Foods (CWE) Plc	Distress	Distress	Distress	Distress	Distress
Lanka Tiles Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Laugfs Gas Plc	Non-Distress	Non-Distress	Distress	Distress	Distress
Laxapana Batteries Plc	Distress	Distress	Non-Distress	Non-Distress	Non-Distress
Lee Hedges Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lion Brewery Ceylon Plc	Non-Distress	Non-Distress	Non-Distress	Distress	Distress
Lotus Hydro Power Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Mahaweli Reach Hotels Plc	Distress	Distress	Distress	Distress	Distress
Mercantile Shipping Company Plc	Distress	Distress	Non-Distress	Distress	Distress
Millennium Housing Developers Plc	Non-Distress	Non-Distress	Distress	Distress	Distress
Morison Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Muller And Phipps (Ceylon) Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Nestle Lanka Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Panasian Power Plc	Distress	Non-Distress	Non-Distress	Distress	Distress
Pegasus Hotels of Ceylon Plc	Non-Distress	Non-Distress	Non-Distress	Distress	Non-Distress

Appendix V: Results of Springate Model on Distressed Listed Companies

Company	2014	2015	2016	2017	2018
ACL Cables Plc	Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Acme Printing & Packaging Plc	Distress	Distress	Distress	Distress	Distress
Cargills Ceylon Plc	Distress	Distress	Distress	Distress	Non-Distress
Carson Cumberbatch Plc	Distress	Distress	Distress	Distress	Distress
Ceylon Beverage Holdings Plc	Non-Distress	Non-Distress	Non-Distress	Distress	Distress
Ceylon Hospitals Plc (Durdans)	Distress	Distress	Distress	Distress	Distress
Ceylon Hotels Corporation Plc	Distress	Distress	Distress	Distress	Distress
Ceylon Printers Plc	Non-Distress	Non-Distress	Distress	Distress	Distress
Ceylon Tea Brokers Plc	Distress	Distress	Distress	Distress	Distress
Chemanex Plc	Distress	Distress	Non-Distress	Non-Distress	Non-Distress
CIC Holdings Plc	Distress	Distress	Distress	Distress	Distress
Citrus Leisure Plc	Distress	Distress	Distress	Distress	Distress
City Housing & Real Estate Co.	Distress	Distress	Distress	Distress	Distress

Plc					
Colombo Dockyard Plc	Distress	Distress	Distress	Distress	Distress
Convenience Foods (Lanka) Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Diesel & Motor Engineering Plc	Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Dipped Products Plc	Distress	Distress	Distress	Distress	Distress
Distilleries Company of Sri Lanka Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Asiri Hospital Holdings Plc	Distress	Distress	Distress	Distress	Distress
Anilana Hotels and Properties Plc	Distress	Distress	Distress	Distress	Distress
Beruwala Resorts Plc	Distress	Distress	Distress	Distress	Distress
Blue Diamonds Jewellery Worldwide Plc	Distress	Distress	Distress	Distress	Distress
Bogawantalawa Tea Estates Plc	Distress	Distress	Distress	Distress	Distress
Brown & Company Plc	Non-Distress	Distress	Distress	Distress	Distress
E B Creasy & Company Plc	Distress	Distress	Distress	Non-Distress	Distress
Eden Hotel Lanka Plc	Distress	Distress	Distress	Distress	Distress
Elpitiya Plantations Plc	Non-Distress	Distress	Distress	Non-Distress	Non-Distress
Expolanka Holdings Plc	Non-Distress	Non-Distress	Distress	Distress	Distress
Hapugastenne Plantations Plc	Distress	Distress	Distress	Distress	Distress
Haycarb Plc	Non-Distress	Distress	Distress	Non-Distress	Non-Distress
Hayleys Fibre Plc	Distress	Distress	Distress	Non-Distress	Non-Distress
Hikkaduwa Beach Resort Plc	Distress	Distress	Distress	Distress	Distress
Horana Plantations Plc	Distress	Distress	Distress	Distress	Distress
HVA Foods Plc	Distress	Distress	Distress	Distress	Distress
Industrial Asphalts (Ceylon) Plc	Distress	Distress	Distress	Distress	Non-Distress
Kahawatte Plantations Plc	Distress	Distress	Distress	Distress	Distress
Kelani Valley Plantations Plc	Non-Distress	Distress	Distress	Distress	Distress
Lanka Walltiles Plc	Distress	Distress	Non-Distress	Non-Distress	Non-Distress
Lankem Ceylon Plc	Distress	Distress	Distress	Distress	Distress
Lucky Lanka Milk Processing Company Plc	Distress	Distress	Distress	Distress	Distress
Mackwoods Energy Plc	Non-Distress	Distress	Distress	Distress	Distress
Madulsima Plantations Plc	Distress	Distress	Distress	Distress	Distress
Malwatte Valley Plantations Plc	Distress	Distress	Distress	Non-Distress	Distress
Marawila Resorts Plc	Distress	Distress	Distress	Distress	Distress
Maskeliya Plantations Plc	Distress	Distress	Distress	Distress	Distress
MTD Walkers Plc	Distress	Distress	Distress	Distress	Distress
Namunukula Plantations Plc	Non-Distress	Distress	Distress	Non-Distress	Non-Distress
Nawaloka Hospitals Plc	Distress	Distress	Distress	Distress	Distress
Odel Plc	Non-Distress	Distress	Distress	Distress	Distress

Palm Garden Hotels Plc	Distress	Distress	Distress	Distress	Distress
Paragon Ceylon Plc	Non-Distress	Distress	Distress	Distress	Distress
Royal Ceramics Lanka Plc	Distress	Distress	Distress	Distress	Distress
Sigiriya Village Hotels Plc	Distress	Distress	Distress	Distress	Distress
Sri Lanka Telecom Plc	Distress	Distress	Distress	Distress	Distress
Swadeshi Industrial Works Plc	Non-Distress	Non-Distress	Non-Distress	Distress	Distress
Swisstek (Ceylon) Plc	Distress	Distress	Non-Distress	Non-Distress	Non-Distress
Tal Lanka Hotels Plc	Distress	Distress	Distress	Distress	Distress
Talawakelle Tea Estates Plc	Non-Distress	Non-Distress	Distress	Non-Distress	Non-Distress
Tess Agro Plc	Distress	Distress	Distress	Distress	Distress
Singhe Hospitals Plc	Distress	Distress	Distress	Distress	Distress
Tokyo Cement Company (Lanka) Plc	Non-Distress	Non-Distress	Distress	Non-Distress	Non-Distress

Appendix VI: Results of Grover Model on Non- Distressed Listed Companies

Company	2014	2015	2016	2017	2018
Abans Electricals Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Access Engineering Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
ACL Plastics Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Agstar Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Alumex Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Amaya Leisure Plc	Non-Distress	Non-Distress	Distress	Non-Distress	Non-Distress
Cargo Boat Development Company Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Central Industries Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Ceylon Cold Stores Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Ceylon Tobacco Company Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Chevron Lubricants Lanka Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Colombo City Holdings Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Colombo Land & Development Company Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Commercial Development Company Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Dankotuwa Porcelain Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Dialog Axiata Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Dilmah Ceylon Tea Company Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Asia Siaka Commodities Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Asiri Surgical Hospital Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress

Bairaha Farms Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Bansei Royal Resorts Hikkaduwa Plc	Non-Distress	Distress	Non-Distress	Non-Distress	Non-Distress
Bukit Darah Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
C M Holdings Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
C T Holdings Plc	Non-Distress	Grey	Non-Distress	Grey	Non-Distress
C. W. Mackie Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Dolphin Hotels Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Galadari Hotels (Lanka) Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Gestetner Of Ceylon Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Harischandra Mills Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Hayleys Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Hemas Holdings Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Hotel Sigiriya Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Hunas Falls Hotels Plc	Non-Distress	Grey	Non-Distress	Non-Distress	Non-Distress
Hunters & Company Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
John Keells Holdings Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Keells Food Products Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
John Keells Hotels Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Kegalle Plantations Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Kelani Cables Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Kelani Tyres Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Kotmale Holdings Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lake House Printers and Publishers Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lanka Aluminum Industries Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lanka Ashok Leyland Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lanka Ceramic Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lanka IOC Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lanka Milk Foods (CWE) Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lanka Tiles Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Laugfs Gas Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Distress
Laxapana Batteries Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lee Hedges Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lion Brewery Ceylon Plc	Non-Distress	Non-Distress	Non-Distress	Distress	Non-Distress
Lotus Hydro Power Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Mahaweli Reach Hotels Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Grey
Mercantile Shipping Company Plc	Distress	Distress	Non-Distress	Distress	Non-Distress
Millennium Housing Developers Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Grey

Morison Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Muller And Phipps (Ceylon) Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Nestle Lanka Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Panasian Power Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Pegasus Hotels of Ceylon Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress

Appendix VII: Results of Grover Model on Distressed Listed Companies

Company	**2014**	**2015**	**2016**	**2017**	**2018**
ACL Cables Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Acme Printing & Packaging Plc	Distress	Distress	Non-Distress	Distress	Distress
Cargills Ceylon Plc	Non-Distress	Non-Distress	Grey	Distress	Non-Distress
Carson Cumberbatch Plc	Non-Distress	Non-Distress	Non-Distress	Distress	Non-Distress
Ceylon Beverage Holdings Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Ceylon Hospitals Plc (Durdans)	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Grey
Ceylon Hotels Corporation Plc	Distress	Distress	Distress	Non-Distress	Distress
Ceylon Printers Plc	Non-Distress	Non-Distress	Non-Distress	Distress	Distress
Ceylon Tea Brokers Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Chemanex Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
CIC Holdings Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Grey
Citrus Leisure Plc	Non-Distress	Distress	Non-Distress	Non-Distress	Distress
City Housing & Real Estate Co. Plc	Non-Distress	Distress	Distress	Distress	Distress
Colombo Dockyard Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Convenience Foods (Lanka) Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Diesel & Motor Engineering Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Dipped Products Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Distilleries Company of Sri Lanka Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Asiri Hospital Holdings Plc	Non-Distress	Distress	Non-Distress	Non-Distress	Non-Distress
Anilana Hotels and Properties Plc	Non-Distress	Non-Distress	Distress	Distress	Distress
Beruwala Resorts Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Blue Diamonds Jewellery Worldwide Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Bogawantalawa Tea Estates Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Brown & Company Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
E B Creasy & Company Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Eden Hotel Lanka Plc	Non-Distress	Distress	Distress	Distress	Distress
Elpitiya Plantations Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Expolanka Holdings Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Distress

Hapugastenne Plantations Plc	Non-Distress	Distress	Distress	Grey	Distress
Haycarb Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Hayley's Fiber Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Hikkaduwa Beach Resort Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Distress
Horana Plantations Plc	Non-Distress	Non-Distress	Distress	Distress	Non-Distress
HVA Foods Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Industrial Asphalts (Ceylon) Plc	Non-Distress	Non-Distress	Distress	Distress	Non-Distress
Kahawatte Plantations Plc	Non-Distress	Distress	Distress	Distress	Distress
Kelani Valley Plantations Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lanka Walltiles Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Lankem Ceylon Plc	Distress	Distress	Distress	Distress	Distress
Lucky Lanka Milk Processing Company Plc	Non-Distress	Non-Distress	Non-Distress	Distress	Distress
Mackwoods Energy Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Madulsima Plantations Plc	Distress	Distress	Distress	Distress	Distress
Malwatte Valley Plantations Plc	Non-Distress	Distress	Non-Distress	Non-Distress	Distress
Marawila Resorts Plc	Distress	Distress	Grey	Distress	Distress
Maskeliya Plantations Plc	Distress	Distress	Distress	Distress	Non-Distress
MTD Walkers Plc	Distress	Non-Distress	Non-Distress	Non-Distress	Distress
Namunukula Plantations Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Nawaloka Hospitals Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Odel Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Palm Garden Hotels Plc	Distress	Distress	Distress	Distress	Distress
Paragon Ceylon Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Distress
Royal Ceramics Lanka Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Sigiriya Village Hotels Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Sri Lanka Telecom Plc	Non-Distress	Non-Distress	Distress	Distress	Distress
Swadeshi Industrial Works Plc	Non-Distress	Non-Distress	Non-Distress	Distress	Non-Distress
Swisstek (Ceylon) Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Tal Lanka Hotels Plc	Distress	Distress	Non-Distress	Non-Distress	Non-Distress
Talawakelle Tea Estates Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress
Tess Agro Plc	Non-Distress	Grey	Distress	Distress	Distress
Singhe Hospitals Plc	Distress	Non-Distress	Distress	Distress	Distress
Tokyo Cement Company (Lanka) Plc	Non-Distress	Non-Distress	Non-Distress	Non-Distress	Non-Distress

Appendix VIII: Collected Data for Non-Distressed Sample

	Years	Working Capital/ Total Assets	Retained Earnings / Total Assets	EBIT/Total Assets	Market Value of Equity/ Book value of Equity	Sales/Total Assets	Profit Before Tax/Current Liabilities	ROA
ABANS ELECTRICALS PLC	2018	0.18010	0.19854	0.07608	0.01479	1.44060	0.02914	0.01620
	2017	0.12162	0.19010	0.06606	0.02340	1.16629	0.00334	-0.00148
	2016	0.17824	0.19650	0.08669	0.02873	1.18204	0.07113	0.03118
	2015	0.14700	0.32455	0.08089	0.83820	1.68529	0.13211	0.05933
	2014	0.14940	0.28729	0.12486	0.68544	2.05587	0.13867	0.06434
ACCESS ENGINEERING PLC	2018	0.12712	0.26417	0.08599	3.71800	0.54372	0.26090	0.05783
	2017	0.24431	0.28277	0.11018	7.88308	0.52020	0.53279	0.09443
	2016	0.41955	0.27061	0.08719	2.72912	0.45943	0.61821	0.08262
	2015	0.36308	0.32429	0.10040	2.12357	0.61592	0.67492	0.09600
	2014	0.39529	0.28164	0.14557	2.21386	0.72010	0.75009	0.13779
ACL PLASTICS PLC	2018	0.54890	0.55760	0.09005	1.50417	0.99986	0.36467	0.06135
	2017	0.65130	0.57472	0.22269	3.58924	1.19769	1.70990	0.14642
	2016	0.58006	0.47261	0.25375	4.25260	1.11962	1.45351	0.18367
	2015	0.57054	0.37578	0.14555	4.17451	1.26250	1.14311	0.09129
	2014	0.62392	0.28351	0.11640	1.66534	1.21022	0.74448	0.07879
AGSTAR PLC	2018	0.31483	0.18909	0.04087	0.54759	0.71727	0.06849	0.02296
	2017	0.40625	0.21749	-0.09177	1.18946	0.79317	-0.27381	-0.12266
	2016	0.30912	0.24786	0.07833	0.64755	0.30431	0.17632	0.05306
	2015	0.39279	0.25454	0.11244	1.15061	0.37533	0.23848	0.06410
	2014	0.36281	0.19353	0.07101	1.04621	0.35294	0.04730	0.01364
ALUMEX PLC	2018	-0.00124	0.13812	0.09508	1.01141	0.69127	0.16060	0.05997
	2017	0.19480	0.20601	0.24892	2.93863	1.11794	0.72816	0.18015
	2016	0.20330	0.21389	0.32237	6.17779	1.40741	0.93488	0.24229
	2015	0.11411	0.11597	0.23204	5.62279	1.22877	0.65378	0.18014
	2014	0.18061	0.07847	0.19156	6.29841	1.19976	0.58304	0.14256
AMAYA LEISURE PLC	2018	0.03401	0.39943	0.22958	1.49166	0.09836	2.21658	0.22554
	2017	-0.27471	0.16311	0.22003	1.75254	0.09519	0.54048	0.17466
	2016	-0.32479	0.15862	0.12603	1.89682	0.08721	0.28127	0.09800
	2015	-0.30458	0.06378	0.13550	1.82904	0.07849	0.28049	0.10550
	2014	-0.38579	0.14690	0.18818	16.77304	0.12073	0.42989	0.17850
CARGO BOAT DEVELOPMENT COMPANY PLC	2018	0.12041	0.06833	0.07655	15.81067	0.02990	4.55359	1.57297
	2017	0.13895	0.05467	0.06694	22.90855	0.02603	9.90851	2.07577
	2016	0.10876	0.04660	0.05471	24.08523	0.02428	10.12604	1.98798
	2015	0.19022	0.04515	0.06475	36.24227	0.02347	24.93928	2.93771
	2014	0.22409	0.08347	0.14631	35.64469	0.03282	23.88310	1.53159

CENTRAL INDUSTRIES PLC	2018	0.44916	0.51824	0.07438	1.05420	1.23692	0.29310	0.04513
	2017	0.50764	0.52780	0.11636	1.92149	1.34403	0.63608	0.07939
	2016	0.53437	0.54722	0.18591	3.35734	1.45030	1.38080	0.13336
	2015	0.43320	0.44291	0.11749	2.56060	1.36019	0.46939	0.08418
	2014	0.43506	0.45125	0.07846	2.83693	1.27128	0.42229	0.05751
CEYLON COLD STORES PLC	2018	0.08390	0.64884	0.18028	18.32706	0.84828	1.29700	0.14772
	2017	0.08595	0.63699	0.26325	26.39918	0.93904	1.84051	0.21354
	2016	0.11558	0.65208	0.20536	22.46927	0.84898	1.41655	0.15885
	2015	0.09988	0.67612	0.12182	15.87482	0.74324	1.07894	0.08951
	2014	0.07214	0.68651	0.11394	10.96482	0.69603	1.21145	0.09852
CEYLON TOBACCO COMPANY PLC	2018	0.08656	0.12358	0.91829	11.60044	5.15082	1.23285	0.60280
	2017	0.08144	0.10868	0.92944	9.29359	5.58234	1.24476	0.58775
	2016	0.03852	0.07145	0.90309	7.92224	5.38798	1.13950	0.55684
	2015	0.02956	0.05421	0.93809	11.77622	5.70288	1.17559	0.56950
	2014	0.11624	0.13085	0.91639	12.83013	5.67914	1.29876	0.55684
CHEVRON LUBRICANTS LANKA PLC	2018	0.37443	0.54624	0.45207	8.11382	1.78994	1.57161	0.32826
	2017	0.40583	0.60882	0.60864	17.97350	1.97510	2.95987	0.45841
	2016	0.28648	0.46273	0.64081	11.83471	1.71562	1.66757	0.49392
	2015	0.38514	0.58013	0.58811	17.50654	1.64143	2.09763	0.43887
	2014	0.48030	0.71011	0.55129	37.53321	1.77864	3.50314	0.42410
COLOMBO CITY HOLDINGS PLC	2018	0.56708	0.97383	0.12812	23.76604	0.05984	7.55169	0.13666
	2017	0.04698	0.97042	0.12289	34.46927	0.01652	6.28802	0.12732
	2016	0.06985	0.97088	0.21440	35.42607	0.02732	10.48541	0.23726
	2015	0.06183	0.93645	0.08168	16.94138	0.04426	1.51868	0.09825
	2014	-0.08515	0.79282	0.06116	5.67605	0.04089	0.51221	0.04236
COLOMBO LAND & DEVELOPMENT COMPANY PLC	2018	0.12797	0.59154	0.04767	0.75639	0.01443	1.40718	0.03501
	2017	0.13901	0.58564	0.32250	1.03897	0.01343	10.17486	0.23278
	2016	0.19943	0.45236	0.13550	1.36492	0.01691	0.90064	0.11926
	2015	0.18823	0.45494	0.10455	1.84449	0.01561	1.45180	0.07172
	2014	0.09490	0.45127	0.04298	3.16689	0.01638	0.23201	0.02478
COMMERCIAL DEVELOPMENT COMPANY PLC	2018	0.03471	0.12930	0.11789	1.99113	0.13117	8.93856	0.10862
	2017	0.02914	0.11944	0.16856	2.01376	0.12875	9.32711	0.15500
	2016	0.06835	0.11633	0.15824	2.31784	0.13924	8.59305	0.13805
	2015	0.05711	0.10837	0.14961	3.11678	0.15355	7.49295	0.12585
	2014	0.08902	0.10662	0.18322	3.51803	0.14731	6.61861	0.14701
DANKOTUWA PORCELAIN PLC	2018	0.16959	-0.05308	-0.06131	0.99008	0.43475	-0.27679	-0.02758
	2017	0.26571	-0.02191	0.03502	1.40038	0.60754	0.28256	0.03479
	2016	0.26363	-0.02868	0.04314	1.67340	0.57601	0.33851	0.01794
	2015	0.17698	-0.05278	0.01296	1.15453	0.68584	-0.04040	-0.00491
	2014	0.19730	-0.05122	0.02488	0.93852	0.76331	0.06837	0.01092
DIALOG AXIATA PLC	2018	-0.04629	0.29915	0.08058	0.97775	0.52777	0.15934	0.02722
	2017	-0.11780	0.32359	0.09735	1.54718	0.54373	0.31082	0.07358
	2016	-0.10056	0.29039	0.10223	1.28881	0.54808	0.32698	0.07759

	2015	-0.17805	0.26257	0.08338	1.49671	0.53769	0.18565	0.04910
	2014	-0.06960	0.24332	0.07667	1.86492	0.50891	0.28572	0.06105
DILMAH CEYLON TEA COMPANY PLC	2018	0.53925	0.14990	0.09823	9.00939	0.79098	1.49364	0.10281
	2017	0.54285	0.86559	0.06392	4.66402	0.57599	0.42733	0.06540
	2016	0.64661	1.08902	0.16311	15.64350	0.68936	3.17712	0.15424
	2015	0.71078	1.05541	0.08626	22.75727	0.79339	2.10451	0.08659
	2014	0.71045	1.15092	0.09270	18.71233	0.82014	1.80162	0.09430
ASIA SIAKA COMMODITIES PLC	2018	0.05199	0.08905	0.12542	0.36689	0.33033	0.05434	0.03378
	2017	0.04295	0.09372	0.08520	0.43093	0.23268	0.03706	0.02575
	2016	0.03312	0.09680	0.10053	0.46293	0.26186	0.06463	0.03768
	2015	0.08777	0.08945	0.13410	0.43731	0.23720	0.10311	0.06646
	2014	0.08941	0.09523	0.18394	0.73205	0.28963	0.13701	0.09083
ASIRI SURGICAL HOSPITAL PLC	2018	0.07800	0.21314	0.14370	3.92956	0.66856	1.78403	0.11157
	2017	0.05307	0.20473	0.05777	5.53477	0.62034	0.90875	0.05652
	2016	0.12485	0.23689	0.10713	5.74663	0.62674	1.46510	0.08931
	2015	0.04802	0.15820	0.08787	5.71211	0.59477	0.98509	0.09148
	2014	0.13862	0.11715	0.09813	6.16274	0.51607	0.51676	0.10573
BAIRAHA FARMS PLC	2018	0.14087	0.51539	0.12919	2.13178	1.09581	0.60675	0.08882
	2017	0.12728	0.48913	0.29385	2.51735	1.15778	1.94044	0.23180
	2016	0.16071	0.30530	0.09811	2.06653	1.08506	0.25066	0.07266
	2015	0.20256	0.30232	0.03805	2.69642	1.16947	0.07855	0.02122
	2014	0.16120	0.32478	0.02732	2.04510	1.21883	0.05589	0.01725
BANSEI ROYAL RESORTS HIKKADUWA PLC	2018	0.27538	0.07221	-0.00169	24.29085	0.19097	0.72353	0.01394
	2017	0.24737	0.07598	-0.00516	22.38949	0.18196	0.43043	0.00683
	2016	0.24606	0.08403	0.01777	31.80332	0.19647	0.84384	0.02188
	2015	0.17654	0.06155	-0.11278	20.35296	0.07753	-1.86140	-0.10164
	2014	0.39057	0.14688	0.01967	22.81295	0.23794	0.15784	0.00615
BUKIT DARAH PLC	2018	-0.00220	0.91927	0.02220	157.13524	0.02591	1.20975	0.02204
	2017	-0.00282	0.92648	0.01608	281.22176	0.02001	1.51525	0.01585
	2016	-0.00263	0.92721	0.02286	403.29299	0.02698	2.32111	0.02261
	2015	0.02160	0.92849	0.06319	698.77245	0.06685	6.24400	0.06272
	2014	0.00649	0.92982	0.05201	311.47836	0.05582	6.77360	0.05165
C M HOLDINGS PLC	2018	0.09660	0.70809	-0.01149	12.80195	0.04067	-0.19889	-0.01413
	2017	0.14345	0.72234	-0.05912	26.54189	0.02923	-4.71653	-0.06523
	2016	0.14509	0.82026	0.11218	24.86999	0.02245	7.92509	0.10506
	2015	0.11715	0.77382	0.05539	13.03224	0.03667	1.69108	0.04080
	2014	0.04527	0.77774	0.03150	18.33092	0.04760	0.39156	0.01777
C T HOLDINGS	2018	0.00648	0.13809	0.00417	178.6265	0.01730	6.61222	0.14185

PLC					9			
	2017	0.00522	0.50853	-0.01824	127.0420 6	0.00425	5.42484	0.16564
	2016	0.10244	0.51820	-0.01141	96.54799	0.02119	2.65528	0.07100
	2015	0.01860	0.52354	-0.02749	123.4765 8	0.00348	1.98105	0.04714
	2014	-0.00063	0.54503	0.03382	180.9499 0	0.04336	0.00769	0.39132
C. W. MACKIE PLC	2018	0.19005	0.40803	0.09886	0.72847	2.03617	0.15191	0.05192
	2017	0.33812	0.43882	0.10746	0.95558	2.03195	0.22412	0.06600
	2016	0.33806	0.45888	0.12284	1.42121	2.04351	0.32498	0.08844
	2015	0.33370	0.46170	0.12256	1.93713	2.24594	0.32460	0.07970
	2014	0.27465	0.39947	0.11156	1.56530	2.00229	0.24135	0.06885
DOLPHIN HOTELS PLC	2018	0.02977	0.42002	0.08046	1.71547	0.38100	0.77459	0.06301
	2017	-0.02039	0.35212	0.05478	1.45677	0.35431	0.28992	0.04048
	2016	-0.02435	0.34659	0.08603	2.25523	0.37802	0.78934	0.06691
	2015	-0.05354	0.33915	0.12281	2.84939	0.45005	0.62144	0.08884
	2014	0.07093	0.21993	0.02746	1.98765	0.19803	0.19458	0.03126
GALADARI HOTELS (LANKA) PLC	2018	0.20145	-0.71465	0.00264	3.32339	0.13426	0.50060	0.01870
	2017	0.16890	-0.75015	0.00165	4.28446	0.12843	0.43983	0.02755
	2016	0.16290	-0.80934	0.02306	6.34858	0.15898	0.69686	0.03178
	2015	0.12046	-0.90025	0.01620	7.03669	0.15515	0.45175	0.02131
	2014	0.08025	0.93460	0.01661	7.28896	0.15864	0.42947	0.01577
GESTETNER OF CEYLON PLC	2018	0.25383	0.34029	0.15752	1.20726	1.41689	0.46750	0.13102
	2017	0.11394	0.18822	0.11689	0.88104	1.33457	0.23609	0.09364
	2016	0.25111	0.24911	0.10128	1.78273	1.47812	0.25689	0.08678
	2015	0.12461	0.26787	0.17219	2.07241	1.73397	0.33697	0.13534
	2014	0.04085	0.24695	0.13624	3.10031	2.16365	0.33691	0.11654
HARISCHANDRA MILLS PLC	2018	0.29186	0.61483	0.15239	5.57921	1.87151	0.69703	0.11190
	2017	0.27869	0.64623	0.14701	4.94127	1.87602	0.67334	0.11655
	2016	0.27816	0.61188	0.13178	4.38935	1.87188	0.65821	0.08169
	2015	0.22833	0.59908	0.17106	4.15231	1.86700	0.58687	0.13425
	2014	0.16826	0.58403	0.12858	4.09923	1.78579	0.42772	0.10351
HAYLEYS PLC	2018	-0.14631	0.42854	0.07874	0.66992	0.00962	0.18171	0.03703
	2017	-0.03491	0.52325	0.06665	2.07475	0.01312	0.42069	0.03640
	2016	-0.08818	0.16844	0.08106	2.74118	0.01795	0.26850	0.04720
	2015	0.02367	0.15208	0.07269	3.00238	0.01566	0.47821	0.04145
	2014	-0.11430	0.14724	0.07162	3.44276	0.01599	0.18448	0.03429
HEMAS HOLDINGS PLC	2018	0.02244	0.60031	0.13226	30.61934	0.04150	5.44529	0.13737
	2017	0.24072	0.54960	0.31884	7.97357	0.04659	6.54114	0.33649
	2016	0.48865	0.36090	0.02023	22.33548	0.05121	0.55752	0.03031
	2015	0.29079	0.50420	0.08231	16.72016	0.06454	0.53102	0.07142
	2014	0.02607	0.56696	0.10785	19.75616	0.07570	0.81398	0.08842

HOTEL SIGIRIYA PLC	2018	0.10788	0.25839	0.08355	2.92405	0.66953	0.63619	0.05606
	2017	0.09907	0.32344	0.12167	3.45967	0.62539	0.90021	0.12903
	2016	0.16297	0.32136	0.16848	6.46048	0.66952	1.46472	0.13375
	2015	0.08107	0.32008	0.15790	8.35663	0.65389	1.22134	0.15394
	2014	0.02995	0.27696	0.08160	7.26070	0.63567	0.62535	0.08277
HUNAS FALLS HOTELS PLC	2018	0.07597	0.50489	-0.02755	6.56822	0.30538	-0.43656	-0.03152
	2017	0.04702	0.52656	0.00866	5.41207	0.34481	0.19197	0.00773
	2016	-0.01810	0.52357	0.02079	4.04432	0.36660	0.23868	0.01571
	2015	-0.05289	0.50655	0.00973	4.25595	0.36451	0.08613	0.00763
	2014	-0.00785	0.52751	0.05353	4.84225	0.37297	0.58612	0.05256
HUNTERS & COMPANY PLC	2018	0.10423	0.08544	0.01344	1.37537	0.15673	0.57605	0.01280
	2017	0.20953	0.16988	0.02190	9.44182	0.33233	0.31717	0.01731
	2016	0.20540	0.16674	0.01489	10.26557	0.30879	0.29732	0.01533
	2015	0.20901	0.16682	0.01981	15.31314	0.27924	0.58281	0.01828
	2014	0.09240	0.05507	0.00283	8.36418	0.25687	-0.02241	-0.00281
JOHN KEELLS HOLDINGS PLC	2018	0.38202	0.48775	0.12640	2.48251	0.01045	20.90579	0.16461
	2017	0.51583	0.43138	0.10178	2.05142	0.00972	13.51138	0.13939
	2016	0.53470	0.39592	0.12646	1.17216	0.01067	7.38338	0.16435
	2015	0.47905	0.37090	0.09148	1.43497	0.01061	5.84955	0.12762
	2014	0.43478	0.31026	0.08247	1.22090	0.01015	4.72917	0.09918
KEELLS FOOD PRODUCTS PLC	2018	0.24405	0.08968	0.13879	4.99296	1.28313	0.97032	0.09956
	2017	0.20399	0.05311	0.15870	4.84290	1.26664	0.91344	0.11501
	2016	0.26965	0.11510	0.17719	6.29071	1.25740	1.34236	0.13887
	2015	0.23753	0.09863	0.14603	8.54781	1.12997	0.99273	0.11263
	2014	0.17478	0.04745	-0.01427	4.05157	1.09122	-0.02962	0.00188
JOHN KEELLS HOTELS PLC	2018	0.08391	0.24255	0.10652	1.66205	0.91940	21.70984	0.11435
	2017	0.08250	0.18687	0.10086	1.57356	1.04481	15.60812	0.10570
	2016	0.03178	0.13901	0.08517	4.99481	1.05068	30.68156	0.08724
	2015	0.00431	0.10793	0.07037	3.60207	1.06760	12.07864	0.06837
	2014	-0.00739	0.07547	0.03556	16.06965	1.05018	3.21695	0.03600
KEGALLE PLANTATIONS PLC	2018	0.02440	0.30025	0.06453	0.32462	0.36334	0.16213	0.03417
	2017	0.03280	0.32549	0.04031	0.46263	0.35712	0.10598	0.03392
	2016	0.10741	0.30527	0.01231	0.42389	0.30146	0.04333	0.01582
	2015	0.32363	0.41176	0.00647	0.32641	0.28397	0.12557	0.01782
	2014	0.50998	0.41343	0.04824	0.65206	0.34755	0.68781	0.04981
KELANI CABLES PLC	2018	0.44435	0.43169	0.05189	0.65210	1.28470	0.11452	0.03164
	2017	0.47677	0.45421	0.08571	0.90649	1.26071	0.24505	0.06663
	2016	0.48230	0.44829	0.13659	1.46964	1.29913	0.39612	0.09748
	2015	0.41916	0.37976	0.09969	1.34165	1.27345	0.23284	0.06615
	2014	0.46440	0.40213	0.08891	1.27257	1.34541	0.24188	0.05864
KELANI TYRES PLC	2018	0.53289	0.63997	0.00071	0.44058	0.40961	0.46496	0.01738
	2017	0.61767	0.69187	0.56519	0.74538	0.31221	17.94516	0.56483
	2016	0.32888	0.46099	0.26864	1.29516	0.41109	4.88837	0.26638

	2015	0.21959	0.32851	0.25791	2.95806	0.55412	1.25773	0.25355
	2014	0.31031	0.20084	0.26000	1.93563	0.67089	4.22552	0.24370
KOTMALE HOLDINGS PLC	2018	0.44953	0.10219	1.40225	2.23322	1.47577	23.51064	1.37209
	2017	0.42515	0.05866	1.09091	2.83240	1.16436	19.44211	1.07144
	2016	0.47896	0.13894	0.16416	1.15452	0.22660	4.34904	0.13241
	2015	0.41583	0.04695	0.18132	0.81726	0.18302	2.82845	0.13426
	2014	0.32995	-0.10232	0.16245	1.00924	0.16794	2.65240	0.13435
LAKE HOUSE PRINTERS AND PUBLISHERS PLC	2018	0.16706	0.25043	0.07705	4.39599	0.97604	0.46688	0.04236
	2017	0.12802	0.23336	0.08447	3.94946	0.94367	0.49418	0.06967
	2016	0.13971	0.24788	0.09575	4.33813	1.07688	0.42326	0.06606
	2015	0.15747	0.21634	0.11342	4.51871	1.17779	0.57230	0.06046
	2014	0.06153	0.17941	0.12092	5.05176	1.19140	0.51220	0.06891
LANKA ALUMINIUM INDUSTRIES PLC	2018	0.03592	0.22593	0.14060	0.58788	0.75587	0.24015	0.07040
	2017	0.00017	0.19965	0.12545	0.74639	0.76605	0.18534	0.06844
	2016	0.11947	0.18309	0.09933	1.07458	0.72287	0.14921	0.05391
	2015	0.11070	0.14614	0.12879	1.43943	0.70659	0.21689	0.08288
	2014	0.08361	0.10815	0.07870	0.82607	0.66618	0.07712	0.02296
LANKA ASHOK LEYLAND PLC	2018	0.40100	0.33697	0.10231	0.78358	2.17984	0.18440	0.07073
	2017	0.43316	0.35326	0.07716	1.46509	2.00317	0.13173	0.04184
	2016	0.42052	0.34653	0.06852	1.48189	1.68571	0.12567	0.03893
	2015	0.41373	0.31124	0.09753	1.81921	1.42497	0.17914	0.05722
	2014	0.38241	0.30157	0.11309	2.12723	1.41448	0.10390	0.03336
LANKA CERAMIC PLC	2018	0.02309	0.13861	0.24455	1.58487	0.15201	1.25662	0.15479
	2017	-0.00016	0.43033	0.32747	2.80082	0.17426	4.70630	0.29901
	2016	0.00086	0.12866	0.25802	7.23698	0.18480	1.19721	0.22717
	2015	0.04306	0.12770	0.24951	8.82548	0.14368	2.69297	0.21504
	2014	-0.00228	0.03946	0.11058	7.49412	0.16689	0.58150	0.05288
LANKA IOC PLC	2018	0.30170	0.35779	-0.04202	0.96384	2.77141	-0.05718	-0.02258
	2017	0.45805	0.51831	0.12348	3.16983	3.17880	0.79548	0.12024
	2016	0.37347	0.43119	0.10246	2.52591	2.84454	0.40976	0.08933
	2015	0.39986	0.44807	0.08880	3.64703	3.39409	0.42464	0.08010
	2014	0.32273	0.35080	0.21194	3.21393	3.03109	0.58411	0.17837
LANKA MILK FOODS (CWE) PLC	2018	0.10505	0.13763	0.02066	2.08347	0.15491	0.88597	0.02288
	2017	0.11881	0.12631	0.01852	2.02958	0.17430	0.56369	0.01985
	2016	0.11594	0.12541	0.00521	2.89900	0.23006	-0.10379	-0.00168
	2015	0.10291	0.11265	-0.00233	2.01892	0.16051	0.02812	0.00560
	2014	0.11499	0.12503	0.00377	2.96475	0.23360	0.02517	0.00420
LANKA TILES PLC	2018	0.33007	0.54921	0.12628	2.11829	0.70409	1.32269	0.11539
	2017	0.32402	0.52569	0.14924	3.45643	0.61921	1.36047	0.14269
	2016	0.25087	0.38195	0.16086	2.33679	0.89247	0.65574	0.20649
	2015	0.18290	0.32015	0.14107	2.42905	0.83501	0.44318	0.15100
	2014	0.31960	0.46675	0.18185	3.07898	0.72156	1.50364	0.08491
LAUGFS GAS	2018	-0.24942	-0.02034	0.00910	0.32294	0.64194	-0.15175	-0.06357

PLC	2017	-0.02689	0.17802	0.03148	0.47555	0.43861	-0.08775	-0.01094
	2016	0.13576	0.24352	0.07109	0.91887	0.48672	0.26683	0.07369
	2015	0.08273	0.37051	0.15116	2.85878	0.82370	0.79844	0.03548
	2014	0.08742	0.33138	0.13967	2.88738	0.93226	0.67673	0.10506
LAXAPANA BATTERIES PLC	2018	0.02606	0.05112	0.13106	2.20968	1.40793	0.15069	0.03375
	2017	0.05924	0.11760	0.17102	2.94353	1.35694	0.31561	0.09713
	2016	0.11927	0.17715	0.14345	3.17780	1.28524	0.38491	0.13736
	2015	0.10481	0.08459	0.09053	3.22903	0.70879	0.25771	0.05382
	2014	0.05147	0.07004	0.08585	3.90091	0.50842	0.33273	0.05086
LEE HEDGES PLC	2018	0.33479	0.83371	0.09151	15.87046	0.00103	12.83746	0.11421
	2017	0.73861	0.81662	-0.00228	15.03939	0.00179	1.65188	0.04381
	2016	0.75771	0.82501	-0.00357	23.40737	0.00169	1.98949	0.03058
	2015	0.76912	0.83168	-0.00381	51.48355	0.00132	5.15803	0.04591
	2014	0.79296	0.82880	0.31007	49.87092	0.00116	28.07790	0.35079
LION BREWERY CEYLON PLC	2018	-0.01875	0.18254	0.11038	1.91818	0.92060	0.22917	0.06097
	2017	-0.05461	0.14067	-0.03160	1.87441	0.68217	-0.14923	-0.04545
	2016	-0.01333	0.21686	0.14144	2.06243	1.28159	0.37367	0.07411
	2015	-0.06173	0.17315	0.12672	2.72117	1.22821	0.25503	0.04608
	2014	0.05904	0.15271	0.09777	3.05634	1.07221	0.20510	0.05581
LOTUS HYDRO POWER PLC	2018	0.19391	-0.01121	0.03141	11.64086	0.17254	3.14629	0.02629
	2017	0.13121	0.01334	0.03336	16.62972	0.12912	4.38060	0.03234
	2016	0.15880	0.08764	0.05853	16.35355	0.14440	5.17401	0.05351
	2015	0.15618	0.12005	0.09831	7.01825	0.17877	6.66308	0.08439
	2014	0.00779	0.05065	0.01027	4.48336	0.10547	3.08707	0.01924
MAHAWELI REACH HOTELS PLC	2018	-0.01100	-0.00092	-0.00865	1.39020	0.35830	-0.22814	-0.02546
	2017	0.00391	0.02381	0.02556	2.10970	0.39020	0.12811	0.00505
	2016	0.02124	0.01761	0.06567	2.42121	0.40408	0.53082	0.03747
	2015	-0.00809	-0.02121	0.04399	2.81787	0.39064	0.29994	0.01655
	2014	-0.02843	-0.03923	0.05171	3.56440	0.42140	0.31331	0.02983
MERCANTILE SHIPPING COMPANY PLC	2018	0.04997	0.21482	0.01863	2.83929	0.15794	0.06951	0.03092
	2017	0.02257	0.18060	-0.05761	1.93262	0.14977	-0.14721	-0.07452
	2016	0.08185	0.22957	0.21877	2.44536	0.12687	0.60034	0.20532
	2015	-0.15537	0.02732	-1.90710	2.84412	0.13604	-4.17738	-1.89757
	2014	-0.02028	0.68732	-0.04485	4.52177	0.01495	-0.33277	-0.03400
MILLENNIUM HOUSING DEVELOPERS PLC	2018	0.20203	0.19276	-0.01412	3.11249	0.29947	-0.02473	-0.01389
	2017	0.26826	0.22326	0.03026	3.37840	0.47353	0.07464	0.02293
	2016	0.39906	0.21818	0.04942	1.83462	0.31946	0.17066	0.04468
	2015	0.49531	0.21934	0.06477	3.70578	0.39304	0.29190	0.05530
	2014	0.49664	0.20514	0.06696	4.61530	0.36537	0.38110	0.06730
MORISON PLC	2018	0.25807	0.21464	0.08193	0.47118	0.86130	0.20810	0.07913
	2017	0.45569	0.22683	0.08480	0.54974	1.16832	0.26463	0.09059
	2016	0.52492	0.20390	0.07216	1.53516	1.20189	0.24795	0.06531
	2015	0.59723	0.17974	0.07539	1.61210	1.02476	0.32123	0.06334

	2014	0.61293	0.19989	0.06543	1.83688	1.35705	0.42091	0.06348
MULLER AND PHIPPS (CEYLON) PLC	2018	0.37032	0.50455	-0.01542	6.41239	0.01157	4.25151	0.06127
	2017	0.37707	0.47407	0.12023	2.76637	0.01116	3.16200	0.19399
	2016	0.41253	0.51771	-0.01314	1.90865	0.01140	6.78173	0.05933
	2015	0.46749	0.54004	0.06555	2.85036	0.01090	18.43957	0.13396
	2014	0.73669	0.49991	0.04392	2.03793	0.06479	12.63130	0.12452
NESTLE LANKA PLC	2018	-0.05172	0.28869	0.29149	7.59614	2.11435	0.59287	0.19740
	2017	-0.12028	0.27373	0.31380	8.10706	2.41398	0.51021	0.23342
	2016	0.05790	0.37220	0.43071	13.78167	2.74424	0.87381	0.33107
	2015	0.01009	0.32869	0.44694	14.48742	2.86276	0.85056	0.34023
	2014	-0.01590	0.32965	0.44184	16.92201	3.05475	0.86221	0.35158
PANASIAN POWER PLC	2018	-0.20525	0.13455	0.08713	1.65494	0.09043	0.08243	0.02867
	2017	0.11481	0.10789	0.04267	1.46344	0.06715	-0.00040	0.00234
	2016	0.14421	0.15681	0.08582	1.93423	0.09589	0.79043	0.05394
	2015	0.20815	0.22449	0.14335	2.48193	0.09984	3.99137	0.12448
	2014	-0.14674	0.16702	0.10364	7.63918	0.11411	0.51081	0.09401
PEGASUS HOTELS OF CEYLON PLC	2018	0.02143	0.18477	0.03440	2.25730	0.26762	0.95470	0.03689
	2017	-0.00705	0.15862	0.00290	4.73186	0.19736	0.27840	0.01389
	2016	0.10618	0.20476	0.05726	7.14403	0.29239	1.51363	0.06666
	2015	0.07648	0.16409	0.05788	13.96342	0.27707	2.06603	0.06428
	2014	0.02768	0.11454	0.04174	11.23250	0.25067	1.07085	0.04771

Appendix IX: Collected Data for Distressed Sample

Company	**Year**	Working Capital/ Total Assets	Retained Earnings/ Total Assets	EBIT/Total Assets	Market Value of Equity/ Book value of Equity	Sales/Total Assets	Profit Before Tax/Current Liabilities	ROA
ACL CABLES PLC	2018	0.28898	0.33565	0.05759	1.03768	0.88307	0.13945	0.04731
	2017	0.31526	0.35615	0.13894	1.69941	0.92300	0.35848	0.11482
	2016	0.32301	0.28846	0.09034	1.60419	0.86334	0.26786	0.06921
	2015	0.21582	0.20606	0.06861	0.85773	0.88484	0.15941	0.05511
	2014	0.17033	0.19649	0.01763	0.97253	0.94436	0.03364	0.01466
ACME PRINTING & PACKAGING PLC	2018	-0.14693	-0.36319	0.03727	0.22499	0.61537	-0.05631	-0.03211
	2017	-0.16759	-0.33391	0.04780	0.39675	0.81027	-0.03685	-0.02549
	2016	-0.10412	-0.25987	0.03736	0.28280	0.67264	-0.02617	-0.01551
	2015	-0.10985	-0.21933	-0.07978	0.32446	0.61629	-0.21906	-0.07786
	2014	-0.07288	-0.17255	0.00772	0.44934	0.75943	-0.09591	-0.06187
CARGILLS CEYLON PLC	2018	-0.13533	0.30461	0.24424	11.92276	0.00191	0.88797	0.20088
	2017	-0.36248	0.31786	0.14154	5.28514	0.00235	0.24433	0.10381

	2016	-0.18457	0.36859	0.06870	8.18687	0.00228	0.17910	0.05292
	2015	-0.08017	0.36464	0.03763	8.19236	0.01070	0.03005	0.00506
	2014	-0.02929	0.12174	0.06268	2.18809	1.11751	0.06650	0.03268
CARSON CUMBERBATCH PLC	2018	-0.09558	0.74963	0.06207	20.63322	0.06839	0.36361	0.04854
	2017	-0.11839	0.75605	0.02122	22.12432	0.02507	0.07049	0.00906
	2016	-0.09278	0.78134	0.03410	24.80267	0.04066	0.25503	0.02738
	2015	-0.06656	0.82254	0.04853	57.01346	0.05370	0.54277	0.04417
	2014	-0.08758	0.74981	0.05489	72.12862	0.06214	0.32623	0.03654
CEYLON BEVERAGE HOLDINGS PLC	2018	-0.15618	0.39303	0.09572	21.52715	0.10388	0.36690	0.07152
	2017	-0.11382	0.40553	0.06549	27.40394	0.07196	0.34161	0.03478
	2016	0.00347	0.41532	0.11097	30.11141	0.11874	0.82606	0.08520
	2015	0.04442	0.45073	0.13629	38.39340	0.14342	1.35009	0.10098
	2014	0.06087	0.40468	0.12621	24.96836	0.13258	0.79750	0.07373
CEYLON HOSPITALS PLC (DURDANS)	2018	-0.08515	0.22717	0.02521	1.21904	0.54156	0.18276	0.02564
	2017	-0.05107	0.22785	0.02618	1.16026	0.52714	0.19603	0.03476
	2016	-0.06165	0.30408	0.05340	1.46296	0.69927	0.27326	0.05081
	2015	-0.04106	0.30178	0.04816	1.94579	0.68805	0.21260	0.03852
	2014	-0.02249	0.27809	0.06823	1.92343	0.63536	0.22988	0.04462
CEYLON HOTELS CORPORATION PLC	2018	-0.26983	0.08334	0.01612	1.93415	0.00461	-0.03086	-0.01655
	2017	-0.26773	0.22118	0.18283	4.15464	0.00617	0.37217	0.15424
	2016	-0.21845	-0.80184	0.03638	5.92994	0.00757	0.02183	0.00966
	2015	-0.24140	-0.83846	-0.01653	6.26345	0.00943	-0.09809	-0.05456
	2014	-0.34455	-0.82020	-0.00158	4.45192	0.05017	-0.09331	-0.04089
CEYLON PRINTERS PLC	2018	-0.05131	-0.06679	-0.02877	0.38442	1.77655	-0.10139	-0.06496
	2017	-0.02040	-0.00881	-0.11196	0.57706	1.57368	-0.28426	-0.11795
	2016	0.18086	0.06953	-0.04057	0.36964	1.08225	-0.12998	-0.04119
	2015	0.37193	0.34121	-0.01714	4.45752	1.82211	-0.05607	-0.02014
	2014	0.57132	0.54658	0.19742	6.25396	2.04788	1.24673	0.13226
CEYLON TEA BROKERS PLC	2018	0.06951	0.06614	0.16694	0.31606	0.31426	0.09781	0.05117
	2017	0.10364	0.08178	0.11805	0.44411	0.31288	0.05480	0.03096
	2016	0.16297	0.09359	0.10247	0.66948	0.38270	0.05528	0.02972
	2015	0.14649	0.07267	0.13149	0.44601	0.37607	0.07831	0.04727
	2014	0.05847	0.04103	-0.00157	0.42531	0.18262	0.06346	0.03960
CHEMANEX PLC	2018	0.72172	0.88547	0.15727	7.36058	0.35824	3.78772	0.15217
	2017	0.50828	0.68947	0.11133	3.57009	0.44528	1.03094	0.10609
	2016	0.48558	0.39512	0.06643	3.09405	0.71580	0.39955	0.04989
	2015	0.53677	0.43900	-0.02472	5.61981	0.73011	-0.24595	-0.02959
	2014	0.30707	0.39324	-0.00353	2.60980	0.54419	0.00561	-0.00815
CIC HOLDINGS PLC	2018	-0.10776	0.14024	0.03820	0.40091	0.82183	-0.01487	-0.03449
	2017	-0.02153	0.20355	0.08827	0.68873	0.75792	0.07449	0.01701
	2016	0.03537	0.20527	0.10575	1.27114	0.85110	0.16862	0.07546
	2015	0.04413	0.19167	0.10452	1.86681	0.93782	0.16925	0.06973
	2014	0.01006	0.14053	-0.00617	1.36752	0.76395	-0.06127	-0.11108

CITRUS LEISURE PLC	2018	-0.03880	0.06997	-0.01190	0.48907	0.01815	-0.40153	-0.02915
	2017	-0.02109	0.09764	0.00339	0.80745	0.01725	-0.27734	-0.01456
	2016	0.00825	0.10907	-0.00056	0.96357	0.00851	-0.11465	-0.00834
	2015	-0.06824	0.12469	-0.00295	1.39118	0.00586	0.01272	0.00067
	2014	0.04850	0.12342	-0.00713	2.24185	0.00081	0.02202	0.00178
CITY HOUSING & REAL ESTATE CO. PLC	2018	-0.01461	-0.37660	-0.01871	0.36187	0.06978	-0.01596	-0.02144
	2017	-0.10999	-0.32239	-0.01347	0.38989	0.14248	-0.01248	-0.01414
	2016	-0.08308	-0.34364	-0.06617	0.52496	0.21052	-0.03999	-0.03027
	2015	-0.06635	-0.31534	-0.08039	1.03317	0.36376	-0.07845	-0.05404
	2014	-0.00589	-0.25343	-0.00918	0.92516	0.23281	0.00820	0.02320
COLOMBO DOCKYARD PLC	2018	0.33648	0.54208	-0.00326	0.65646	0.87480	0.03271	0.00961
	2017	0.31868	0.48535	-0.01621	0.80840	0.72149	-0.01049	-0.00853
	2016	0.27597	0.43735	-0.02360	0.56759	0.52537	-0.04808	-0.02276
	2015	0.31792	0.50682	-0.04377	1.39035	0.83716	-0.10078	-0.04115
	2014	0.39122	0.58673	-0.00369	2.28689	0.83377	0.04230	0.01273
CONVENIENCE FOODS (LANKA)PLC	2018	0.56341	0.64376	0.20637	3.52932	1.53448	0.92631	0.13647
	2017	0.53685	0.67025	0.14486	3.97162	1.59772	0.84632	0.09000
	2016	0.44602	0.64871	0.16305	2.97358	1.76221	0.69933	0.10192
	2015	0.39746	0.57820	0.30888	3.78319	1.92831	0.84185	0.18251
	2014	0.27892	0.52083	0.17571	2.83968	1.89589	0.60611	0.12129
DIESEL & MOTOR ENGINEERING PLC	2018	0.06785	0.23590	0.05126	0.19746	1.56191	0.03550	0.01247
	2017	0.10771	0.27995	0.07284	0.35885	1.94517	0.08479	0.02775
	2016	0.14699	0.30487	0.07092	0.50966	1.83881	0.12996	0.03842
	2015	0.13552	0.31163	0.06199	0.64308	1.53240	0.11230	0.03199
	2014	0.15538	0.31652	0.04437	0.69805	1.24557	0.05452	0.01817
DIPPED PRODUCTS PLC	2018	0.07329	0.55118	0.03467	2.16577	0.32414	0.08769	0.02336
	2017	-0.07587	0.44846	0.06820	1.90033	0.28274	0.14408	0.05630
	2016	-0.05943	0.42920	0.03387	2.08827	0.29313	0.06304	0.02411
	2015	-0.03916	0.42364	0.10182	2.39196	0.41682	0.25750	0.09995
	2014	-0.00081	0.45159	0.07520	4.12290	0.46790	0.22163	0.07531
DISTILLERIES COMPANY OF SRI LANKA PLC	2018	-0.05897	-0.01940	0.32796	4.02397	3.74776	0.44389	0.18034
	2017	-0.29934	-1.30641	0.40985	3.45816	3.95874	0.41929	-3.07079
	2016	-0.04713	0.59405	0.12146	4.34762	1.03886	0.53926	0.07638
	2015	-0.09620	0.59423	0.20566	5.00513	0.79658	0.92858	0.15816
	2014	-0.07271	0.46850	0.14508	3.63093	0.78045	0.47361	0.08756
ASIRI HOSPITAL HOLDINGS PLC	2018	-0.24898	0.08754	0.13940	2.62755	0.21342	0.26009	0.07195
	2017	-0.19614	0.06195	0.12972	3.21494	0.20751	0.28507	0.07571
	2016	-0.16933	0.06044	0.08391	3.81161	0.18839	0.21968	0.04471
	2015	-0.86482	0.18056	0.08189	1.50431	0.18367	0.05582	0.05006
	2014	-0.07490	0.18218	0.11171	4.08324	0.18521	0.49266	0.18521
ANILANA HOTELS AND PROPERTIES	2018	-0.26800	-0.83856	-0.45120	0.72970	0.04153	-1.78704	-0.50355
	2017	-0.07104	-0.24534	-0.00830	0.35096	0.04316	-0.17953	-0.03439
	2016	-0.05178	-0.20723	-0.01886	0.60040	0.04469	-0.24230	-0.04129

PLC	2015	0.13506	-0.16388	-0.03709	1.42402	0.02407	-0.48161	-0.07140
	2014	0.09960	-0.09467	-0.02920	2.32667	0.01679	-0.14551	-0.02584
BERUWALA RESORTS PLC	2018	-0.16288	0.19067	0.09380	0.90475	0.41117	0.22574	0.04666
	2017	-0.15402	0.14986	0.09963	1.01948	0.37854	0.25535	0.05344
	2016	0.12861	0.09989	0.08138	1.44288	0.40941	0.20122	0.04247
	2015	0.08163	0.07221	0.02832	2.64934	0.37550	0.01099	-0.00812
	2014	0.04713	0.07538	0.04541	3.05344	0.37029	0.07798	0.01952
BLUE DIAMONDS JEWELLERY WORLDWID E PLC	2018	0.42388	-1.17418	-0.11734	1.54048	0.14325	-0.66081	-0.08216
	2017	0.56049	-1.14516	-0.24723	3.22328	0.10102	-1.63992	-0.23805
	2016	0.60395	-0.89422	-0.29779	7.50619	0.20799	-2.27671	-0.27351
	2015	0.71001	-0.50543	-0.25007	7.89528	0.16826	-3.54608	-0.23810
	2014	0.57615	-0.30125	-0.13474	6.51653	0.15901	-0.74602	-0.11423
BOGAWANT ALAWA TEA ESTATES PLC	2018	-0.08491	0.21246	0.10751	0.26840	0.76226	0.33576	0.03628
	2017	-0.09204	0.17831	0.05027	0.50637	0.67947	0.09488	0.02277
	2016	-0.01753	0.13189	0.01939	0.28264	0.70765	0.00491	0.00087
	2015	-0.02282	0.10923	0.04903	0.32567	0.74226	0.15589	0.03129
	2014	0.00895	0.09386	0.00870	0.37192	0.73052	-0.06177	-0.01089
BROWN & COMPANY PLC	2018	-0.02821	0.42081	0.04060	0.88173	0.41840	0.06149	0.02333
	2017	0.05234	0.46581	0.02403	0.47031	0.44483	0.16309	0.05438
	2016	0.09669	0.46121	0.04310	0.64702	0.43419	0.07792	0.02209
	2015	0.06976	0.48103	0.07676	0.89943	0.31677	0.18553	0.05972
	2014	0.10942	0.51757	0.16158	1.40621	0.38035	0.46480	0.11290
E B CREASY & COMPANY PLC	2018	0.09044	0.33880	0.10739	1.09398	0.78869	0.11127	0.04103
	2017	0.03257	0.35218	0.12419	1.00598	0.87762	0.16867	0.08124
	2016	0.00934	0.35564	0.11015	1.19708	0.87586	0.16507	0.06349
	2015	-0.14292	0.36769	0.10103	1.20704	0.87376	0.15346	0.06564
	2014	-0.02565	0.41778	0.10920	1.70773	0.96514	0.18786	0.08194
EDEN HOTEL LANKA PLC	2018	-0.45239	-0.07254	0.01461	0.23301	0.09928	-0.09144	-0.05617
	2017	-0.14280	-0.02569	-0.01371	0.65296	0.14730	-0.17365	-0.04734
	2016	-0.22839	0.02256	0.01550	0.51284	0.14162	-0.05195	-0.01392
	2015	-0.13233	0.04129	-0.00449	0.37455	0.12574	-0.26126	-0.04420
	2014	-0.06542	0.08196	0.01964	0.56997	0.12465	0.04185	0.00300
ELPITIYA PLANTATIO NS PLC	2018	0.05094	0.41608	0.10842	0.70486	0.59897	1.10379	0.05608
	2017	0.03166	0.42027	0.10546	1.12112	0.52547	0.90511	0.08558
	2016	-0.01282	0.34152	0.05807	0.67748	0.45317	0.37071	0.04047
	2015	-0.03098	0.31881	0.08767	0.76549	0.50963	0.46773	0.06720
	2014	-0.01220	0.29520	0.10660	0.82557	0.57956	0.58293	0.07120
EXPOLANKA HOLDINGS PLC	2018	0.01778	0.10097	-0.05105	11.35970	0.02069	-0.43556	-0.03483
	2017	0.13075	0.18314	-0.06275	22.02452	0.01917	-7.46243	-0.08282
	2016	0.32212	0.29482	-0.04203	63.01309	0.01999	-3.28484	-0.04226
	2015	0.37741	0.33091	0.05868	29.75071	0.02065	5.22510	0.05837
	2014	0.31846	0.29306	0.15369	35.13352	0.02180	13.35601	0.15322
HAPUGASTE	2018	-0.27709	0.08368	-0.04834	0.23353	0.70082	-0.23326	-0.07938

NNE PLANTATIONS PLC	2017	-0.19476	0.16226	0.07782	0.47830	0.81303	0.15203	0.02741
	2016	-0.21049	0.12828	-0.03532	0.24756	0.64278	-0.18082	-0.05380
	2015	-0.16533	0.16839	-0.07046	0.39239	0.67314	-0.34934	-0.07945
	2014	-0.10462	0.24066	0.06321	0.71758	0.86208	0.20272	0.03690
HAYCARB PLC	2018	0.20791	0.53193	0.08140	1.28373	0.80620	0.27488	0.07681
	2017	0.15511	0.49387	0.12342	1.45239	0.72469	0.34971	0.11025
	2016	0.14240	0.46446	0.07465	1.53514	0.64693	0.18641	0.06310
	2015	0.18164	0.50519	0.07115	1.98901	0.73950	0.23888	0.05866
	2014	0.22511	0.51965	0.11663	1.95039	0.99478	0.29281	0.09874
HAYLEYS FIBRE PLC	2018	0.67119	0.68570	0.03799	6.03501	0.64743	1.52800	0.11618
	2017	0.66334	0.64726	0.29309	6.82668	0.58281	4.03090	0.32521
	2016	0.15490	0.18243	0.02073	6.07949	0.75711	0.17546	0.02806
	2015	0.13889	0.12109	0.00240	1.62175	0.76052	0.02895	0.00388
	2014	0.12083	0.05896	0.03473	1.83116	0.51770	0.15469	0.02358
HIKKADUWA BEACH RESORT PLC	2018	-0.15452	0.02582	0.01013	0.43883	0.04983	-0.07125	-0.02493
	2017	-0.04913	0.19027	0.03805	1.27518	0.16411	0.34173	0.04221
	2016	-0.01094	0.15885	0.03326	1.53553	0.16796	0.32065	0.03315
	2015	-0.02080	0.17034	0.04928	6.27380	0.20154	0.34557	0.04964
	2014	0.28404	0.10525	0.05502	1.62137	0.17405	0.30872	0.05478
HORANA PLANTATIONS PLC	2018	-0.10226	0.29800	0.05186	0.16497	0.60868	0.13305	0.02283
	2017	-0.08581	0.29605	0.01289	0.29808	0.54818	-0.06082	-0.01175
	2016	-0.09470	0.31412	-0.01230	0.22494	0.53453	-0.13291	-0.02313
	2015	-0.03139	0.32951	0.03456	0.27765	0.64601	0.17446	0.01849
	2014	-0.04998	0.34278	0.06909	0.35322	0.73617	0.31468	0.04452
HVA FOODS PLC	2018	0.06953	-0.00127	0.04708	0.30431	0.82274	0.03803	0.02920
	2017	0.06771	-0.03539	0.00633	0.50924	0.66568	-0.02296	-0.01569
	2016	0.07577	-0.02181	0.00979	0.51949	0.61807	-0.01872	-0.01573
	2015	0.08034	-0.00715	0.01487	0.73108	0.69211	-0.00613	-0.00203
	2014	0.15334	-0.00615	-0.00376	1.18439	0.66813	-0.02020	-0.01608
INDUSTRIAL ASPHALTS (CEYLON) PLC	2018	-0.10068	0.71118	0.73993	2.05616	0.06717	4.12773	0.72196
	2017	-0.04653	-0.04774	-0.02317	2.98285	0.18578	-0.18084	-0.07292
	2016	0.05161	0.02237	-0.06205	2.26055	0.48148	-0.15426	-0.06809
	2015	0.22166	0.11894	0.03798	3.41873	0.44551	0.07614	0.02023
	2014	0.35358	0.15938	0.01718	9.28905	0.53708	-0.02187	-0.00356
KAHAWATTE PLANTATIONS PLC	2018	-0.42133	-0.00685	-0.00871	0.85710	0.67715	-0.11349	-0.05427
	2017	-0.33132	0.02890	0.04892	0.87633	0.82685	0.01062	0.00394
	2016	-0.28411	0.00647	-0.00473	0.87568	0.64246	-0.08702	-0.03205
	2015	-0.24295	0.01043	-0.03502	0.97097	0.67524	-0.14721	-0.04756
	2014	-0.12552	0.05321	0.05738	1.02748	0.79668	0.13275	0.03026
KELANI VALLEY PLANTATIONS PLC	2018	0.00916	0.42382	0.07468	0.98492	0.66777	0.42009	0.04970
	2017	-0.00687	0.40697	0.03144	0.92601	0.55697	0.06279	0.00629
	2016	0.01005	0.37171	-0.00409	0.71912	0.58116	-0.19772	-0.01761
	2015	0.04814	0.40783	0.04243	0.68439	0.88221	0.30456	0.02082

	2014	0.11954	0.41929	0.07644	0.88080	0.78519	0.74300	0.06316
LANKA WALLTILES PLC	2018	0.09610	0.34030	0.12538	1.36510	0.42403	0.51674	0.08836
	2017	0.10585	0.38386	0.16155	2.74160	0.51473	0.77981	0.11890
	2016	0.08642	0.33243	0.14335	2.44217	0.50369	0.65508	0.10097
	2015	0.00976	0.33613	0.12823	2.26951	0.54849	0.27075	0.09213
	2014	-0.00339	0.30250	0.07381	1.83099	0.45496	0.09055	0.03396
LANKEM CEYLON PLC	2018	-0.22170	0.01495	0.01921	0.13171	0.56191	-0.11784	-0.06881
	2017	-0.21632	0.08423	-0.02262	0.20850	0.56319	-0.13742	-0.08366
	2016	-0.22483	0.16953	-0.00535	0.23767	0.72217	-0.07201	-0.04635
	2015	-0.14342	0.21750	0.04236	0.38293	0.64867	0.03211	0.02123
	2014	-0.12399	0.20742	0.00032	0.48691	0.77233	-0.04860	-0.03329
LUCKY LANKA MILK PROCESSING COMPANY PLC	2018	-0.12608	-0.20810	-0.07677	0.20916	0.86504	-0.30864	-0.14661
	2017	-0.06722	-0.06325	-0.01172	0.43653	0.91725	-0.13376	-0.05015
	2016	0.02847	-0.01655	0.01527	0.99623	0.87106	-0.05912	-0.02181
	2015	0.03352	0.00727	0.02060	1.50020	0.96071	-0.09187	-0.03267
	2014	-0.08008	0.05256	0.10301	2.02032	1.17039	0.04417	0.00922
MACKWOODS ENERGY PLC	2018	0.34375	-0.01625	0.00595	2.37435	0.00857	-0.26506	-0.02262
	2017	0.35854	0.00620	-0.01538	2.63445	0.03150	0.01408	-0.00308
	2016	0.40826	0.01067	0.08165	3.58830	0.24089	-0.96674	-0.10505
	2015	0.52306	0.12590	-0.01445	5.91317	0.29638	-0.07224	-0.01275
	2014	0.54857	0.15376	0.01052	10.96925	0.26583	0.61089	0.02529
MADULSIMA PLANTATIONS PLC	2018	-0.26099	-0.63901	-0.03565	0.26984	0.37229	-0.21601	-0.10418
	2017	-0.17907	-0.55164	0.05412	0.82705	0.49548	0.08454	0.00848
	2016	-0.22418	-0.53671	-0.03074	0.45816	0.35089	-0.17759	-0.05573
	2015	-0.16265	-0.50299	-0.03361	0.55797	0.36719	-0.24172	-0.05657
	2014	-0.36794	-0.43199	-0.01586	0.12425	0.45372	-0.12263	-0.05707
MALWATTE VALLEY PLANTATIONS PLC	2018	-0.19340	0.18946	0.02760	0.02874	0.76617	0.09859	0.01720
	2017	0.14604	0.24222	0.09993	0.08001	0.77309	0.68573	0.09303
	2016	0.09779	0.16821	0.02319	0.22838	0.48262	0.08024	0.01165
	2015	-0.15033	0.16490	-0.04605	0.25710	0.54643	-0.29199	-0.05293
	2014	0.18205	0.22629	0.01269	0.38479	0.68579	0.08848	0.00461
MARAWILA RESORTS PLC	2018	-0.16083	-0.24438	0.02863	0.59280	0.27524	0.02835	-0.00071
	2017	-0.14950	-0.18071	-0.01976	0.73825	0.26204	-0.22653	-0.04938
	2016	-0.08604	-0.11456	0.02175	0.93530	0.24213	-0.06556	-0.00874
	2015	-0.26703	-0.10391	-0.02018	0.72019	0.18372	-0.16260	-0.04822
	2014	-0.21435	-0.05255	0.03968	0.80019	0.21787	0.02693	0.00742
MASKELIYA PLANTATIONS PLC	2018	-0.18605	-0.16908	0.11970	0.15321	0.97091	0.21047	0.05403
	2017	-0.25318	-0.20743	0.03595	0.34254	0.77783	-0.04298	-0.02087
	2016	-0.23316	-0.19692	-0.05963	0.12241	0.74369	-0.25916	-0.10642
	2015	-0.14286	-0.12298	-0.02335	0.15126	0.79431	-0.14975	-0.04147
	2014	-0.03835	-0.07659	-0.01051	0.24149	0.81303	-0.13056	-0.02194
MTD WALKERS	2018	-0.18449	-0.17673	-0.06688	0.27014	0.01657	-0.25531	-0.12294
	2017	0.11867	-0.05284	-0.00731	0.68671	0.01502	-0.21460	-0.03657

PLC	2016	0.23972	-0.01740	-0.01033	1.63109	0.01469	-0.34141	-0.02271
	2015	0.05769	0.00630	0.04754	4.66196	0.05155	0.65206	0.03943
	2014	-0.11958	-0.04029	-0.01500	6.17932	0.01060	-0.02959	-0.00858
NAMUNUKULA PLANTATIONS PLC	2018	-0.04540	0.50130	0.13520	0.80791	0.63619	0.79468	0.08371
	2017	-0.03669	0.53405	0.11954	1.30794	0.60660	0.80031	0.09705
	2016	-0.07264	0.48779	0.02846	1.01888	0.47385	0.09375	0.01724
	2015	-0.04585	0.47416	0.04578	0.84780	0.56443	0.24113	0.03890
	2014	0.17688	0.54313	0.13444	1.92812	0.65885	1.58599	0.10576
NAWALOKA HOSPITALS PLC	2018	0.15677	0.00270	0.09422	0.71449	0.33840	0.10179	0.04301
	2017	0.10545	-0.03189	-0.00146	0.82991	0.29227	-0.12673	-0.04970
	2016	0.18692	0.03248	0.02523	0.97507	0.35543	-0.08604	-0.01600
	2015	0.12919	0.08182	0.06312	1.09429	0.42020	0.07937	0.01513
	2014	0.03592	0.13299	0.08555	1.51455	0.62075	0.13795	0.03166
ODEL PLC	2018	-0.06878	0.12746	0.03996	0.92490	0.49563	0.02330	0.00899
	2017	-0.01379	0.14028	0.06230	1.00842	0.55853	0.13566	0.03407
	2016	-0.03616	0.13196	0.04874	2.07328	0.58918	0.12528	0.02539
	2015	0.14878	0.14786	0.03558	2.80081	0.71474	0.07856	0.01887
	2014	0.37515	0.14634	0.05480	3.37514	0.70990	0.16890	0.03731
PALM GARDEN HOTELS PLC	2018	-0.28705	-0.18318	0.06026	0.66984	0.31788	0.08502	0.02486
	2017	-0.22721	-0.23349	0.00149	1.14629	0.25721	-0.11414	-0.02671
	2016	-0.07686	-0.23825	-0.00061	3.87092	0.24259	-0.10445	-0.00905
	2015	-0.06918	-0.28588	-0.00589	7.17300	0.25605	-0.67944	-0.05577
	2014	-0.22115	-0.25707	-0.00409	0.57652	0.28761	-0.24273	-0.06731
PARAGON CEYLON PLC	2018	0.29468	0.22021	-0.22216	17.03675	0.11816	-0.37897	-0.44387
	2017	0.32712	0.43942	-0.11631	14.75706	0.20571	-0.25431	-0.07260
	2016	0.45987	0.41169	-0.16798	14.16963	0.17835	-0.43365	-0.15043
	2015	0.68725	0.65850	-0.01080	58.95865	0.30169	0.02383	0.00139
	2014	0.67175	0.64743	0.03763	30.55866	0.92515	0.45903	0.02966
ROYAL CERAMICS LANKA PLC	2018	-0.14225	0.38989	0.13958	0.87139	0.18027	0.40671	0.10594
	2017	-0.08065	0.42487	0.12368	1.77629	0.25216	0.41090	0.08960
	2016	-0.07210	0.42695	0.10810	1.94668	0.23929	0.51005	0.08383
	2015	-0.08015	0.39756	0.07248	1.80611	0.18997	0.19066	0.05588
	2014	-0.03572	0.39913	0.09028	2.07088	0.18508	0.27929	0.06553
SIGIRIYA VILLAGE HOTELS PLC	2018	0.04679	0.20781	0.11818	1.01893	0.42895	0.31608	0.06356
	2017	-0.01395	0.18238	0.04892	0.99571	0.34828	0.05072	0.00963
	2016	0.00873	0.25961	0.09972	1.88843	0.38160	0.31631	0.06373
	2015	0.12204	0.20400	0.00849	1.94555	0.29717	-0.02980	-0.01270
	2014	0.15937	0.25725	0.04950	3.11068	0.34994	0.28377	0.02371
SRI LANKA TELECOM PLC	2018	-0.08845	0.28855	0.01329	0.03971	0.34210	0.08682	0.01376
	2017	-0.17789	0.30305	0.00193	0.04407	0.33343	0.04486	0.01069
	2016	-0.13365	0.34094	0.00988	0.05862	0.36515	0.07715	0.01460
	2015	-0.07274	0.38859	0.02301	0.11253	0.39360	0.12553	0.01677
	2014	0.00857	0.40365	0.02249	0.13576	0.39337	0.24737	0.03357

SWADESHI INDUSTRIAL WORKS PLC	2018	0.03706	0.05039	0.05752	2.48356	1.16809	0.02758	0.01186
	2017	-0.10417	0.01795	-0.03640	2.22405	1.28423	-0.15782	-0.08668
	2016	-0.05389	0.16004	0.07031	2.27568	2.08680	0.02734	0.01330
	2015	-0.09024	0.17350	0.07493	1.31935	2.36181	-0.09237	-0.07588
	2014	-0.11386	0.27629	0.09344	4.89119	2.25763	0.04753	0.02505
SWISSTEK (CEYLON) PLC	2018	-0.01006	0.08412	0.13242	1.61991	0.42549	0.61231	0.10332
	2017	0.00745	0.04531	0.13815	5.88472	0.43771	0.76586	0.10316
	2016	-0.00357	-0.00976	0.10711	7.90859	0.39993	0.67350	0.05745
	2015	-0.01356	-0.06137	0.09426	6.01948	0.30847	0.49124	0.08359
	2014	-0.05376	-0.17423	0.08343	3.11811	0.34686	0.26880	0.05381
TAL LANKA HOTELS PLC	2018	-0.05489	-0.18844	0.05919	0.65310	0.53147	0.15868	0.01817
	2017	-0.06483	-0.21631	0.06190	0.74658	0.52944	0.12101	0.01940
	2016	-0.08393	-0.28828	0.05866	1.10908	0.57251	-0.12490	-0.02512
	2015	-0.09032	-0.27390	-0.01667	1.10523	0.41346	-0.26326	-0.03772
	2014	-0.01871	-0.26495	-0.09473	1.72159	0.28221	-0.82911	-0.11576
TALAWAKEL LE TEA ESTATES PLC	2018	0.16977	0.47585	0.13648	0.58323	0.89285	1.02468	0.12267
	2017	0.08688	0.43448	0.08046	0.70835	0.84087	0.57733	0.06245
	2016	0.02454	0.30781	0.05718	0.36853	0.91560	0.33573	0.03040
	2015	0.02437	0.30245	0.09327	0.35653	1.23879	0.45984	0.06090
	2014	0.02437	0.30245	0.09327	0.37232	1.23879	0.45984	0.06090
TESS AGRO PLC	2018	-0.32584	-0.48901	-0.03163	0.44796	0.55333	-0.18251	-0.08893
	2017	-0.20756	-0.38736	-0.08799	0.93633	0.56719	-0.38507	-0.10620
	2016	0.01751	-0.16204	-0.05355	0.98495	0.60083	-0.29352	-0.08972
	2015	0.05417	-0.06398	-0.04681	1.32390	0.67367	-0.25980	-0.07691
	2014	0.22190	0.02464	0.00591	1.58981	0.54869	-0.14480	-0.02775
SINGHE HOSPITALS PLC	2018	-0.10971	-0.60734	-0.02731	1.24312	0.55868	-0.36944	-0.05611
	2017	-0.10077	-0.51405	-0.03427	1.48388	0.43105	-0.38955	-0.08289
	2016	0.00068	-0.40694	-0.04446	1.71921	0.30911	-0.41496	-0.07689
	2015	0.08106	-0.33447	-0.03105	1.94392	0.24768	-0.30193	-0.07213
	2014	-0.21244	-0.34762	-0.08662	1.47771	0.22860	-0.67026	-0.18342
TOKYO CEMENT COMPANY (LANKA) PLC	2018	-0.02770	0.37679	0.20725	0.51004	0.73762	0.80460	0.18320
	2017	-0.00317	0.38277	0.21355	1.75251	1.16297	0.88070	0.16657
	2016	0.01989	0.31571	0.11789	1.59770	0.81855	0.44666	0.08501
	2015	-0.07005	0.28651	0.08192	1.42914	0.98373	0.22176	0.04817
	2014	-0.03534	0.27364	0.11639	2.97437	0.95959	0.38019	0.08326