

**School of Business**

**Predicting Financial Distress Amongst Public Listed Companies in  
Malaysia using Altman's Z-Score Model and Auditors' Opinion on  
Going Concern**

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**This thesis is presented for the Degree of  
Doctor of Philosophy in Accounting and Finance  
of  
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## DECLARATION

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgment has been made.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

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Date : 26 December 2018

## ABSTRACT

Over the last five decades, the prediction of financial distress, pioneered by the Beaver univariate test and Altman Multiple Discriminant Analysis, is of paramount importance for stakeholders as a tool for timely identification of financial distress or “early warning system” for signs of business collapses. The Altman’s Z-Score Model, developed based on the United States data, is commonly used to predict financial status of Public Listed Companies (PLCs) in Malaysia. Given the problem statement, the objectives of this research are to improve the accuracy of the Altman’s Z-Score Model to predict financial distress amongst PLCs in Malaysia, and to develop the best model with the highest accuracy to predict financial distress amongst PLCs in Malaysia.

The framework in this study utilizes two major concepts, namely, the Altman’s Z-Score Model as the base model and the Auditors’ Opinion on going concern. The Auditors’ Opinion refers to the opinion expressed by the auditors in the audited financial statements and concerns its ability to continue as a going concern. Under the going concern assumption, a company is viewed as continuing in business for the foreseeable future with neither the intention nor the necessity of liquidation, ceasing trading or seeking protection from creditors pursuant to laws or regulations. Since prior studies have not used the Altman’s Z-Score Model with Auditors’ Opinion to predict financial distress, the employment of these models as a tool to alert early signal of business collapse is a significant contribution.

The research hypotheses are synthesized between the six independent variables affecting the dependent variable to test the mean Z-Score for PN17 (unhealthy) and NPN17 (healthy) companies. Mixed research method has been used, namely, quantitative (5 variables of the Altman’s Z-Score Model) and qualitative (Auditors’ Opinion as the 6<sup>th</sup> variable). The triangulation is established using five financial distress prediction models that employ the Multiple Discriminant Analysis (MDA) and Logistic Regression Analysis (LRA), with the revised models formulated based on data of PLCs in Malaysia.

The original 5 variables in the Altman's Z-Score Model has a prediction accuracy of 82.14% on average for the current and 1 year prior to financial distress and 70.71% on average for 2 to 5 years prior to financial distress. The revised model with 6 variables using LRA has been statistical proven to be the best model in Malaysia, with the highest prediction accuracy of 82.86% on average for the current and 1 year prior to financial distress and 77.5% for 2 to 5 years prior to financial distress. It has enhanced the relevance and financial distress prediction accuracy amongst PLCs in Malaysia which will benefit the investors, PLCs, regulators, researchers and other stakeholders.

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## GLOSSARY OF KEY ABBREVIATIONS

ANOVA	: Analysis of Variance
ANN	: Artificial Neural Network
Bursa Malaysia	: Bursa Malaysia Securities Berhad (Malaysian Stocks Exchange)
CA 1965	: Malaysian Companies Act, 1965
CA 2016	: Malaysian Companies Act, 2016
FRS	: Financial Reporting Standards
FSRC	: Malaysian Financial Statements Review Committee
GCO	: Modified Going Concern Opinion
GDP	: Gross Domestic Products
LRA	: Logistic Regression Analysis
MANOVA	: Multivariate Analysis of Variance
MASB	: Malaysian Accounting Standards Board
MASBs	: Malaysian Accounting Standards
MDA	: Multiple Discriminant Analysis
NPN17	: Non-Practice Note 17
PLCs	: Public Listed Companies

PN17	: Practice Note 17
SC	: Securities Commission Malaysia
SPSS	: Statistical Package for the Social Sciences

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## RELATED PRESENTATIONS

### PRESENTATIONS

- a) Presented summary of proposal for research topic on “Predicting Financial Distress amongst Public Listed Companies in Malaysia Using Altman’s Z-Score Model and Auditors’ Opinion on Going Concern” at the Postgraduate Research Colloquium organized by Asia e University in Kuala Lumpur, Malaysia, on 16<sup>th</sup> December 2012.
- b) Presented research paper on “Predicting Financial Distress amongst Public Listed Companies in Malaysia - the Accuracy and Effectiveness of Altman’s Z-Score Model” at the Postgraduate Research Conference 2015 organized by Asia e University in Kuala Lumpur, Malaysia, on 4<sup>th</sup> October 2015.
- c) Presented research paper on “Predicting Financial Distress amongst Public Listed Companies in Malaysia – Evaluating and Improving Accuracy of Altman’s Z-Score Model” at the North Borneo Research Colloquium 2016 organized by Curtin University Sarawak, Malaysia, on 18<sup>th</sup> and 19<sup>th</sup> April 2016.

## CHAPTER ONE

### 1 INTRODUCTION

#### 1.1 Introduction

This chapter provides an overview of the background and significance of study, research aims and objectives, research questions, research gaps, scope of study and theoretical framework of this research.

In the early and mid-1990s, the Malaysian economy had experienced a high growth with an annual Gross Domestic Products (GDP) growth of 7% to 8%. During this high economic growth period, Malaysian companies, including Public Listed Companies (PLCs), had adopted high growth strategies by diversifying their businesses without proper cost-and-benefit analysis which were made possible by easy access to financing from financial institutions (Abu-Bakar, 2001). Mohd-Nasir and Abdullah (2004) revealed that the gearing ratio of the distressed sub-sample was 12 times higher than the gearing ratio of non-financial distress companies. In 1998, the interest rate increased significantly exceeding double-digit and the Malaysian currency depreciated drastically against major currencies of other countries. These factors had caused companies with high debts, incurred in the 1990s, being unable to service the debts that resulted in a total of 276 Bursa Malaysia (Malaysian Stocks Exchange) listed companies having their non-performing loans taken over by the National Asset Management.

The volatility of the world economies from the 2000s and 2010s, with the global financial crisis particularly the Eurozone debt crisis and slowing down of the economy of major developed countries, had resulted in challenging business environment for the PLCs in Malaysia.

## **1.2 Background of Study**

Prediction of financial distress has been of considerable interest to stakeholders, financial institutions, regulatory bodies and government. Early identification of financial distress of PLCs is crucial in view of numerous challenges faced by these companies in both domestic and international markets.

Malaysia, as a developing country, is exposed to the vulnerability of global economy due to the country's open and export dependent economy. Any global recession will have detrimental effects on the Malaysian PLCs. Therefore, this study attempts to develop a prediction model which focuses on the PLCs in Malaysia to gauge the warning signals of financial distress in order to strategize their survival techniques.

This research focuses on prediction of financial distress amongst the PLCs in Malaysia, using the Altman's Z-Score Model as the base model and the Auditors' Opinion on going concern as an additional variable. A revised financial prediction model using Malaysian data could enhance the accuracy, relevance and potentially broaden the applications in Malaysia.

## **1.3 Problem Statement**

The Asian financial crisis had adversely affected Malaysia's economy in July 1997, resulting in the PLCs in Malaysia to fall into financial distress because they were unable to cope with the unexpected downturn. The subprime mortgage crisis and financial crisis outbreak of the period between 2007 and 2008 in the United States had affected the entire world economy. This global recession also had detrimental effects on the Malaysian PLCs.

At its height, at 1<sup>st</sup> September 2010, there were 36 financial distressed PLCs classified as PN17 by Bursa Malaysia. These figures are taken and highlighted as the problem statement in this research, as they were the latest and most recent data available at the time of registration for this study.

The financial distress prediction research findings in developed economies, according to Her and Choe (1999), cannot be applied to companies in Malaysia due

to the differences in market structures, socio-economic factors, provision and implementation of law, political environment and accounting standards. However, the Altman's Z-Score Model (based on data of the United States of America) is commonly used in predicting the financial status of PLCs in Malaysia. In addition, according to the World Bank report, market capitalization of PLCs in Malaysia as a percentage of GDP was 144.9 in 2017. The market capitalization of the PLCs was RM 1.9 trillion with over 900 PLCs as at 31 December 2017 (Bursa Malaysia Annual Report, 2017). Therefore, the identification of financial distress would enable corrective actions to be taken to assist in preventing the failure of PLCs which would have significant and multiple impacts on Malaysia's economy. In view of the above, the researcher is motivated to assess the accuracy of the Altman's Z-Score Model to predict financial distress amongst the PLCs in Malaysia; and to improve and / or develop the best model with the highest accuracy to predict financial distress amongst the PLCs in the Malaysian context.

#### **1.4 Significance of Study**

The significance of the study stems from the fact that, while it ensures research continuity into the subject of the application of Altman's Z-Score Model in predicting financial distress of companies, it also incorporates the Auditors' Opinion on going concern as an additional independent variable which is relevant and imperative in the evaluation of contemporary company financial status.

In addition to shedding light on how financial accounting information is being used to determine the financial hardship or distress of companies, from the point of view of Malaysian companies, this study also contributes to bridging the gap that exists in exploring financial distress amongst the PLCs in Malaysia.

Also, this study will be able to shed more light on evaluation of the financial distress situation of PLCs in Malaysia including the application of the Altman's Z-Score Model and the Auditors' Opinion on going concern in the context of Malaysian PLCs.



On the whole, the significance of the investigation will be presented critically as Significance and Implications in section 6.4 in the final discussion and recommendations in Chapter 6 of this study. The sub-headings of the significance of the study will be presented as follows:

1. Theoretical Contribution (see section 6.4.1);
2. Implication to Practice or Managerial Implication (see section 6.4.2);
3. Implication to the Regulatory Authority (see section 6.4.3); and
4. Implication to Society and Investors (see section 6.4.4).

### **1.5 Justification for Auditors' Opinion on Going Concern**

Besides the multivariate techniques including that of the Altman's Z-Score Model, the Auditors' Opinion on going concern is also used to predict the financial distress of the company. However, the reliability of the Auditors' Opinion on going concern has been a subject of studies with mixed finding results that are inconclusive.

The Altman's Z-Score Model, the base theory for this study, is a quantitative model where the required information for the five financial variables is obtained from audited financial statements. These financial statements quantify information concerning the financial position of an entity and the results of its operations.

An auditor's report with its opinion adds a qualitative dimension to that information (Altman and McGough, 1974). In short, the Auditors' Opinion on going concern incorporates the quantitative information from the financial statements and qualitative information about the company to be audited before arriving at the Auditors' Opinion stated in the auditors' report in the audited financial statements.

The Auditors' Opinion is the best platform to convey professional judgment pertaining to a company's viability as it is an expression of the company's financial and other issues that may affect its ability to continue operations in the future. One of the Auditors' Opinions that signals an early warning of a company's viability is their

opinion on going concern. Going concern is an assumption that a company will continue operations for a foreseeable future and it has no intention to liquidate its operations. Therefore, the Auditors' Opinion on going concern, which may indicate financial distress, could be used as a tool and technique to enhance the financial distress prediction model.

On 1<sup>st</sup> August 2012, Silver Bird Group Berhad and two wholly-owned subsidiaries filed an action suit in the Kuala Lumpur High Court in relation to financial irregularities against both their external and internal auditors. This suit, premised on alleged negligence and breach of duty of care and/or their duties and responsibilities as auditors, is believed to be the first such legal action by a PLC in Malaysia against the auditors. The warning signs of business failure provided by the financial distress prediction model could have detected the factors contributing to such financial distress much earlier (Oh, 2012). This effort to predict financial distress could reduce bankruptcy costs, avoid financial distress and contribute towards business and financial environment stability. In addition, such prediction knowledge and skills can be useful for statutory auditors who are required by law to determine a company's ability to continue its existence as a going concern which creates the much needed transparency and accountability for effective corporate governance.

## **1.6 Research Aims and Objectives**

### **1.6.1 Research Aims**

In an attempt to develop a model to predict financial distress amongst the PLCs in Malaysia, using the Altman's Z-Score Model, the aims of this study are as follows:-

- a) To improve the accuracy of the Altman's Z-Score Model to predict financial distress amongst the PLCs in Malaysia; and
- b) To develop the best model with the highest accuracy to predict financial distress amongst the PLCs in Malaysia.

### **1.6.2 Research Objectives**

To achieve the first aim of this study, the prediction accuracy of the Altman's Z-Score Model was developed into a revised 5-Variable model using the said Malaysian data and subsequently redeveloped into the 6-Variable model, thus setting the three research objectives as follows:-

- a) To determine the prediction accuracy of the 5-Variable Altman's Z-Score Model to predict financial distress amongst the PLCs in Malaysia.
- b) To develop the revised 5-Variable Altman's Z-Score Models using Malaysian data to predict financial distress amongst the PLCs in Malaysia.
- c) To develop a 6-Variable model based on the 5-Variable Altman's Z-Score Model and the Auditors' Opinion on going concern, as the sixth variable, using Malaysian data to predict financial distress amongst the PLCs in Malaysia.

To achieve the second aim of this study, a comprehensive comparison is made of the accuracy of models based on the 5-Variable and 6-Variable prediction models, thus setting the fourth research objectives as follows:-

- d) To compare and analyze the 5-Variable and 6-Variable prediction models to establish the best model with the highest accuracy to predict financial distress amongst the PLCs in Malaysia.

### **1.7 Research Gaps**

There are several research gaps in the existing literature, from different perspectives, such as gaps in terms of studies that focus on financial distress in Malaysia. By focusing on the PLCs in Malaysia, this study attempts to fill this gap. Another area of a research gap relates to studies that focus on the use of the Altman's Z-Score Model in Malaysia. To fill this gap, this study seeks to investigate the application of the

Altman's Z-Score Model on the PLCs in Malaysia, employing the MDA and LRA at the same time for comparison purpose.

Besides these gaps, studies that have attempted to study financial distress in Malaysia with the aim of developing a revised financial distress prediction model suitable for Malaysia are limited and inconclusive. To offer a solution that will help to reduce such limitation and inconclusiveness, this study will develop a revised Altman's Z-Score Model where Auditors' Opinion on going concern is included as the sixth variable of the new model. In this manner, where the literature search has not found instances of the combination of the Altman's Z-Score Model and the Auditors' Opinion on going concern in the multivariate prediction model, this research will fill the research gap and constitute a seminal study.

## **1.8 Research Questions**

The progressive development of different stages in this study has necessitated a holistic approach that requires the following questions to be addressed, and presented in a summarized format as the research matrix in section 1.9 below.

### **1.8.1 Main Research Questions**

- a) How can the accuracy of the Altman's Z-Score Model be improved to predict financial distress amongst the PLCs in Malaysia?
- b) Which is the best model with the highest accuracy to predict financial distress amongst the PLCs in Malaysia?

### **1.8.2 Secondary Research Questions**

The following questions correspond to achieving the first aim of this study:-

- a) What is the prediction accuracy of the 5-Variable Altman's Z-Score Model in predicting financial distress amongst the PLCs in Malaysia?
- b) Can the prediction accuracy of the 5-Variable Altman's Z-Score Model be improved by using the data of the PLCs in Malaysia?

- c) Can the prediction accuracy of the 5-Variable Altman's Z-Score Model be improved by incorporating another variable, the Auditors' Opinion on going concern, as the 6-Variable model using the data of the PLCs in Malaysia?

The following questions correspond to achieving the second aim of this study:-

- d) What is the best revised model that can be used with the highest prediction accuracy for financial distress amongst the PLCs in Malaysia?

## 1.9 Research Matrix

The following matrix in Table 1.1 below is developed to enable a better understanding of the overall research aims, research objectives, and the main and secondary research questions in this study.

**Table 1-1 The Research Matrix for This Study**

Research Aims	Research Objectives	Main Research Questions	Secondary Research Questions
a) To improve the accuracy of Altman's Z-Score Model to predict financial distress amongst the PLCs in Malaysia; and	a) To determine the prediction accuracy of the 5-Variable Altman's Z-Score Model to predict financial distress amongst the PLCs in Malaysia. b) To develop a revised 5-Variable Altman's Z-Score Models, using Malaysian data, to predict financial distress amongst the PLCs in Malaysia.	a) How can the accuracy of Altman's Z-Score Model be improved to predict financial distress amongst the PLCs in Malaysia.	a) What is the prediction accuracy of the 5-Variable Altman's Z-Score Model in predicting financial distress amongst the PLCs in Malaysia?
			b) Can the prediction accuracy of the 5-Variable Altman's Z-Score Model be improved by using the data of the PLCs in Malaysia?
			c) Can the prediction accuracy of the 5-Variable Altman's Z-Score Model be improved by incorporating another variable, the Auditors' Opinion on going concern, as the 6-Variable model using the data of the PLCs in Malaysia?
b) To develop the best model with the highest accuracy to predict financial distress amongst the PLCs in Malaysia.	c) To develop a 6-Variable model based on the 5-Variable Altman's Z-Score Model and the Auditors' Opinion on going concern, as the sixth (6 <sup>th</sup> ) variable, using Malaysian data, to predict financial distress amongst the PLCs in Malaysia. d) To compare and analyze the 5-Variable and 6-Variable prediction models to establish the best model with the highest accuracy to predict financial distress amongst the PLCs in Malaysia.	b) Which is the best model with the highest accuracy to predict financial distress amongst the PLCs in Malaysia	d) What is the best revised model that can be used with the highest prediction accuracy for financial distress amongst the PLCs in Malaysia?

### **1.10 Scope of the Study**

The scope of study will set the research direction of this study. This research, focusing on the PLCs in Malaysia, is an attempt to develop a financial prediction model using the Altman's Z-Score Model and the Auditors' Opinion on going concern. It defines the financial distress companies as the PLCs that triggered any of the criteria pursuant to Practice Note 17 (PN17) of the Main Market Listing Requirements of Bursa Malaysia which came into effect on 3<sup>rd</sup> January 2005 and revised on 3<sup>rd</sup> August 2009 and 22<sup>nd</sup> September 2011.

As at 1<sup>st</sup> September 2010, 36 PLCs were classified as under PN17 by Bursa Malaysia. 35 PN17 companies, to be matched with 35 non-PN17 (NPN17) companies as paired samples with similar industry and size (measured by closest asset); and for the same financial period, are selected for this research to minimize bias in selecting the control group or holdout sample. Six (6) years of financial statements will be analyzed from the date the PLCs have been classified as the PN17 companies.

The base theory in this study is the Altman's Z-Score Model which is a quantitative model that requires information for the five financial variables obtained from the annual audited financial statements which quantify information concerning the financial position of an entity and the results of its operations. An auditor's report with its opinion, according to Altman and McGough (1974), adds a qualitative dimension to that information.

The Auditors' Opinion is the best platform to convey professional judgment pertaining to a company's viability as it is an expression of the company's financial position and others issues that may affect its ability to continue operations in the future. One of the Auditors' Opinions that signal as early warning of a company's viability is the going concern opinion which is an assumption that a company will continue operations for a foreseeable future and has no intention to liquidate its operations. Therefore, the Auditors' Opinion on going concern which may indicate financial distress could be used as a tool to enhance the financial distress prediction model.

## 1.11 Theoretical Framework

The theoretical framework used in this study utilizes two major concepts, namely, the Altman's Z-Score Model and the Auditors' Opinion on going concern.

### 1.11.1 The Altman's Z-Score Model

The five variables in the Altman's Z-Score Model are formulated as follows:-

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5$$

Where:

$X_1$  = Working Capital / Total Assets

$X_2$  = Retained Earnings / Total Assets

$X_3$  = Earnings before Interest and Taxes / Total Assets

$X_4$  = Market Value of Equity / Book Value of Debt (Total Liabilities)

$X_5$  = Sales / Total Assets

Z = Overall index or Z-Score

Z-Score < 1.81 indicates financial distress (Distress Zone)

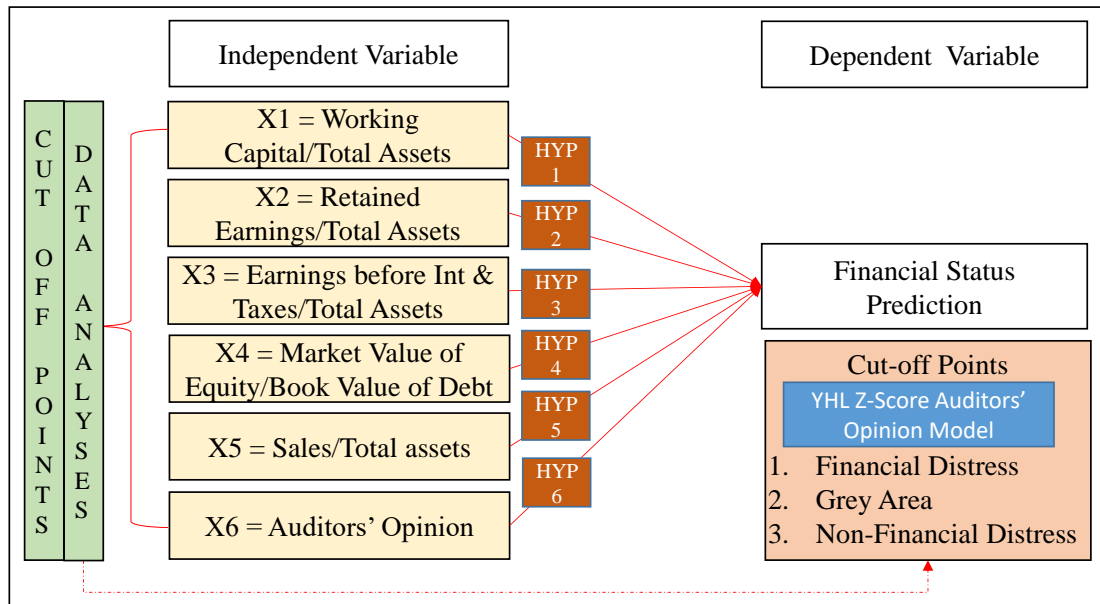
Z-Score between 1.81 and 2.99 indicates uncertain or grey area (Grey Zone)

Z-Score > 2.99 indicates non-financial distress (Safe Zone)

### 1.11.2 Factors that Contribute to Financial Distress

The auditors formed their opinion on going concern in the auditors' report based on the financial and non-financial factors that contribute to financial distress. The non-financial factors that caused financial distress amongst the PLCs in Malaysia based on the findings of Sawandi, Ahmad and Saad (2006) are fraud, non-compliance and potential breaches of regulations, incomplete records, related party transactions, lack of due diligence, poor internal control, product or service failure and limited access to financing or funding.

As stated previously, since the literature search has not found instances where the Altman's Z-Score Model is used in combination with the Auditors' Opinion on going concern it is imperative to fill the research gap with a new model financial distress prediction model known as the YHL Z-Score Auditors' Opinion Model whose theoretical framework is illustrated in Figure 1.1 below:



**Figure 1-1 Theoretical Framework for This Study**

Source: Researcher's own work

In this new model known as YHL Z-Score Auditors' Opinion Model, the Auditors' Opinion on going concern will incorporate the Altman's Z-Score Model as illustrated below:

$$Z = \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \beta_6X_6$$

Where:

$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$  and  $\beta_6$  = Coefficients formulated based on Malaysian data

X1 = Working Capital / Total Assets

X2 = Retained Earnings / Total Assets

X3 = Earnings before Interest and Taxes / Total Assets



$X4 = \text{Market Value of Equity} / \text{Book Value of Debt}$

$X5 = \text{Sales} / \text{Total Assets}$

$X6 = \text{Auditors' Opinion on going concern}$

$Z = \text{Overall index or Z-Score}$

The objective of the new model is to improve the accuracy of the Altman's Z-Score Model, using Malaysian data to predict financial distress amongst the PLCs in Malaysia.

## **1.12 Thesis Outline**

This thesis comprises six chapters as follows:-

### Chapter 1: Introduction

The introduction chapter presents an overview of the study, incorporating the background and significance of the study, an explanation of and justification to include the Auditors' Opinion on going concern, an espousal of the research aims and objectives of the study summarized as a research matrix. Next, the research gaps are identified followed by a set of main and secondary research questions that defines the scope of this study with a theoretical framework.

### Chapter 2: Public Listed Companies in Malaysia and Key Concepts

This chapter provides an introduction to the PLCs in Malaysia and the definitions of key concepts are explained. In addition, the financial reporting requirements are presented to provide a comprehensive overview of the industry in Malaysia, and an extensive enunciation of the financial distress, followed by the need for the Auditors' Opinion on going concern.

### Chapter 3: Review of Literature

This chapter presents a literature review relating to this study which includes a review of prior research related to the area of study conducted internationally and domestically in Malaysia. The international literature review is followed by univariate models such as the MDA, LRA (Logit Analysis) and Probit Analysis which are discussed including the Recursive Portioning. The Malaysian literature review that follows highlights an extensive focus on the Auditors' Opinion on going concern in conjunction with the Altman's Z-Score Model with which it combined to form the new theoretical framework in this study.

#### Chapter 4: Research Methodology and Hypotheses Development

This chapter captures the research methodology to achieve the research aims and objectives of this study, starting with an overall outline of the study and followed by the preparatory details that include explanations of literature review pertaining to the research methodology of this study. Subsequently, the research flow of this study, the research design, the research framework and research hypotheses are presented. The data acquisition and the data analyses strategy are presented in sequence, highlighting the presence of ethical considerations. Next, the prediction classification is offered.

#### Chapter 5: Results, Analysis and Discussion

This chapter deals with the research analysis, findings and results of this study. The data analyses done, with the aim to determine the best statistical model with the highest prediction accuracy of the financial distress for the PLCs in Malaysia, are discussed to ensure that the objective of this research is to collect the Malaysian data of the PLCs in Malaysia and compare its performance against the modified Altman's Z-Score Models to determine its prediction accuracy. Commencing with an explanation of the models tested together with the data collected, the hypotheses testing of X-Variables, and the hypotheses testing of Z-Score are discussed and presented. This is followed by the comparison of model characteristics, as discussed in the MDA and LRA for 5-Variables using the Malaysian data, followed by the MDA and LRA for 6-Variables of the Malaysian data. The completion of this stage

led to selecting the best model: the 6-Variable model using LRA with the highest accuracy to predict the financial distress among the PLCs in Malaysia.

## Chapter 6: Discussion, Recommendations and Conclusion

This final chapter summarises the findings and draws the conclusion on the findings of the empirical analysis presented in Chapter 5. The hypotheses on X Variables and the hypotheses on Z-Score are discussed, followed on by the Multiple Discriminant Analyses and Logistic Regression Analyses. The recall discussion on the research gaps, research strategy and research objectives are repeated to provide a balanced discussion of the whole study, including the research questions and the contribution to knowledge, the significance and implications, limitations and delimitations of the study as well. The recommendations for future studies include recommendations to how the PLCs can further improve its financial distress prediction.

In conclusion, the best statistical model with the highest accuracy has been recommended to predict the accuracy of the financial distress of the PLCs in Malaysia

### 1.13 Chapter Summary

In this introduction chapter, the researcher started with an overview of the study streamlined into the specific areas of interest for investigation. The background of the study was established in great detail for the benefit of the readers. Significance of the study section has identified in clear terms before the researcher introduced and justified the Auditors' Opinion on going concern in the study.

Next, the research aims and objectives of the study were highlighted for the reader's clear understanding. Following this the research questions were raised. Research gaps and scope of study were discussed and presented to cover the outline of the study. The major section of the research framework was presented in reference to the Altman's Z-Score Model and the factors contributing to the financial distress. The chapter was concluded with the thesis outline.

## CHAPTER TWO

### 2 PUBLIC LISTED COMPANIES IN MALAYSIA AND KEY CONCEPTS

#### 2.1 Introduction

This chapter introduces the Public Listed Companies (PLCs) in Malaysia, defines the key concepts in this study, and highlights the regulatory Acts of Parliament that govern the operation of the capital market in Malaysia.

The capital market in Malaysia is currently governed by the following Acts:

- Capital Market and Services (Amendment) Act 2007
- Securities Industry (Central Depositories Act) 1991
- Securities Commission (Amendment) Act 2011
- Futures Industry Act 1993
- Offshore Companies Act 1990
- Labuan Offshore Securities Industry Act 1995

The Bursa Malaysia is an exchange holding company approved under Section 15 of the Capital Market and Services Act, 2007. It operates the only fully integrated stock exchange in Malaysia. Since the 1990s, the Malaysian corporate sector has grown rapidly with a total market capitalisation of listed companies on the Main Board and Second Board of Bursa Malaysia having grown by an average of 40% per year throughout this period (KLSE, 2002).

According to the Bursa Malaysia Berhad Annual Report 2017, Bursa Malaysia is today one of the largest bourses in Asia with a market capitalisation of RM1.9 trillion as at 31 December 2017, and over 900 listed companies offering a diverse choice of portfolios to investors around the world.

## **2.2 The Capital Market Regulatory Framework**

The regulatory framework of the Malaysian capital market has been developed to perform the following functions:-

- a) To enable efficient mobilization and allocation of capital
- b) To provide a high level of market confidence
- c) To ensure fair markets and protection of investors
- d) To encourage innovation with minimum compliance cost

## **2.3 Historical Background of Bursa Malaysia**

In 1930, the Singapore Stockbrokers' Association was established as the first formal securities organisation in Malaysia. It was re-registered as the Malayan Stockbrokers' Association in 1937. The Malayan Stock Exchange was formed in 1960 and the public trading of shares commenced. The Stock Exchange of Malaysia was established in 1964 following the formation of Malaysia in 1963. With the secession of Singapore from Malaysia in 1965, the Stock Exchange of Malaysia was renamed as the Stock Exchange of Malaysia and Singapore.

In 1973, the currency inter-changeability between Malaysia and Singapore ceased, and the Stock Exchange of Malaysia and Singapore was divided into the Kuala Lumpur Stock Exchange Berhad and the Stock Exchange of Singapore. The Kuala Lumpur Stock Exchange was incorporated in 1976 as a company limited by guarantee to take over the operations of the Kuala Lumpur Stock Exchange Berhad in the same year. In 2004, the Kuala Lumpur Stock Exchange Berhad changed its name to Bursa Malaysia Berhad (Bursa Malaysia) following its demutualisation exercise to enhance competitiveness and to respond to global trends in the exchange sector to be more customer-driven and market-oriented. Bursa Malaysia was listed on the Main Board of Bursa Malaysia Securities Berhad in 2005 (Corporate history, n.d., para 1-4).

The PLCs are required to comply with the requirements of Bursa Malaysia and the Securities Commission. Bursa Malaysia previously comprised of three boards,

namely, the Main Board, the Second Board, and the Malaysian Exchange of Securities Dealing and Automated Quotation (MESDAQ). But since August 2009, Bursa Malaysia has been restructured into two boards. The Main Board and the Second Board have been merged to become the Main Market and MESDAQ. MESDAQ was subsequently replaced with Access, Certainty and Efficient (ACE) Market.

The LEAP Market, or the Leading Entrepreneur Accelerator Platform Market, was introduced by Bursa Malaysia into the Malaysian capital markets with some fanfare in the mid-2017, amidst a rather challenging economic climate. The LEAP Market is a platform for Small and Medium Enterprises (SMEs) to raise funds and visibility in the capital market, despite not being able to meet the criteria for listing on the Main Market and the ACE Market, in an efficient, regulated and transparent marketplace. The LEAP Market is only accessible to Sophisticated Investors, that is, entities with total net assets exceeding RM10 million, or individuals whose net personal assets exceed RM3 million or whose gross annual income exceed RM300,000.

The revised structure of Bursa Malaysia was in line with the change of regulatory approach for the PLCs. Prior to the revised structure, a company intending to list on Bursa Malaysia requires the approval of both the Bursa Malaysia and Securities Commission. The role of approval for listing has been taken over solely by Bursa Malaysia. The Securities Commission, on the other hand, is now focused on compliance, standards and adequate corporate disclosure, and resolution of conflicts of interest.

#### **2.4 Going Public Listed in Malaysia**

In general, as a business needs long-term funding but it wishes to retain its control and independence, according to the London Stock Exchange - A Practical Guide to Listing, the following four options can be considered::

1. Bank finance, generally in long-term loans
2. Further investment from existing shareholders, possibly in conjunction with additional bank finance

3. Venture capital, with the venture capital providers generally taking a substantial equity position on the understanding that they will have an “exit” via a trade sale or flotation in three to five years
4. A listing with accompanying capital-raising on a public stock exchange

These options will have their advantages and disadvantages depending on a wide range of factors specific to the company’s business and stakeholders. Every option will inevitably have major implications on the ownership, control and strategy of the business.

#### **2.4.1 Decision to Go for Listing**

Most successful privately-owned companies that have ambitious plans will ultimately reach at stage where they consider seeking listing on a stock exchange. Having reached a certain threshold of size and profitability, private companies will probably look into public listing to attract public investors for further funding requirements and business expansion.

As a general rule, access to capital is a major stimulus behind the decisions of most companies to go for public listing. A company may go for public listing or flotation in the future as the natural step forward after assessing its vision, mission, goals and objectives of the stakeholders.

In a survey of new stock market entrants, Roell (1996) has documented five reasons why owners of companies decide to go public, in descending order of claimed importance, namely:-

- a) Access to new finance including prospects to growth by acquisition, funds for organic expansion and refinancing of current borrowings.
- b) Enhanced company image and publicity as public listing is widely regarded as a marketing device.
- c) To motivate management and employees whose share participation schemes will help retain them;

- d) As a means for initial owners to cash out by liquidating all or part of their shareholdings; and
- e) Exploiting mispricing by timing the new issue of shares via public listing in the capital market to take advantage of excessively optimistic investor sentiment.

An additional reason for public listing, according to Amihud and Mendelson (1988), is that going public makes the company's shares more liquid and therefore the shares will be more valuable to its owner. And Benveniste and Spindt (1989) had further contended that public listing allows entrepreneurs to use share prices to infer investor valuations of their companies.

Having justified the reasons for going public listing, embarking on a listing exercise will have significant impact on the Board of Directors, management, employees, regulatory requirements and the day-to-day operations of the company. Meeting the goals and objectives of stakeholders, acceptance of the benefits of listing, preparations for listing involving company-wide support and buy-in, dilution of control, availability of time and resources, and compliance of post-listing disclosures and requirements including on-going cost of maintaining listing status are key considerations to take into account prior to public listing (Going Public: A Practical Guide).

Meeting the listing requirements and going through the public listing processes could be very challenging and demanding but rewarding. Even when public listing appears to be the best route after considering all the options, the company must review the following carefully:-

1. Listing factors for consideration (see section 2.4.2)
2. Main advantages of public listing (see section 2.4.3)
3. Main disadvantages of public listing (see section 2.4.4); and
4. Post-listing continuing obligations (see section 2.4.5).



## **2.4.2 Listing Factors for Consideration**

The SC will take into consideration whether a company has met the standards required for listing purpose in terms of quality, size, operations, as well as management expertise and experience before approving the listing of a company.

The Main Market is meant for listing of established companies with a profit track record of three (3) to five (5) full financial years or companies with a sizeable business. Generally, the attributes that a company should have for listing on the Main Market are as follows:

1. Identifiable Core Business

Majority ownership and majority control of an identifiable core business which is the principal source of operating revenue or after-tax profit. A core business premised on owning investment in other listed corporations or businesses will not qualify.

2. Good Management

Effectively managed by capable people in terms of experience and qualification with proper management continuity in place.

3. No Conflict of Interest

Any conflict of interest must be satisfactorily resolved.

4. Strong Business Prospect

Involved in a growth industry, possessing sizeable brand equity and market share, making inroads against its competitors and having a core business that is well positioned to reap returns.

5. Healthy Financial Position

Positive cash flow from operating activities as well as sufficient working capital for at least twelve (12) months.

## 6. Good Corporate Governance

Having a strong corporate governance policy and compliance-driven practices.

The ACE and LEAP Market, with lower listing requirements, are alternative sponsor-driven markets designed for companies of all business sectors that have excellent growth potential. In general, according to the *Going Public: A Practical Guide to Listing on Bursa Malaysia*, the following attributes would allow a Sponsor to decide that a company is suitable to list on the ACE Market:-

### 1. Growth Prospect

Core business and its industry are expected to have a visible growth trajectory within the foreseeable future.

### 2. Capable Directors and Management

Leadership team of good standing and who has demonstrated the capability and ability to grow the business.

### 3. Commitment to Compliance

Sufficient systems, procedures, policies, controls and resources in place to ensure continuous compliance with the relevant rules and regulations.

### 4. Responsible Directors

Directors are fully aware of and understand their fiduciary obligations.

### 5. Risk Management

Internal control and risk management systems are in place in alignment with the company's business and growth plans.

## 6. Good Corporate Governance

Founders, promoters, directors and management team should have a good track record in corporate governance and are not in situations of conflict of interest with the company.

If a company is committed to proceed with the public listing exercise, it should analyse its strength and position in the market given that these factors will be crucial in persuading investors to buy and hold the shares once the floatation is implemented. The unity of the Board of Directors behind all the collective decisions taken and their ability to explain and promote the company's public listing plan are very crucial, reiterated by articulations in the publication of A Practical Guide to Listing – London Stock Exchange.

### **2.4.3 Main Advantages of Public Listing**

The relative importance of each argument in favour of a listing exercise depends on each company's circumstances. The main benefits of listing, according to the Going Public: A Practical Guide to Listing on Bursa Malaysia, are as follows:-

1. Shares of a company could be publicly traded to give the shareholders an opportunity to unlock the value of the company and realize their investment.
2. The valuation of a company is not only based on a company's historical performance but it also reflects the prospects and potential of the company.
3. A company will have access to capital to meet its expansion plans and goals via Initial Public Offerings (IPO) fund raising. In addition, further fund raising exercise could be made through rights issue, placement of new shares, and issuance of other type of securities and to tap the debt capital markets such as bond issue.
4. With greater access to capital, the PLCs have the potential to acquire other companies or businesses to facilitate growth. They will have the capacity to offer their shares as currency to facilitate acquisition and growth strategies. In

addition, enhanced control, information management and operating systems as part of the regulatory requirements will help facilitate sustainable growth in the implementation of the business plan.

5. Listing status will enhance the credibility of the company as its perceived risk is generally lower due to strict compliance of listing requirements and disclosures, and continuing post-listing obligations.
6. A listed company will generally be perceived more positively in terms of its financial and business strength when compared with private companies. The listing status will also enhance the visibility and profile of the company. It will receive better media coverage, thus raising the awareness of the company's branding, products and services.
7. Employee Share Schemes are powerful tools to align the interests of the employees with the goals of the company. They will attract and retain high quality talent human capital and increase long-term affiliation and commitment to the company.
8. Creation of liquidity in the shares of the company will help broaden the shareholders base while enabling the existing shareholders such as venture capitalist and institutional investors to realize their investments. The PLCs tend to attract professional and reputable institutional investors who may in turn provide additional expertise and facilitate wider business networks and opportunities.

According to A Practical Guide to Listing – London Stocks Exchange, in terms of marketing, a privately owned company may often find itself at a disadvantage position if the majority of its competitors are listed. As a listed company, it may be seen by customers and suppliers as being more financially reliable. In addition, the rigorous post-listing disclosures tend to result in better systems and controls, improved management information system, and greater operating efficiency for the business as a whole.

#### **2.4.4 Main Disadvantages of Public Listing**

It is of paramount importance that a company considering for public listing exercise appreciates the drawbacks which are likely to happen. Some of these drawbacks are one-off effects before and during floatation process, with other effects continuing beyond the listing. According to the source - A Practical Guide to Listing: London Stocks Exchange, the main disadvantages of public listing generally identified by directors and advisers include:-

1. Susceptibility of Market Conditions

The price and liquidity of the PLCs are affected by market conditions beyond their control such as market rumour, economic developments or events in the same industry.

2. Potential Loss of Control

Ceding management control to outside shareholders as a result of floatation and risk of being taken over by unwelcome acquirer(s) may result in potential loss of control of the existing shareholders.

3. Disclosure Requirements and On-Going Reporting

The process of listing exercise and subsequent listing both involve the company in a much higher degree of disclosure and reporting as compared to a private company. This will result in additional investment in management information systems and a more rigorous application of compliance control.

4. Loss of Privacy

Due to greater accountability to outside shareholders, the directors may lose privacy and autonomy enjoyed by private company.

## 5. Costs

High cost will be incurred in public listing exercise, raising additional capital and maintaining the listing status. If a PLC is relatively small, the costs may outweigh the benefits of being listed.

## 6. Management Time

Both the listing exercise and post-listing obligations, including investor relations activities, will consume a significant portion of management time which could otherwise be directed to run the business.

## 7. Directors' Responsibilities and Restrictions

The Directors of a PLC will have greater responsibilities such as greater disclosure of salaries and related party transactions. There are also restrictions imposed on the Directors of PLC such as restrictions on share dealing and price sensitive information.

Similarly, Roell (1996) had found that disadvantages of public listing include costs, under-pricing of share price, cost of information disclosure, constraints on the freedom in making business decisions, tax implications and danger of loss of control.

### **2.4.5 Post-listing Continuing Obligations**

A company will have long-term implications of being a public listed company. According to the *Going Public: A Practical Guide to Listing on Bursa Malaysia*, continuing listing obligations in terms of disclosure and communication to the public will have to be complied. Its post-listing continuing obligations include:-

1. Disclosure of price-sensitive information which may impact the company's share price or the trading activities of its shares.

2. Keep track of the trading activities of the company's shares and, when necessary, response to unusual market activity (UMA) queries by the relevant authorities.
3. Response to rumours or reports that may cause excitement in the stock market.
4. Disclosure of significant matters related to the company such as:
  - a) the issuance of new shares or securities
  - b) the proposal to undertake material transactions, for instant acquisition or disposal of assets
  - c) the merger or formation of joint venture
  - d) a major change in management
  - e) the introduction of new products and services, agreements, discovery and other new business activities that will impact on its business
  - f) any default on payment of interest and principal of borrowings
  - g) any change in principal activities and business direction
5. To announce or disclose periodic financial reporting as follows:-:
  - a) Quarterly report to be released within two months from the end of each financial quarter.
  - b) Audited financial statements to be released within four months from the financial year end.
  - c) Annual report (containing audited financial statements) to be released within six months from the financial year end.
6. Keep track of the company's compliance and maintaining the minimum public spread requirements.
7. Continuously disclose information on certain transactions by directors and related parties. In addition, there are strict rules against insider trading

including prohibition from trading of the company's shares during a specific period in conjunction with corporate exercise or a major transaction.

The PLCs that triggered any of the criteria pursuant to Practice Note 17 (PN17) of the Main Market Listing Requirements of Bursa Malaysia, as explained in detail in section 2.6.3 above, will be designated as PN17 companies categorized as financially distressed companies. The PN17 companies will be suspended from the Bursa Malaysia trading and they are required to improve their financial situation before the suspension would be lifted. In the event that these companies failed to restructure and regularize its operations after being designated as a PN17 company, they will be delisted from Bursa Malaysia.

## **2.5 Requirements of Financial Reporting**

The two main statutes governing the financial reporting of Malaysian companies are the Companies Act, 1965 (CA 1965) and the Financial Reporting Act, 1997 (Lazar and Tan, 2011). On 31 January 2017, the Companies Act 2016 (CA 2016) and Companies Regulations 2017 came into force. In accordance with the CA 2016, companies are required to ensure that accounting and other records and registers are properly kept, returns to be submitted and financial statements are to be presented including other matters governing share capital. Also, the CA 2016 requires companies to prepare and present the financial statements in accordance with all approved accounting standards in compliance with the requirements of the Financial Reporting Act, 1997.

All the PLCs have to comply with the reporting standards issued by the Malaysian Accounting Standards Board (MASB) known as the Malaysian Accounting Standards (MASBs) prior to year 2006. However, with effect from year 2007, the MASB had adopted the International Financial Reporting Standards (IFRS) which was renamed as the Malaysian Financial Reporting Standards (MFRS). The Financial Reporting Act mandates the MASB to issue and / or adopt the MFRS. All entities should apply the MFRS issued by the MASB in preparing and presenting the financial statements for filing of financial statements to regulatory authorities such as



Bank Negara (Central Bank of Malaysia), Bursa Malaysia (Malaysian Stock Exchange), Securities Commission and Companies Commission of Malaysia.

The PLCs, their subsidiaries, associates, or companies jointly controlled by them have to comply with the FRS and private companies may apply the Private Entity Reporting Standards (PERS). The PERS are the MASBs issued by the MASB prior to 1 January 2005 except for the removal of certain standards. However, the FRS adoption is optional to private companies.

In February 2014, the MASB issued the Malaysian Private Entities Reporting Standard (MPERS), setting a new milestone for financial reporting of private entities in Malaysia. The MPERS is based substantially on the International Financial Reporting Standard for Small and Medium-sized Entities (IFRS for SMEs) issued by the IASB in July 2009. The new reporting framework, known as the MPERS Framework, is effective for financial statements beginning on or after 1 January 2016.

## **2.6 Definitions of Financial Distress**

There are numerous definitions of financial distress, with similar core characteristics or features. These definitions of financial distress are presented and discussed in the sections below.

### **2.6.1 Financial Distress in Previous Studies**

Fitzpatrick (1932) had described the five stages that a company would go through as it reached failure or financial distress, namely, incubation, financial embarrassment, financial insolvency, total insolvency and confirmed insolvency. Altman (1970) had made the distinction between technical insolvency and insolvency in a bankruptcy case. A company is classified as technically insolvent when it is unable to meet its cash obligations. In other words, the current liabilities exceed current assets. Insolvency implies that total liabilities have exceeded total assets, thus indicating negative net worth of the company. A company is also classified as insolvent when it is in shareholders' deficit position.

Following the 1997 financial crisis, the Bursa Malaysia issued the Practice Note 4 (PN4) in 2001 which outlines the criteria it uses to identify companies that are required to regularize their financial conditions. The deadline given to these financially distressed companies was 31 December 2002, failing which these companies will be de-listed. The following four criteria have been outlined by Bursa Malaysia, and the fulfillment of at least one criteria results in the company being referred to as “an affected listed issuer”.

- a) Deficit in the adjusted shareholders’ equity
- b) Appointment of receivers and/or managers over the property of the listed issuers
- c) Adverse opinions or disclaimers in respect of the going concern from the Auditor
- d) Appointment of special administrators pursuant to the provisions of the Pengurusan Danaharta Nasional Berhad Act, 1998

The Bursa Malaysia implemented the PN4 classification in 2002. The decision on categorizing a company into the PN4 was made the by Bursa Malaysia only if the listed company fulfills one of the above criteria. Trading of shares of these affected companies is either suspended or restricted.

### **2.6.2 Reclassification from PN4 to PN17**

This research defines financial distress companies as PLCs that triggered any of the criteria pursuant to Practice Note 17 (PN17) of the Main Market Listing Requirements of Bursa Malaysia which came into effect on 3 January 2005, and it was revised twice on 3 August 2009 and 22 September 2011.

According to Mohammed (2012) in his study of the PLCs on Bursa Malaysia, listed in the Practice Note 17 (PN17), the classification as PN17 implies that the classified companies are under financial distress. While his main aim was to draw a comparison between Altman’s Z-score Model and the financial liquidity ratios in determining financial default of companies listed in Bursa Malaysia, the author noted

that classification under PN17 relies on methods other than the use of financial prediction techniques such as the Altman's Z-Score Model. Moreover, the sample study only comprised 34 companies listed under PN17 and they were delisted from the Bursa Malaysia.

The findings of Mohammed's study had concluded that the financial ratios alongside the Altman Z-Score Model can be used to detect financial distress among companies although it would be very helpful to compare the ratios with industry averages or against other competitor companies in the same industry in order to make the classification more precise and helpful to investors. Nevertheless, the study found that there were other companies that were faced with financial distress but they were not classified under PN17.

Furthermore, from the study by Mohammed (2012), this researcher has analysed, among other things, the conditions that lead to companies being listed under PN17 category. His analysis revealed that, while the PN17 classification implies companies are experiencing financial difficulties, there was a higher possibility of leaving out companies that are likely to face financial distress using the present methods used by the Bursa Malaysia. Another category under which companies listed on the Bursa Malaysia are those listed in the PN4. According to Hussein, the Ministry of Finance, Nassir Mohamad and Hasan (2005), companies listed under the PN4 are listed companies that have failed to fulfil the financial conditions required of them to carry on business on the Bursa Malaysia. The classification under the PN4 is a move that works to ensure that affected PLCs take appropriate steps to restructure in order to mitigate chances of bankruptcy.

There are numerous motivations for changes in the standing of a company's listing on the Bursa Malaysia, from the PN4 to the PN17. As noted above, according to the Bursa Malaysia, a company is classified under the PN4 when it is showing signs of being unable to meet its financial obligations (SC 2012). For a change from the PN4 to the PN17, the reasons include changes in management and the company's risk profile, level or extent of the management team's experience, prudence, financial appetite of the company and over-gearing.

Mohammed (2012) had recognized that the Main Board counters on the Bursa Malaysia have been linked to high quality stocks and a broad array of investment prospects for investors. However, they do not form the basis upon which a company on the Bursa Malaysia is reclassified under the PN17 companies. Retail investors are doubtful of investing in a PN17 company.

The study by Kok (2010) reveals that the companies listed under the PN17 normally have a number of financial difficulties. As such, prospective investors and stockholders are quite apprehensive when some of the stocks they hold are for companies that are classified as the PN17 companies. For that reason, Kok (2010) had noted that the investors or stockholders are usually confronted with a dilemma of whether to cut down losses or look forward to a rebound when in possession of such shares. The reasons for companies to be categorized under the PN17 include company stockholders' funds that should be in excess of 25% of their entire paid-up capital; receivers have been selected to take control of the assets of the companies; the termination of some of their subsidiaries and allied companies; the auditors have expressed unfavourable opinions on the companies; failure of the company to honour loan interest and principal repayments; the companies have suspended or closed down their operations; and the companies do not have any noteworthy businesses or operations.

According to Kok (2010), even though many investors may be surprised why a number of companies have turned into the PN17, this listing is important since further and careful scrutiny most likely will reveal that such companies are generally poorly managed or they have very poor track records. Therefore, Kok (2010) further noted that along with other reasons, investors may choose to continue holding on to the companies already listed under the PN17 because the investors fail to keep a proper track of the company's financial performance. Another reason is that investors may not be aware that they are holding on to shares of companies that are undergoing financial distress despite being listed or classified under the PN17. Also, Mohammed (2012) had noted that, under some circumstances, the stockholders never even realize that these companies have been classified under the PN17 or delisted from the Bursa Malaysia.

### **2.6.3 Prescribed Criteria and Requirements of PN17 Companies**

The PN17 is a category assigned by the Bursa Malaysia to companies in financial distress. PN17 companies will be given time, typically one year, to come up with an improved plan or risk having their shares being taken off the stock market. According to Yusli, the Chief Executive Officer of Bursa Malaysia, the Bursa Malaysia was probably one of the few stock markets in the world to actually have such a classification for troubled companies (New Straits Time, 2010).

PN17 sets out the following:

1. The criteria in relation to the financial condition and level of operations of a listed issuer, which if triggered will give rise to an obligation for the listed issuer to comply with the provisions of this Practice Note; and
2. The requirements that must be complied with by a PN17 company.

#### **2.6.3.1 Prescribed Criteria of PN17 Company**

Pursuant to paragraphs 8.04(2) of the Listing Requirements, where a PLC, also known as a listed issuer, triggers any one or more of the following Prescribed Criteria, it must comply with the provisions of paragraph 8.04 and this Practice Note:

- a) The shareholders' equity of the listed issuer on a consolidated basis is 25% or less than the issued and paid-up capital (excluding treasury shares) of the listed issuer and such shareholders' equity is less than RM40 million.
- b) Receivers or managers have been appointed over the asset of the listed issuer, its subsidiary or associated company which asset accounts for at least 50% of the total assets employed of the listed issuer on a consolidated basis.
- c) A winding up of a listed issuer's subsidiary or associated company which accounts for at least 50% of the total assets employed of the listed issuer on a consolidated basis.
- d) The auditors have expressed an adverse or disclaimer opinion in the listed issuer's latest audited financial statements.

- e) The auditors have expressed a modified opinion with emphasis on the listed issuer's going concern in the listed issuer's latest audited financial statements and the shareholders' equity of the listed issuer on a consolidated basis is 50% or less than the issued and paid-up capital (excluding treasury shares) of the listed issuer.
- f) A default in payment by a listed issuer, its major subsidiary or major associated company, as the case may be, as announced by a listed issuer pursuant to Practice Note 1 and the listed issuer is unable to provide a solvency declaration to the Exchange.
- g) The listed issuer has suspended or ceased:-
  - a) All of its business or its major business; or
  - b) Its entire or major operations, for any reasons whatsoever including, amongst others, due to or as a result of:
    - i. The cancellation, loss or non-renewal of a licence, concession or such other rights necessary to conduct its business activities;
    - ii. The disposal of the listed issuer's business or major business; or
    - iii. A court order or judgment obtained against the listed issuer prohibiting the listed issuer from conducting its major operations on grounds of infringement of copyright of products, etc., or as noted in (h) below.
- h) The listed issuer has an insignificant business or operations.

#### **2.6.3.2 Requirements to be Complied by PN17 Company**

##### 1) Regularisation Plan

Pursuant to paragraph 8.04(3) of the Listing Requirements, a PN17 company must regularise its condition by undertaking a regularisation plan. A PN17 company and its Principal Adviser must ensure that the regularisation plan:

- a) is sufficiently comprehensive and capable of resolving all problems, financial or otherwise that had caused the PN17 company to trigger the Prescribe Criteria;
- b) enables the PN17 company to regularise its financial condition and level of operation, such as the PN17 company no longer triggers any of the Prescribed Criteria; and
- c) is fair and reasonable to the PN17 company and its shareholders and will increase shareholder value.

## 2) Disclosure Obligations of PN17 Company

Pursuant to paragraph 8.04(3)(b) of the Listing Requirements, a PN17 company must announce to the Exchange

- d) On an immediate basis (First Announcement) upon the PN17 company triggering one or more of the Prescribed Criteria
  - i. That the listed issuer is a PN17 company pursuant to this Practice Note;
  - ii. The listed issuer's obligations pursuant to this Practice Note;
  - iii. The consequences of non-compliance with such obligations; and
  - iv. The status of the listed issuer's regularisation plan or the status of its endeavours to formulate such plan, whichever is applicable, or where neither a plan nor any endeavours to formulate such as plan has been undertaken, an appropriate negative statement to such effect;
- e) Within 3 months from the First Announcement, on whether the regularisation plan will result in a significant change in the business direction or policy of the PN17 company;
- f) The status of its regularisation plan and the number of months to the end of the relevant time frames, as may be applicable, on a monthly basis (Monthly Announcement) until further notice from the Exchange;

- g) Its compliance or non-compliance with a particular obligation imposed pursuant to this Practice Note, on an immediate basis;
  - h) Details of the regularisation plan which announcement must fulfil the requirements set out in paragraph 4 below (Requisite Announcement); and
  - i) Where the PN17 company fails to regularise its condition, the dates of suspension and de-listing of its listed securities, immediately upon notification of suspension and de-listing by the Exchange.
- 3) The Requisite Announcement must:
- a) Contain details of the regularisation plan and sufficient information to demonstrate that the PN17 company is able to comply with all the requirements set out above after implementation of the regularisation plan;
  - b) Include a timeline for the complete implementation of the regularisation plan; and
  - c) Be announced by the PN17 Company's Principal Adviser.
- 4) Before a PN17 Company makes the Requisite Announcement, it must ensure that:
- a) All agreements to be entered into with third parties as part of the regularisation plan, have been duly executed by all parties to such agreements;
  - b) Where the regularisation plan involves a compromise or arrangement with the PN17 company's creditors, the PN17 company has taken reasonable steps to procure the agreement-in-principle of such creditors; and
  - c) The Monthly Announcements must be made on the first market day of each month beginning with the month following the date of the First Announcement.
- 5) Obligations to Regularise



If a PN17 company undertakes a regularisation plan which will result in a significant change in the business direction or policy of the PN17 Company, it must:

- a) Submit the plan to the SC for approval, within 12 months from the date of the First Announcement; and
- b) Complete the implementation of the plan within such timeframe as may be prescribed by the SC.

If a PN17 company undertakes a regularisation plan which will not result in a significant change in the business direction or policy of the PN17 company, it must:

- a. Submit to the Exchange the plan and obtain the Exchange's approval to implement the plan within 12 months from the date of the First Announcement;
- b. Complete the implementation of the plan within 6 months from the date the plan is approved by the Exchange. However, for cases which involve court proceedings, a PN17 company has up to 12 months from the date of the plan is approved by the Exchange, to complete the implementation of the plan; and
- c. Record a net profit in two (2) consecutive quarterly results immediately after the completion of the implementation of the plan. The PN17 company must ensure that the relevant quarterly results are subjected to a limited review by an external auditor before they are announced to the Exchange.

Due to the stringent post-listing continuing obligations, the PLCs will have to monitor closely all the factors that may trigger any of the criteria above. The Bursa Malaysia, on the other hand, is trying to pre-empt PN17 cases by engaging the PLCs with trend of losses repeating and revenue shrinking significantly. A financial distress prediction model for financial distress specifically formulated for the PLCs in Malaysia will therefore be very useful to provide early signals of financial distress before these PN17 criteria are triggered.

## **2.7 Auditors' Opinion on Going Concern**

The most fundamental judgment by an auditor concerning the future in relation to a company is its ability to continue as a going concern. Under the going concern assumption, an entity is viewed as continuing in business for the foreseeable future with neither the intention nor the necessity of liquidation, ceasing trading or seeking protection from creditors pursuant to laws or regulations.

Since the going concern assumption is a fundamental principle in the preparation of the financial statements, management of the company has a responsibility to assess the entity's ability to continue as a going concern. In assessing whether the going concern assumption is appropriate, management takes into account all available information or the foreseeable future, which should be at least, but not limited to, twelve (12) months from the balance sheet date.

The auditor's responsibility is to consider the appropriateness of the management's use of the going concern assumption in the preparation of the financial statements and consider if there are material uncertainties about the entity's ability to continue as a going concern that need to be disclosed in the financial statements. In planning the audit, the auditor should consider whether there are events or conditions which may cast significant doubt on the entity's ability to continue as a going concern.

Companies may receive a going concern opinion as a result of uncertainties from two main sources, namely, financial distress and litigation. Ultimately, the decision of an auditor as to the danger of a company's ceasing as a going concern must rest upon the auditor's judgement.

The auditor will review and assess the conclusions drawn from the evidence obtained during the course of an audit as the basis for the expression of an opinion on the financial statements. The types of auditor's report are set out below.

### **2.7.1 Unqualified Report**

An unqualified opinion is expressed when the auditor concludes that the financial statements give a true and fair view in accordance with the identified financial

reporting framework. An unqualified opinion also indicates implicitly that any changes in accounting principles or in the method of their application, and the effects thereof, have been properly determined and disclosed in the financial statements.

### **2.7.2 Modified Reports**

An auditor's report is considered to be modified in the following situations:

- 1) Matters that do not affect the Auditor's Opinion
  - a) Emphasis of matter
- 2) Matters that do affect the Auditor's Opinion
  - a) Qualified opinion
  - b) Disclaimer of opinion or
  - c) Adverse opinion

The auditor will modify the auditor's report by adding a paragraph to highlight a material matter regarding a going concern problem. The auditor will consider modifying the auditor's report by adding a paragraph if there is a significant uncertainty, the resolution of which is dependent upon future events and which may affect the financial statements. For instance, a lawsuit where the ultimate outcome of the matter cannot be presently be determined and no provision for any liability that may result has been made in the financial statements.

A qualified opinion will be expressed when the auditor concludes that an unqualified opinion cannot be expressed but that the effect of any disagreement with the management, or limitation of scope is not so material and pervasive as to require an adverse opinion or a disclaimer opinion. A qualified opinion will be expressed as being "except for" the effects of the matter to which the qualification relates.

A disclaimer of opinion will be expressed when the possible effect of a limitation on scope is so material and pervasive that the auditor has not been able to obtain sufficient appropriate audit evidence and accordingly is unable to express an opinion on the financial statements.

An adverse opinion will be expressed when the effect of a disagreement is so material and pervasive to the financial statements that the auditor concludes that a qualification of the report is not adequate to disclose the misleading or incomplete nature of the financial statements.

The Altman's Z-Score Model was developed to predict financial distress. On the other hand, the auditor does not attempt any such prediction. An unqualified opinion is not a guarantee that a company will continue as a going concern and a modified audit opinion because of going concern is not a prediction of financial distress. An opinion expressing doubts concerning a company's ability to continue as a going concern is based on the uncertainty of the fairness of presentation of the financial statements.

The Auditors' Opinion on going concern, which may indicate financial distress, could be used as a tool and technique to enhance the financial distress prediction. Therefore, the Auditors' Opinion on going concern is included in this study as an additional variable for the revised financial distress prediction model for the PLCs in Malaysia.

### **2.7.3 PLCs in Malaysia and Going Concern Issues**

According to Malaysian Financial Statements Review Committee (FSRC), which is an arm of the Malaysian Institute of Accountants (MIA), matters relating to the going concern of the PLCs are as essential as the adequacy of related aspects of financial statements yet most of the PLCs do not take it seriously (FSRC 2009). Instead, FSRC (2009) notes, the PLCs are concerned with discussing financial reporting and tend to ignore going concern.

The going concern assumption allows a fair judgment to be made relating to the concerned PLCs presupposing that the said company will carry on business for the predictable or foreseeable future. This is a fundamental principle. Therefore even when looked at the perspective of the previous section dealing with the classification of listed companies under PN4 and PN17, the main idea is to safeguard the going concern of the PLCs (Hussein et al. 2005).

According to the FRSC (2009), economic conditions have great impact on the going concern with respect to the investors, the general public and the PLCs. For the investors, the FRSC observes that hard economic conditions may spell risk of losing invested funds. This implies that a threat to the going concern is also a threat to investor confidence.

## **2.8 Chapter Summary**

This chapter discussed the PLCs in Malaysia and defined the key concepts related to this study. It has underlined the importance of the regulatory framework of Malaysian Capital Market, which has been created to perform various functions including regulatory and oversight.

The chapter has also given an overview of the historical background of the Bursa Malaysia traced back to 1930 when the Singapore Stockbroker's Association was established and underwent several transformational changes to result in the formation of the Bursa Malaysia, the Malaysian Stocks Exchange, in 1976.

In addition, this chapter has also reviewed the on-going public listed companies in Malaysia and the decisions these companies had considered before going for public listing. The companies had to consider several factors when deciding to go public including meeting the requirements for listing with regard to quality, size, operations and management experience. A company that goes public enjoys a number of advantages like being able to increase its capital through shares. However, going public also has its disadvantages including, among others, possible loss of control by the management. Companies that have been listed have to observe a number of obligations to remain listed. One of the key requirements of the PLCs is financial reporting.

In reviewing the definition of financial distress in past studies, this chapter has looked at the prescribed criteria and requirements of the PN17 companies in Malaysia. Finally, it underlines the significance of the Auditors' Opinion on going concern, noting that the most important judgement by the auditor is to assess if the company has the ability to continue as a going concern. With the types of auditors'

report, namely, unqualified report and modified report explained, this chapter concludes by reviewing the PLCs in Malaysia and their going concern issues.

## CHAPTER THREE

### 3 REVIEW OF LITERATURE

#### 3.1 Introduction

This chapter presents a review of literature pertinent to this study, thus enabling the researcher to discuss the state of art of the areas selected for investigation, and to identify the gaps that form the foundation of this research.

The literature review is organized in several themes. Each part includes prior research related to the study area conducted internationally and in Malaysia.

#### 3.2 International Literature

Major corporate failures in the recent past especially before the turn of the 20<sup>th</sup> century have prompted an increased interest in financial distress and extended research in the field of financial distress to ward off corporate scandals and mitigate corporate failure by providing mechanisms for early detection of financial problems. For instance, after the fall of corporate oil giant Enron Corporation, Abbott, Parker and Peters (2004) note that there was a dire need for audit committees to be equipped with the right tools to conduct frequent evaluations and mitigate financial frauds in corporate bodies. Previously, Abbott, Park and Parker (2000) had conducted an investigative study using statistical regression in examining if the presence of an independent audit committee alleviates the possibility of fraud in the company. This early study had established that companies with audit committees comprising of autonomous managers who meet no less than two times a year have less likelihood of being sanctioned for fraudulent reporting or doctored financial statements (Abbott et al., 2000).

In a study conducted by Beasley, Carcello, Hermanson and Lapedes (2000), the authors have found that fraudulent companies with corrupted earnings and financial reports have a smaller number of audit committee conventions than companies that

do not experience such fraudulent cases such as misstatement of earnings and financial frauds that may continue for a long time before being detected. This is because the committees do not have the requisite financial tools or mandate to use them. Thus, the study by Abbott et al. (2004) had confirmed the arguments raised by Beasley et al. (2000) in which both studies have shown the importance of audit committees having the right financial tools to mitigate corporate failures that result from financial fraud. An audit committee that regularly conducts meeting has sufficient time to supervise the financial reporting practice, detect and ascertain management risk and monitor internal controls is capable of detecting financial difficulties if it is equipped with the right tools for assessment of financial difficulty or distress.

Another study in the same vein as the ones mentioned above, where the financial statements are mainly targeted for detection of fraudulent reporting, is the one conducted by Kirkos, Spathis and Manolopoulos (2005). Their study had focused on the detection of fraudulent financial statements through the use of data mining techniques of varying approaches. They applied the Altman's Z-Score and found that 35% of all the fraudulent companies (a total of 38 fraudulent companies) presented a significantly low Z-Score value where the Z-Score value was basically less than 1.49, and given that Altman (2002a) had regarded a Z-Score value of 1.81 as the cut-off point to provide an indicator of financial distress for manufacturing companies in the United States. The authors (Kirkos et al., 2005) had inferred that their sample companies in financial distress had shown a tendency of manipulating their financial statements.

Thus, even though Kirkos et al. (2005) had used other methods alongside the Z-Score technique, the Z-Score technique had provided a vital tool for qualifying the other profitability methods. For instance, at the end of the research study, the authors found out that the fraud companies that exhibited low Z-Score presented low profitability. In the same light, the companies that had no fraud but with a high Z-Score had exhibited high profitability. These results were secured when the researchers were using NPTA and EBIT (Net profits to Total Assets ratio and Earnings before Interest and Tax respectively). However, the study had also used 25 other financial ratios.



Altman (2000) had provided the Altman's Z-Score Model as an investigative approach in assessing of the financial distress of industrial corporations. He noted that the Z-Score credit risk model is still very common throughout the world even in the 20th century after its development despite its use as early as in 1968. In between, however, the reviewed literature had shown that there was an immense difficulty in detecting a company's operating and financial difficulties using the traditional ratio analysis. Nevertheless, prior to the development of the modern quantitative techniques of evaluating the credit worthiness of a particular company, there were specific agencies specifically established to avail some types of quantitative information that were used in assessing the credit worthiness of a particular organization or company.

Another need for increased financial vigilance and more accurate tools and techniques for financial distress prediction of company is identified by Outecheva (2007) who argued that there is also a need to identify and distinguish between external and internal risk factors including an examination of the proportion of each identified risk factor within the risk group. In an early undertaking to the task of risk identification, Bibeault (1982) had examined the fraction of all risk factors, each within each risk group and he had uncovered five considerable sources of external risk. The first external source is economic change. Other external sources of risk identified in that undertaking include changes in competition or competitive balance, government constraints, social adjustments, and technological change.

In the study by Bibeault (1982) which involved a survey of 81 companies that went bankrupt due to external risks, he demonstrated that approximately 41% of the companies exhibited waning performance as a result of poor macroeconomic conditions while 31% of the companies had encountered failure due to alterations in the competitive environment. In the same study, 13% of the companies were faced with regulatory restrictions that hindered them from expanding into strategic sectors of the economy. Moreover, 15% of the companies had faced financial distress due to social or technological change.

On the whole, other studies have shown that 80% of all circumstances of financial distress occurred as a result of the management factor, that is, managerial

incompetence. This provides the support for the results of studies highlighted above. Inadequacy in management control seems to be a recurring problem identified by many studies including that of Abbott et al. (2000) who had reiterated the need for autonomous audit committee with the right tools for risk identification. This was also reported by Altman (1993) as the principal basis for the financial distress of many companies. According to Outecheva (2007), one of the highest proportions of default was witnessed in 1980 when poor management made up more than 94% of all business failures.

### 3.3 Univariate Models

The development of the financial distress model started with the use of univariate analysis by Beaver (1966). Altman (1968) was the first to use the multiple discriminant analysis (MDA) to predict financial distress. . He had developed the original Z-Score Model (1968) for public listed manufacturing companies, the ZETA credit risk model (1977) and Z-Score Model (1993) for private companies. The summary of popular statistical techniques used in the financial distress prediction models in academia and the business world are set out in Table 3-1 below:

**Table 3-1 Statistical Techniques Used in Financial Distress Prediction Models**

<i>Type of statistical techniques used in financial distress prediction models</i>	<i>Authors</i>	<i>Year</i>
Univariate	Fitzpatrick	1931
	Ransmer & Foster	1931
	Merwin	1942
	Walter	1957
	Beaver	1966
Multiple / Multivariate Discriminant Analysis (MDA)	Altman	1968
	Deakin	1972
	Edmister	1972
	Blum	1974
	Libby	1975
	Moyer	1977
	Altman, Halderman & Naarayanan	1977
	Altman	1983
	Booth	1983
Fuller, Moon, Gavin & Erwin	1984	

	Casey & Bartczak Lawrence & Bear Aziz, Emanuel & Lawson Altman Grice & Ingram	1985 1986 1988 1993 2001
Logistic Regression Analysis (LRA) or known as Logit; and Probit Analysis	Martin Ohlson Rose & Giroux Zavgren Gentry, Newbold & Whitford Lau Platt & Platt Koh Lynn & Wertheim Johnson & Melicher Barniv, Harthorn, Mehrez & Kline Lennox Barniv, Mehrez & Kline	1977 1980 1984 1985 1985 1987 1990 1991 1993 1994 1999 1999 2000
Catastrophe Theory / Chaos Theory Model	Scapens Lindsay & Campbell	1981 1996
Recursive Partitioning Algorithm (RPA)	Marais, Patell & Wolfsen Frydman, Altman & Kao Tam McKee & Greenstein	1984 1985 1991 2000
Artificial Neural Networks (ANN)	Salchenberger, Cinar & Lash Coates & Fant Tam & Kiang Coates & Fant Nittayagasetwat Serrano-Cinca Lee, Han & Kwon Jo, Han & Lee Serrano-Cinca Luther Zhang, Hu, Patuwo & Indro Yang, Platt & Platt Shah & Murtaza Atiya Charitou	1992 1991-1992 1992 1993 1994 1996 1996 1997 1997 1998 1999 1999 2000 2001 2004
Cumulative Sum Control Chart (CUSUM) Model	Theodossiou Kahya & Theodossiou	1993 1996
Rough Set Analysis	Slowinski & Zopoudinis Daubie	1995 2002

Source: Researcher's own work

Among the great initial steps in assessing a merchant's credit worthiness was the work of Beaver (1967), which involved the use of ratio analysis in assessment of bankruptcy. The work by Beaver (Ibid) mainly involved univariate analysis of various bankruptcy predictors and ended up setting the stage for the multivariate endeavours that later followed the univariate attempts at predicting bankruptcy or financial distress. Beaver's (1967) method in corporate distress risk assessment mainly applied three criteria to select 30 financial ratios that were ultimately used in analysing 79 failed companies within a period of five years before default. The first of the three criteria is popularity or frequency of the financial ratios in appearing in the existing literature. Secondly, he had relied on the performance of the ratios in the past studies. And lastly, he had relied on the use of ratios within the background of a cash-flow theory. Within the framework of the cash-flow theory, the company is conceived as a reservoir of liquid assets. The reservoir is thus filled by inflows (cash inflows) and emptied by outflows (cash outflows).

Since the cash-flow theory had formed a significant part of Beaver's univariate risk assessment model, and solvency forms a vital part of the assessing the financial worthiness of the company, there are several aspects about the model that should be clarified (Outecheva, 2007). In essence, the cash-flow framework brings out four propositions that are basically hinged upon logical knowledge as opposed to the theoretical derivations. The first of these logical propositions suggests that the greater the quantity of liquid assets and secondly, the greater the quantity of cash flows from operations, then the risk of default will be lower. Thirdly, the higher the amount of debt retained and fourthly, the higher the amount of cash outflows from operations, then the risk of default will be greater.

Using the above criterion, Beaver (1966) conducted a comparison of means of failed or financial distress companies with that of the non-financial distress companies. He had demonstrated that failed companies exhibited lower financial ratios. And he was able to show that even five years before the bankruptcy, the financial ratios of the failed companies are significantly lower when compared to the companies that are financially healthy or non-financial distress. On the same point, Outecheva (2007) had noted that the financial ratios become substantially worse as default looms.

The identified logical constructions allowed Beaver (1966) to perform a dichotomous classification test of the capacity of the various specific accounting measures to predict a company's financial default and to come up with six most authoritative ratios. The most powerful ratios included total debt to total assets ratio, company's current ratio, net income to total assets ratio, working capital to total assets ratio, cash flow to total debt and no-credit interval.

However, despite the meticulous work carried out by Beaver, Outecheva (2007) had pointed out that there are difficulties encountered when approaching the analysis via the classification model due to the possibility of two types of errors: (a) Type I error involves misclassification of a company that is financially in trouble, and (b) Type II error involves misclassifying a financially sound company. The damage that can result from these two types of errors provides a rationale for extra alertness when conducting the assessment of companies via the classification models.

The fact that Type I error is as high as 22% prior to default while Type II error is 5% (Outecheva, 2007) makes it essential that the classification model be approached with great care. In fact, Outecheva added that the Type I error becomes bigger with increasing number of years before a company's default even though the Type II error remains considerably unchanged. The univariate analysis predictors used by Beaver performed well in short-term prediction but has a number of limitations. For instance, Collins and Green (1982), while comparing a number of bankruptcy models, had noted that the univariate model had several limitations, one of which is the single ratios by Beaver that did not capture time variation of financial ratios. The implication of this limitation is that accounting ratios have their forecasting capacity one by one, and therefore it is not possible to carry out analysis, for example, of rates of change of ratios over time.

Still on the limitations of the univariate model used by Beaver, Anjum (2012) had asserted that single ratios may generate incompatible or contradictory results if diverse ratio classifications are used for the same company. This argument was previously articulated by Outecheva (2007) who had asserted that a serious problem could arise with a conclusion since the results would be inconsistent and thus confusing. A good and desirable model is therefore one that provides categorical

results that are precise and clearly consistent to mitigate the possibility of misclassification which can have dire outcome on the company (Anjum, 2012).

The third limitation identified by Altman (2002a) is concerned with the high correlation among a number of accounting variables. This limitation, also pinpointed by McKee and Greenstein (2000), pointed out that since a number of accounting variables have a high correlation, it may be incorrect to embark on interpreting a single financial ratio in isolation. The overriding relationship between and among accounting variables implies that one accounting ratio does not have the capability of capturing the multidimensional interrelationships within an organization or a company.

The fourth and final limitation of the classification model is identified by Outecheva (2007). The limitation is basically related to the generalizability of the results and conclusion derived from a studied sample. He had noted that the probability of default for a specific sample is not equivalent to the probability of failure for the population. Given this statistical reality, precise values of the cut-off points attained for the specific sample under study will not have validity for the entire population.

However, prior to the incorporation of the multivariate methods, the work of Beaver (1967) had revealed that numerous indicators could discriminate between matched samples of failed companies and those that did not fail during a 5-year period in the future before the predicted failure. Beaver had questioned the efficacy of the multivariate analysis, that is, whether the Altman's Z-Score Model was the right method to achieve just that (Altman, 2000). Subsequent studies attempted to replicate the approach used by Beaver and even maintained using the 14 variables employed by him. For instance, Deakin (1972) had used the 14 variables employed by Beaver but he took a different direction by applying the variables through a series of multivariate discriminant models. The resulting conclusion from those early attempts had shown the implication of how ratios are vital tools of predicting bankruptcy.

Those early studies, while shedding light on the vitality of ratios as predictors of bankruptcy, did not provide the order in which the various ratios measuring profitability, solvency and company liquidity are important. Various studies cited

different ratios as the most important. Moreover, Altman (2000) had questioned the adaptation of results from ratio and trend analysis for assessing distress of companies. This is because most of the approaches used in arriving at the previous generalizations were mainly concluded through the use of univariate means where the emphasis was on individual indicators of possible financial distress difficulties. This approach in ratio analysis presented a susceptible fault when the main focus and emphasis were on specific indicators such as profitability and solvency. For example, if a company has been assessed using the profitability ratio or the solvency ratios and found to have a poor profitability or solvency record then it is possible that the company is in financial distress. Nonetheless, the situation of the company may be deemed less serious if it has an above average liquidity. As this is already clear, the univariate approach presents a serious ambiguity and inadequate to predict financial distress of companies.

### **3.3.1 Multiple Discriminant Analysis (MDA)**

The above review shows the gradual development of the univariate analysis and identifies various limitations inherent in the model, especially considering the classification model developed and adopted by Beaver. These limitations necessitated the development of a model that would mitigate the problems identified. Proposed and developed by Altman (1968), the Multivariate or Multiple Discriminant Analysis (MDA) quickly attracted the interest of other professionals and it became one of the most evaluated models for predicting financial distress of the companies.

The imperfection of the univariate techniques as tools for analysis in distress risk assessment implies the need for further development of these techniques to make them more efficient as tools for financial distress risk assessment. Altman (2002), identifying the need to eliminate the weaknesses in the univariate model, had formulated a number of questions to help in the development and successful extension of the Beaver's univariate model. The first question seeks to pinpoint the ratios that are most vital in detecting probability of bankruptcy or financial distress. The second question seeks to find out what weights ought to be attached to the

identified ratios. The third question asks how the weights are supposed to be established objectively.

In the Z-Score financial distress analysis model, Altman disputed the quality of the univariate ratio model as an analytical method, suggesting the application of the multiple discriminant analysis with a linear blend of the ratios that “best” distinguishes between the clusters of financial distress and non-financial distress. In his study, Altman had used a sample of 33 bankruptcy cases reported from 1946 to 1965 and juxtaposed them against 33 non-distressed companies from the same industry, ensuring they are of similar size. In addition, the companies Altman used were all from the manufacturing sector in the United States. Moreover, any company among the sample that had value of assets falling below \$1 million was deleted from the sample. Similarly, Beaver had selected 22 financial ratios anchored in how popular the ratios are in the existing literature and their probable significance to the research inquiry. He then grouped the sample into five categories. The first category comprises profitability while the second encompasses liquidity. The other categories consist of activity, leverage, and solvency ratios.

After conducting several statistical tests of the interrelations among various factors including testing for statistical significance and predictive accuracy, Altman was able to identify five ratios which are the most important predictors of financial distress risk for a company. Therefore, the result was an overall score, referred to as the Altman’s Z-Score Model, which can be worked out from the discriminant function below:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5$$

From the equation,

X<sub>1</sub> represents working capital to total assets ratio

X<sub>2</sub> represents the retained earnings to total assets ratio

X<sub>3</sub> represents earnings before interest and taxes to total assets ratio

X<sub>4</sub> represents market value of equity to book value of total debt



X5 represents sales to total assets ratio.

Z represents the overall index or score.

Z-Score  $< 1.81$  indicates financial distress (Distress Zone)

Z-Score between 1.81 and 2.99 indicates uncertain or grey area (Grey Zone)

Z-Score  $> 2.99$  indicates non-financial distress (Safe Zone)

From this model, on the one hand, companies with a lower Z-Score than the cut-off point are considered to be in a state of financial distress. On the other hand, companies exhibiting higher Z-Score than the cut-off point are considered to be financially sound or with non-financial distress. The deduction derived suggests that the lower the company's Z-Score, the higher the probability of the company to default or in financial distress.

The above model developed by Altman is more precise than the univariate model developed by Beaver. In addition, while the level of Type I error was up to 33% on the Beaver's univariate model, Altman's Z-Score Model reduced the Type I error to 6% while the Type II error was reduced from 5% to 3%, with the overall accuracy of the score in the Altman's Z-Score Model at 95%.

After Altman had developed the Z-Score Model and established it as a better alternative for mitigating the weaknesses identified in the earlier models, a number of researchers directly put the techniques classification of the Altman's Z-Score Model under rigorous test for accuracy. According to Outecheva (2007), the Altman's approach in selection of the variables may bring about a search bias if a selected set of extrapolative variables is used for companies in time-periods dissimilar to those used in the original model. Begley, Ming and Watts (1996) had expressed their doubt in the performance of the model during periods corresponding to a different or changing economic situation. For example, changes in bankruptcy laws or buyout actions in the 1980s transformed the likelihood of bankruptcy.

Consequently, the application of the model built before the alterations may amplify the number of errors related to the variables classification. Lastly, Grice and Ingram (2001) had demonstrated that the accuracy of the original model is considerably

lesser in recent times and they proposed re-estimating the coefficients of the discriminant function by means of estimation samples near to the periods under consideration in the test.

In the recent decades, Altman (2002) has acknowledged changes in the precision and the significance of the original Z-Score Model. Even as Type I error accuracy still continues to be higher than 80% one year before the predicted default, Type II error also shoots up considerably. The principal explanation for changes in precision of the model is that the U.S. companies, as a general rule, become more risky. This weakens the meaning of several of the original financial distress predictors in the Altman's Z-Score Model.

Agarwa and Taffler (2007) found that the well-known Taffler UK-based Z-Score Model, originally developed in 1983, have clear predictive ability over a period of 25 years and dominated other prediction approaches. This study also illustrates the economic value to a bank of using such methodologies for default risk assessment purposes.

Almamy et al. (2016) found that cash flow, when combined with the original Z-Score variable, is highly significant in predicting the health of UK companies from 2000 to 2013. A J-UK model was developed to test the health of UK companies. When compared to the Z-Score Model, the predictive power of the model was 82.9%, which is consistent with Taffler's (1982) UK model. Therefore, the extension of Altman's Z Score Model leads to better results and assists users such as researchers, managers, regulators and other practitioners to manage their risk profile more effectively.

### **3.3.2 Logit and Probit Analysis**

#### **3.3.2.1 Ohlson's O-Score (1980)**

The desire to have accurate risk assessment tools and techniques has also led to the development of the LRA (also known as Logit analysis) and the Probit Models. For instance, the development of the Logit analytical model by Ohlson in 1980 originated from his desire to avoid the restrictive assumptions inherent in the MDA alongside

the output of the technique. Ohlson had criticized the MDA output, noting that as a single dichotomous score, it does not provide any meaningful information about the probability of default or financial distress.

He then developed the O-Score Logit method to mitigate the problems he had identified with the Altman's MDA. His method was based on econometric techniques that made use of logistic transformations, namely, the Logit Model. Bordering on the discriminant analysis, the O-Score technique assigns a score to the independent variable after weighting the independent variables. Nonetheless, in contrast to the discriminant analysis, the O-Score technique provides an estimation of the probabilities of default for each company within the study sample. According to Yim and Mitchell (2005), while the Logit and the Discriminant Analysis models are two most prominent methods used in investigating and predicting financial distress in companies, the Logit method integrates non-linear effects and employs the logistic cumulative distribution function to get the most out of the joint probability of failure for the financial distress companies. In addition, they asserted that the approach also allows for maximizing the probability of non-failure for the financially sound companies, as shown in the sample below:

$$F(z) = \frac{1}{1 + e^{(-z)}} = \frac{1}{1 + e^{-(w_0 + w_1 x_1 + \dots + w_n x_n)}}$$

Where

$z$  represents a linear permutation of the independent variables;

$w_0$  is a constant;

$w_i$  stands for coefficients, and  $x_i$  represents independent variables.

In order for the coefficients to be properly estimated, the method of maximum likelihood is applied.

A number of studies have applied the Logit method to study and predict companies in financial distress. The study by Siqueira and Matias (1996) had used the logistic method when studying a sample of 16 Brazilian financial institutions that went out of

business between 1994 and 1995 alongside with 20 other non-failed banking institutions. The best model was able to correctly classify 87% of the defaulted banks and 95% of the non-failed ones.

In another study that employed the Logit technique, in the form of comparison with the discriminant analysis, the Probit and Artificial Neural Network (ANN), Yim and Mitchell (2005) took a sample of 121 companies in Brazil. Of all the 121 companies the researchers used, 29 were in financial distress between 1999 and 2000. The sample included companies across many industries including 4 companies that had failed in the mining sector, 7 in the energy sector, 5 in the construction industry, 4 in the machinery and equipment sector, 4 in the telecommunications sector, 2 in the textile sector and 3 in the food industry. In order to successfully match the failed or financial distress companies with the financially sound or non-financial distress companies, they randomly selected companies with the same size in terms of their asset base.

### **3.3.2.2 Probit Technique- Zmijewski (1984) Probit Model**

Over the last few decades, there have been increased interests in conducting extensive work that focuses on the area of financial distress prediction in Asia. In this regard, there are a number of models that have been proposed or tested by various studies for bankruptcy prediction to establish which model best suits financial distress prediction in the Asian region. For example, the study by Waqas, Hussain and Anees (2014) lauded the performance of Zmijewski (1984) Probit model; in fact, they undertook to measure the model's prediction performance. The Probit model categorizes the companies as financially distressed and non-distressed, using the methodology that advocates the technique of calculating both the financial distress and non-financial distress companies and then probing the accuracy in categorizing the financial distress companies as financial distress and non-financial distress companies as non-financial distress by weighting the Probit model against the shareholders' equity, net income and cash flow ratio. The classification encompasses placing each company into two zones: financial distress and non-financial distress, on account of cut-off point proposed by Zmijewski (1984). The cut-off points for the Probit model are provided in Table 3-2 below:

**Table 3-2 Probit Cut-Off Points**

<b>Zones</b>	<b>Classification</b>
Distressed	$Z < 0.50$
Non-Distressed	$Z > 0.50$

The precision prediction of the model is compared with the forecast of shareholders' equity, net income and cash flow ratio. In Waqas et al. (2014), the researchers had worked out the performance of the model using both the Type I and Type II errors and the general accuracy of financial distress and non-financial distress companies. As mentioned earlier, under the univariate models, Type I errors usually occur when a model wrongly categorizes a financial distress company as non-financial distress.

In 1982, Altman (1993) documented the various types of costs associated with Type I and Type II errors. For Type I error, he had pointed out that the company's management may not be aware of the severity of the situation and as such it may not take proactive actions. Also, the investors or stockholders of the company may end up losing their investment, given that they may not have sufficient information relating to financial distress problem probably present in the company they wish to invest in. In addition, the auditors and the company may be confronted with severe legal penalties from the court that may also imply loss of goodwill on the part of the auditors and the company as a whole.

There are also specific costs associated with Type II errors. Altman (1968) had noted that when a prediction model incorrectly classifies a company that is not financially distressed as financially distressed, then a "self-fulfilling prophecy" is likely to be created. In addition, the auditors may end up spending extra costs to scrutinize and inspect the problems probably present in the company to escape from Type II error.

The model is represented by the following formula:

$$P = \beta_0 + \beta_1(NITL) + \beta_2(TLTA) + \beta_3(CACL)$$

Where

NITL represents the net income to total liabilities ratio;

TLTA represents the ratio of total liabilities divided by total assets; and

CACL represents the ratio of current assets divided by current liabilities.

### **3.3.3 Recursive Partitioning**

In the study by Frydman, Altman and Kao (1985), the researchers used a recursive partitioning for financial classification to investigate financial distress and compare the method with discriminant analysis within the framework of financial distress of the company. Recursive partitioning algorithm refers to a computerized and non-parametric method that is anchored on pattern recognition. The method has features of classical univariate classification as well as multivariate approaches. Therefore, the recursive partitioning classification combines techniques of the classical univariate method and the multivariate method.

The model basically partitions the variable space into numerous bankrupt and non-bankrupt sections. Each partitioned region has an associated probability of default that can be denoted as  $p(1/t)$ , which can be described as the probability of a company or company with the observation vector in proportion to the region that will default or go bankrupt. The probability (of either default or non-default) should be considered as a score of the region. Frydman et al. (1985) then concluded that the recursive partitioning method combines the joint positive features of multivariate information substance and the simplicity characteristic of univariate technique. Given that the recursive partitioning is nonparametric method, it does not fall to the criticisms ascribed to parametric techniques. Moreover, the authors also found that the recursive partitioning algorithm method has superior classification accuracy to the conventional discriminant framework.

Another computer-based model or technique for predicting a company's financial distress is the Artificial Neural Network (Dorsey, Robert, Johnson, John and Walter, 1994). According to Dorsey et al., apart from being able to approximate any Borel measurable functional mapping from input to output at any degree of desired accuracy as long as adequate hidden layer nodes are used, the Artificial Neural Network (ANN) has other merits. The ANN is free of distributional assumptions,

implying that the distributional biases are not introduced into it. Also, the technique mitigates problems of collinearity. And lastly, the technique is a universal approximator that serves as a general model for prediction of financial distress.

In order for the ANN technique to be effective, proper inputs must be selected as well as proper outputs while the weights attached to every input as well as the functional form of every relationship are determined by the ANN rather than being determined by the expert or financial analyst (Caporaletti, Dorsey, Johnson & Powell, 1994).

### **3.4 Malaysian Literature**

The studies by Zulkarnian, Mohamad Ali, Annuar and Zainal Abidin (2001) used 24 financial distress and non-financial distress PLCs from 1980 to 1996. Financial distress companies were defined as those companies that resorted protection under Section 176 of the Malaysian Companies Act, 1965. Utilising stepwise multivariate discriminant analysis, they found that total liabilities to total assets, sales to current assets, cash to current liabilities and market value to debts were important determinants of financial distress in Malaysia.

Using the same definition of financial distress companies, Low, Fauzais and Zainal Ariffin (2001) analysed financial distress using the LRA (also known as Logit analysis). They utilised 26 financial distress companies and 42 non-financial distress companies in 1988. They found that sales to current assets, current assets to current liabilities, change in net income, cash and market securities to total assets were significant determinants of financial distress.

Mohamed, Li and Sanda (2001) compared MDA and the LRA (Logit analysis) model in the analysis of financial distress. Their sample consisted of 26 companies that have sought protection under Section 176 of Malaysian Companies Act, 1965 and 79 non-financial distress companies. Their results showed that when using MDA, debt ratio and total assets turnover were found to be significant but when Logit analysis was used, an additional variable, interest coverage was also found to be significant.

Thus, Mohamed et al. (2001) studies emphasised the importance of leverage ratio as a predictor of financial distress.

Nur Adiana, Halim, Halimatun and Rohani (2008) studies were carried out to fill the gap of comparing the predictive accuracy of MDA, LRA (Logit analysis) and hazard model and to examine which among the variables were essential in predicting companies in financial distress. The predictive accuracy of these three models is not conclusive. Among the ten determinants of corporate performance examined, the ratio of debt to total assets was a significant predictor of financial distress regardless of the methodology used.

Rafindadi and Yusof (2013) carried out a study in which they investigated the prediction of the pattern of corporate failure in periods of financial and currency crisis. In that study, the authors (Rafindadi & Yusof, 2013) are inquisitive of why most models developed in the 1960s were incapable of predicting company failure or financial distress prior to a financial crisis. The study is a good and vital undertaking as it introduces another element and variable of financial or economic crisis into the prediction model.

The theoretical investigation by Rafindadi and Yusof (2013) indicates that modern corporate financial distress prediction in the 21<sup>st</sup> century is a long way from the mechanisms and efficacies of ordinary financial ratios. On account of this, the authors concluded that the pattern of corporate collapse in the Asian region is quite vibrant and beyond the explanatory clout of common ratios. This is also supported by the conclusions of an earlier study conducted by Charitou, Neophytou and Charalambous (2004) who pointed out that corporate collapse patterns need to be put in the context of the all-encompassing impact of exchange rate exposure, exchange rate misplacement, and macroeconomic unpredictability in a number of countries, which manifests as crises. One vital factor that has to be considered is that the propinquity of most Asian nations and their similarities with respect to economic fundamentals and growth expectations and their strongly correlated trading relationships has made it likely for crises to balloon and have an effect on other Asian countries. In so doing, the effect causes spill overs and contagions that is likely to spread from one locus to another.



According to Ciccarelli and Rebucci (2003), in such situations, financial ratios alone are not able to reveal the accurate picture of corporations as on-going interests, principally of massive corporate bodies with colossal capital bases and enterprises throughout the Asian region. Ciccarelli and Rebucci (2003) also argue that there is the chicken and egg relationship of corporate default, which revolves more around the effectiveness of macro-financial pointers than any other measures bearing in mind their strong and persistent influence in creating corporate default in the 21<sup>st</sup> century.

In their part, Rafindadi and Yusof (2013) add that those mechanisms mentioned by Ciccarelli and Rebucci (2003) are especially relevant in the Asian setting, more so taking into account the report of the caprices and unpredictability of exchange rate misalignment produced by the Asian Development Bank. Moreover, according to Claessens, Djankov and Xu (2000), policies that are not consistent could, among other effects, kindle macro-financial factors variables to create economic dysfunctionalities that consequently propagate undesirable economic downturns, not considering how benign the situation may be. Generally, Ciccarelli and Rebucci (2003) further observe, the magnitude of risk discharge during crisis era is moderately impracticable to be adjudged by the financial ratios of 1966. This same conclusion overrides the conclusion made by Rafindadi and Yusof (2013).

The theoretical and conceptual analysis carried out by Rafindadi and Yusof (2013) enabled the author to come up with various conclusions and recommendations in anticipation of the birth of a new model for predicting corporate failure relevant for Malaysia and Asian region. The palliative recommendations made by the author included recommendation for regional economic integration for Asia with (a) a universal currency throughout the Asian region; (b) free market economies in the whole region (c); decreases in the cost of running business in the region; (d) espousal of the culture and spirit of 'Green Entrepreneurship'; and (e) eradication of all issues that can lead to production and investment shocks. Eradication of factors that cause production and investment shocks can be achieved through getting rid of all factors that hamper capital movement, which in turn hinders the influx of foreign investors.

The study by Waqas et al. (2014) undertook to test the applicability of Zmijewski Model by examining the percentages of appropriately forecasted companies in conjunction with Type I and Type II errors. The study found that since insolvency data does not exist in Pakistan therefore it is not possible to work out estimates of probability of financial distress as used by Zmijewski (1984). Thus, Waqas et al. (2014) represented probability of financial distress using three bases. These include shareholder's equity, net income and cash-flow ratio. The researchers also used dummy variable to stand for financial distress. In that study therefore, positive ratios indicated that the specific company is financially sound. On the other hand, if the ratio was zero or negative, it indicated possibility of financial distress. The study also employed ordinary least squares to approximate the coefficients for the approximation of model.

In the study by Mohammed (2012) the researcher analyses, among other things, the conditions that lead to companies being listed under PN17 category. In the analysis, the study reveals that while PN17 classification implies companies experiencing financial difficulties. Another category under which companies listed on Bursa Malaysia are listed is PN4.

There are numerous motivations for the changes in the standing of a company's listing on Bursa Malaysia. The reasons include change in management, changes in the company's risk profile, level or extent of the management team's experience, prudence, financial appetite of the company and over-gearing. Mohammed (2012) recognizes that core board counters on Bursa Malaysia have been linked to high quality stocks and a broad array of investment prospects for investors. Nonetheless, that does not form the basis upon which a company on the Bursa Malaysia is reclassified under PN17 company. Retail investors are doubtful of investing in a PN17 company.

The study by Kok (2010) reveals that the companies listed under PN17 normally have a number of financial difficulties. As such, prospective investors and stockholders are quite apprehensive when some of the stocks they hold are for companies that are classified as PN17 companies. For that reason, Kok (2010) notes, the investors or stockholders are usually confronted with a dilemma of whether to cut

down losses or look forward to a rebound when in possession of such shares. The reasons for companies to be categorized under PN17 include the stockholders' funds should be in excess of 25% of their entire paid-up capital; receivers have been selected to take control of the assets of the companies; the termination of some of their subsidiaries and allied companies; the auditors have expressed unfavorable opinions on the companies; failure of the company to honor loan interest and principal repayments; the companies have suspended or closed down their operations; and the companies do not have any noteworthy businesses or operations.

According to Kok (2010), even though many investors may be surprised why a number of companies turn into PN17, this listing is important since a further and careful scrutiny most likely reveals that such companies are generally poorly managed or have very poor track records. Therefore, Kok (2010) further notes that along with other reasons, investors may choose to continue holding on to the companies already listed under PN17 because the investors fail to keep a proper track of financial performance of the companies. Another reason is that investors may not be aware that they are holding on to shares of companies that are undergoing financial distress hence listed or classified under PN17. Mohammed (2012) adds that in some circumstances, the stockholders never even realize that these companies have been classified under PN17 or delisted from the Bursa Malaysia.

### **3.5 Literature Review of Auditors' Opinion on Going Concern**

Research has been carried out to explore the relative performance of Auditors' Opinion on going concern and statistical models in predicting financial distress. Empirical findings on this topic are mixed. One stream of research such as Altman and McGough (1974), Altman (1983), Levitan and Knoblett (1985), and Koh and Killough (1990) suggests that statistical models outperform Auditors' Opinion on going concern in predicting financial distress and therefore can be a useful aid in the formulation of Auditors' Opinion decision on going concern.

On the contrary, the more recent work by Hopwood, McKeown and Mutchler (1994) suggests that Auditors' Opinion on going concern and statistical models have equivalent performance after making the comparison considerably more reflective of

the auditors' real-world decision environment. Some studies, for example Hopwood, McKeown and Mutchler (1989); and Foster, Ward and Woodroof (1998) have been done to examine the incremental contribution of Auditors' Opinion on going concern in predicting financial distress. It is found that Auditors' Opinion on going concern have incremental contribution in predicting financial distress beyond the traditional financial ratios.

The financial strength of a company influences the going concern views of the auditors. As noted by Altman (1968); Ohlson (1980); Mutchler (1985); Beaver (1996), it is possible to measure the financial strength of a company using the financial ratios. According to Chen & Church (1992), Frost (1997); and Goldstein (1998), the form of proof presented could be either "positive" or "negative", but has to be taken into account by the auditor prior to issuing his individual opinion on going concern. A good example is a company facing liquidity difficulty with a proof that the company could get a bank loan financing. Such an account would make the auditor to present an unqualified opinion and not a qualified opinion. More so, the management attempts to resolve the financial difficulties have to be taken into account by the auditor before he/she issues going concern opinion (Wolk, Tearney & James, 1997).

### **3.5.1 Financial Indicator**

In a study carried out by Beaver (1966), in which he used univariate model and discriminant analysis, he successfully predicted financial distress based on financial ratios. Beaver used 30 financial ratios to examine 79 pairs of both failed and non-failed companies. According to Beaver, analysing ratio of current assets against total assets and analysing ratio of net benefits against total assets can differentiate between those companies will face bankruptcy and those that will not face bankruptcy. Beaver's model correctly predicted 90% and 88% bankruptcy cases respectively.

Altman (1968) applied the multiple discriminant analysis (MDA) to determine a cut-off value he used to establish the criteria determining companies' going concern through financial problems or those in strong financial position. Using this model Altman (1968) predication was 95% accurate.

The study carried out by Altman used five ratios (Altman's ratios) to compute the Z-Score as shown below:

$$\text{Z-Score} = 1.2 \text{ WC/TA} + 1.4 \text{ RE/TA} + 3.3 \text{ EBIT/TA} + 0.6 \text{ MV /BV} + 0.999 \text{ Sales/TA}$$

Where

WC/TA = Working Capital / Total Assets

RE/TA = Retained Earnings / Total Assets

EBIT/TA = Earnings before Interest and Taxes / Total Assets

MV/TA = Market Value of Equity / Book Value of Debt

Sales/TA = Sales / Total Assets.

Z-Score = Overall index or Z-Score

Altman (1968) was able to group companies on the basis of Z-Score as indicated below:

Z-Score greater than 2.99 = Strong company (non-financial distress)

Z-Score between 1.81 and 2.99 = Moderate company

Z-Score less than 1.81 = Weak company (financial distress)

Similarly, Ohlson (1980) had undertaken a study on financial distress and applied the LRA (also referred to as the Logit Analysis) to predict financial distress within companies. As noted by Mutchler et al. (1997), the logic analysis is a better model to address the limitations associated with the MDA Model. In the Ohlson study, it had examined 105 companies facing financial distress and 2,058 companies not in financial distress. It had established that it was possible to predict financial distress with similar accuracy as that of the Altman's model, using seven financial ratios.

Mutchler et al. (1997), in their study, had examined 16 auditors' reports on factors that would reveal if a company is facing financial problems or not. Accordingly, they established that the main indicators included:

- Signs that the company is being targeted for a takeover
- Signs that the company will go bankrupt
- Signs that the company will be restructured
- Net value of the company is negative
- The Company has failed to pay its loan
- The company is having a negative cash
- The company has been given a going concern flag rating in the past year
- Has posted losses from its operation
- It's current assets are deficient
- Has posted financial losses
- Has a difficulty in getting loans

In his study, Boritz (1991) had established that audit firms underline the following factors as important when determining the ability of a company to continue with its future operations as follows:

- Ratio of debts against assets
- Record losses for two years
- Unable to settle its debts
- High debt/equity ratio
- Deception
- Failing stock market value
- Negative assets

According to Citron and Tafler (1992) the most important factor that auditors base on when issuing a going concern opinion is poor financial position of a company. Past studies have shown that statistical models using financial ratios give better explanatory information when compared with the Auditors' Opinions regarding going concern opinion (Altman, 1968; Koh & Killough, 1990).

Nonetheless, a study by Hopwood et al. (1994) had established that the statistical model of financial ratios and models utilizing Auditors' Opinion have no significant difference in their prediction accuracy. Moreover, another earlier study by the same

authors, had found that a statistical model of financial ratios has the same predictive ability as the auditor's judgement (Hopwood et al., 1989).

### **3.5.2 Type of Evidence**

It is important to consider the evidence that will lessen a company's issues on going concern. According to Mutchler et al. (1997), there are two forms of evidence that influences the decision taken by auditors. These are mitigating evidence (positive evidence) and contrary evidence (negative evidence). Mutchler et al. (1997), explain that mitigating evidence influences the judgement of auditors on whether to issue a going concern opinion, while contrary evidence influences the judgement of auditors on whether or not to issue going concern opinion.

Carson et al. (2013) has clearly pointed out the importance of mitigating evidence and contrary evidence before the auditors give the going concern opinion. An example of contrary evidence is the effort by the management to surmount the problem of going concern. In their study, Behn, Kaplan and Krunwiede (2001); and Bell (1991) established that companies in a position to get additional financing or loans (mitigating evidence) do not seem to get a going concern opinion. However, as noted by Reynolds and Francis (2000); and DeFond, Raghunandan and Subramanyam (2002), companies that indicate that they are unable to pay their outstanding loans and the management show no efforts to address the problem of going concern (contrary evidence) are issued with a going concern opinion.

When a company's normal operations are in doubt, auditors issue going concern opinions to warn the public investors about the state of the company, but not as a prediction of bankruptcy. According to Frost (1997), those who rely on financial reports consider the going concerns opinions as initial warning for company failure and view a modified Auditors' Opinion as a financial wakeup call.

A study carried out by Altman and McGough (1974) linked the quality of Auditors' Opinion on going concern with bankruptcy prediction. In this study, Altman and McGough (1974) collected a sample of 34 companies in a period of one year before facing bankruptcy from 1970 to 1973. They used a Z-Score statistical forecasting

model (developed by Altman in 1968) to evaluate the accurateness in bankruptcy prediction founded on Auditors' Opinion on going concern. Altman and McGough (1974) established that statistical predicting model has got an accuracy rate of 82%, nearly double of Auditors' Opinion on going concern.

Similar related studies found similar results that statistical prediction models offers more accurate results than Auditors' Opinions on going concern when predicting bankruptcy (Levitan and Knoblett, 1985; Koh and Killough, 1990; Koh, 1991). Though these studies indicate that Auditors' Opinions on going concern ought to be looked at with some doubts, they as well offer an objective auxiliary tool.

Studies carried out on bankruptcy prediction models are formulated from the univariate to multivariate models. Many of these models have been reviewed and are based on methods developed by Altman (1968); Deakin (1972) as well as Ohlson (1980). Similarly, Zavgren (1983); Aharony, Jones, and Swary (1980) present auditors with different models in bankruptcy as an expert reference tool. However, these models act only as binary option models that help in accuracy of going concern opinion and not on bankruptcy probability. Sadly, those who use financial statements as well are concerned with the happening time for bankruptcy apart from its probability.

In the course of the survival time after the issuing of going concern opinion, the users have to examine associated risk and possibility of bankruptcy at different times in trying to implement earlier strategies. Nonetheless, the binary choice models formulated do not examine the survival time and the process for company failure, and therefore has reduced chances for early preventions (Aharony, Jones and Swary, 1980). Accordingly, knowing the changing process in the course of the survival period is important in real business practices when companies are in financial problems.

### **3.5.3 The Difficulties of Making Correct Going Concern Assessments**

Facing challenges in reaching correct going concern assessment, Carcello and Neal (2000) notes that studies indicate that the going concern evaluation is among the



most complex and difficult audit assignment. Francis (2004) adds that if a company goes bankrupt before an auditor issues a going concern opinion, it is generally viewed as a failure of the audit. The high number of past corporate as well as audit failures shows that it is hard to accurately forecast a company's future. This implies that making accurate going concern evaluation is as difficult (Nogler, 2008). Knechel (2007) points out that, though auditing standards calls for a clear evaluation of a company's going concern situation, companies still collapse without previous forewarning from the auditors.

The previous big collapses like the case of Enron Corporation in the United States led to increase in lawsuits against the auditors, high level media scrutiny and increased regulatory requirements of the audit profession (Fargher and Jiang, 2008).

Some authors like Cheney, (2009); Humphrey, Loft and Woods (2009) have argued that auditors ought to have warned the collapsed companies at initial stage. Indeed, some gone to further assert that if the auditors had performed their jobs well, the collapse could have been prevented (Nogler, 2008). Such collapses have dented the trust in the audit profession. As argued by Cheney, (2009) an auditor is supposed to act as a vital underwriter of financial reports among investors. The financial crisis of 2008 has also increased criticism against auditors for their failure in warning the public and investors about the impending bank failures that started the financial crisis (Humphrey et al., 2009).

An important question was raised regarding why the auditors failed to predict the bank collapses in their audit reports (Sercu, Vander Bauwhede, and Willekens, 2006). In responding to the financial disaster, the international Auditing and Assurance Standards Board (IAASB) presented a report meant to increase the awareness of companies, managers as well as the auditors regarding the importance of carrying out going concern evaluation in view of the recent cases of corporate failures (IAASB, 2009).

In addition, the European Commission in the course of the financial crisis questioned the main role of auditors and underscored the need for more interest in the their role in audit, with the objective of increasing the contribution they play in increasing

financial stability (EC, 2010). Humphrey et al. (2009, p 810) raised questions such as “where were the auditors?” indicating a desire that auditors should have been more proactive in spotting and reporting major corporate failures or financial distress.

#### **3.5.4 Accuracy of Going Concern Opinions**

A number of quantitative studies have analyzed the accuracy of Auditors' Opinion on going concern. This implies looking at the randomly picked bankrupt companies that were issued with going concern opinion by their auditors before going bankrupt (Granath, Kumlin and Lundgren, 2013). Alfredsson and Fransson (2011); and Öhman and Nilsson (2012) argue that the accuracy rate of going concern opinion has been low in the recent past. According to Alfredsson and Fransson (2011); and Öhman and Nilsson (2012) possible explanations of the decline in accuracy rate is, the danger of losing audit contract if the auditors make a going concern opinion, fear of initiating bankruptcy by reporting the companies' financials (Kaplan and Williams, 2012), comparatively low litigation threat in continental nation (Alfredsson and Fransson, 2011) and lastly, it is not always possible for an auditor to predict an impending bankruptcy.

Vanstraelen (1999) points out that the decision by auditors on whether to issue a going concern opinion or not is based on their competence and independence. He adds that this can be viewed as a two-stage process that starts with the ability of the auditor in identifying a company facing going concern problem (Vanstraelen, 1999). The second stage involves the decision on whether to report the going concern problem, which calls for independence. Accordingly, Alfredsson and Fransson (2011) has asserted that in most cases the issue of accuracy in issuing going concern opinion goes down to the ability of identifying companies facing going concern problems.

On the other hand, previous research shows that auditors arrive at different conclusions from the same audit evidence, and that there are differences in how auditing standards are interpreted, which suggest that the going concern assessment involves a great deal of subjective judgment (Sercu et al., 2006; and McCracken and Salterio, 2008).

Regarding the decision whether or not to issue a going concern opinion, Öhman and Nilsson (2012) found that even though several bankrupt companies had displayed signs of financial distress, only a small part of them had received a prior going concern opinion from the auditors implying that the auditors had made an active decision not to issue a going concern opinion, even though they had identified a going concern problem. This could be caused by the fact that auditors face a challenge in standing up to dominant managers who might want to manipulate their financial statements and present them in excessively favourable terms, with a risk of losing the audit assignment if the auditor does not comply with the client (Carcello and Neal, 2000; Humphrey et al., 2009).

On the one hand, there is also a risk that auditors could harm their clients by making the public aware of the financial problems of the companies, which is why auditors might hesitate to express a going concern opinion in the audit report (Myers, Schmidt and Wilkins, 2013). On the other hand, in order to avoid the risk of lawsuits and loss of reputation if auditors fail to identify an upcoming bankruptcy, with Enron Corporation and Arthur Anderson as examples, the auditors may protect themselves by issuing a going concern opinion in the audit report prior to bankruptcy (Francis, 2004; Myers et al., 2013).

Clearly, there are different factors and incentives that will influence auditors' ability to identify going concern problems (a matter of competence) and their decision whether or not to issue a going concern opinion, once a going concern problem has been identified (a matter of independence).

### **3.5.5 Auditor's Competence**

When giving a going concern opinion, Barnes, (2004), and Sikka, Filling and Liew (2009) had argued that the auditors should provide trustworthy audit report, reflecting the present financial position of the company. To achieve this, it is necessary that the auditors possess the right competency and expertise. Sikka (2009) had observed that the auditors hold their position based on the competency and expertise that allow them to arbitrate uncertainty and create objective and true opinions of financial reports that help the investors, the public and markets to reduce

and manage existing risks. They had explained that in a number of cases the auditors' opinion on going concern has been insufficient. This is because the audit profession on some occasions have been rocked with scandals whereby, according to Barnes (2004), the auditors have been criticised for being unable to pinpoint failing companies.

Such cases only increase the concerns regarding the competencies of the auditors and their incentives in constructing the expected objective and true opinion of the companies. Certainly, it is critical that the auditors possess the required competency and professionalism to carry out an accurate going concern evaluation.

According to Gibbins, McCracken and Salterio (2007), when the Chief Financial Officer (CFO) sees that a problem needs to be solved between the auditor and the company, the power of resolving the problem will be given to the party that has most competent expertise. But the CFO often regard himself or herself as having more expertise and insist that they can carry out a better evaluation of the company. In such a case, it is vital that the auditors have a high level of knowledge and expertise regarding the company in case there is a misunderstanding between the CFO and the auditor.

Myers et al. (2013) have argued that companies think that the reason for financial reporting and carrying out audit reports is mainly to comply with existing regulations. Nonetheless, the auditors need to focus on the economic matters to get the whole picture about the company's financial position (Kaplan and Williams, 2012) as this will increase the auditors' competence to establish going concern problems, and to offer accurate opinion on going concern.

### **3.6 Altman's Z-Score Model and Auditors' Opinion**

The development of the Altman's Z-Score Model of risk assessment and prediction is as a direct result of the weaknesses identified in the univariate approach and the careful move by Altman to use the MDA to increase the accuracy in the prediction of financial distress amongst the PLCs. The development of the Altman's Z-Score Model included the financial ratios that constitute five variables in the model

mentioned earlier. These ratios form the basic backbone of the Altman's Z-Score prediction model. In the model, the ratio of working capital to total assets helps in measuring the net liquid assets of the company proportionate to the company's total capitalization. In the ratio, the company's working capital is the division between working capital and total assets (WC/TA). When a company is undergoing operating losses in a consistent manner, its current assets will shrink in relation to total assets. Altman (2002a) concluded that out of the three liquidity ratios used, the WC/TA is the most valuable whereas the other two ratios are current ratio (current assets to current liabilities ratio) and the quick ratio.

The Retained Earnings/Total Assets (RE/TA) is also part of the Altman's Z-Score prediction model. This ratio in the model is a vital tool for measuring the company's cumulative profitability, hence its ability to offer a picture of the company's going concern. Therefore, companies that have a huge amount of RE in comparison to TA imply that they have financed their assets via retention of profits and they have not made use of much debt to finance their activities.

For the Earnings Before Interest and Taxes/Total Assets (EBIT/TA), the ratio measures the proper productivity of the company's assets while excluding any influence of tax or leverage factors. Given that a company's definitive existence is hinged on the earning power of its assets, this ratio seems to be principally suitable for studies dealing with corporate failure, as observed by Kirkos et al. (2005). According to Carlo, Delio and Sara (2014), the EBIT/TA ratio outperforms other profitability measures including cash flow.

Within the Altman's Z-Score Model, there is Market Value of Equity/Book Value of Debt (MVE/BVD) ratio. In addition, there is also the Sales to Total Assets (S/TA) ratio which, in effect, is a tool for measuring the company's ability to handle competitive conditions (Altman (2002a).

In a critical review of the Altman's Z-Score Model, Clark, Foster, Hogan and Webster (1997) had argued that the K & P judgmental model (Kundinya & Puri prediction model) is superior to the Altman's Z-Score Model in predicting companies that have a likelihood of failing or to be in financial distress position. In their study,

Clark et al. had carried out a comparison of the two models (that is, the Altman's Z-Score Model and the K&P judgmental model), using 14 companies from three diverse industries.

In the Altman Z-Score Model, a company with a score of 1.80 and below is classified as failure or in financial distress. A company with score ranging between 1.81 and 2.99 is classified under the grey area which implies under close attention; and any company with a score greater than 2.99 is classified as in non-financial distress. According to Clark et al. (1997), the Altman's model classifies many companies in the grey area (implying a Z-Score of 1.81 to 2.99) and therefore making it difficult for one to predict with precision the outcome of the companies in the grey area. In contrast, Clark et al. (1997) also observed that the K&P judgmental model is more superior in distinguishing financial distress companies and non-financial distress ones, thereby mitigating the grey area problem experienced by the Altman's Z-Score Model.

### **3.6.1 Prediction through Auditors' Opinion on Going Concern**

Empirical studies have identified several factors and variables that affect the Auditors' Opinion on going concern. These variables are related to the audit committee. Moreover, there is evidence that there are also a number of factors that are audit committee-related. Past empirical studies have found a positive relationship between audit committee opinion or board independence and corporate voluntary disclosure.

One such study was carried out by Forker (1992). He had established a positive relationship between the number of external directors on the boards and the comprehensiveness of the financial disclosure given by the corporate body. His findings further showed that audit committee's opinion of the company's going concern is highly related to the comprehensiveness of financial distress detection. Similar findings have also been reported by Laksamana (2008); and Boesso and Kumar (2007). A number of studies have gone beyond that and attempted to give more details of this positive relationship. For instance, Klein (2002); and Beasley (1996) both have determined that the possibility of corporate managers to manage

earning and engage in fraud is reduced when the number of non-executive directors on the board is high because their opinions on the company become more positive. Also, Gul and Leung (2004) have asserted that a larger number of independent directors will enhance the monitoring role of the board, thereby increasing the degree of corporate transparency and enabling a stronger and positive view on the company's going concern since there is increased scrutiny and internal control system in place.

On the contrary, some empirical studies such as Eng and Mak (2003) have found a negative relationship between external directors on audit committees and the degree of voluntary disclosure or positive opinion about the company's going concern. Similarly, some studies such as Ho and Wong, (2001), and Haniffa and Cooke, (2002) have found insignificant difference between independence of the boards and voluntary disclosure.

According to Rashidah and Yaseen (2006), the independence of the board shows the level of its independence from the management of the company. The independence, however, depends on the number of external board directors. Al-Matari, Al-Swidi, Faudziah, and Al-Matari (2012) have noted that the inclusion of independent external directors is a critical to helping the board of directors in overseeing the activities of the management of the company.

Abbott et al. (2004) had explained that the OECD code of corporate governance (2004) outlines that independent board members have the ability to contribute considerably to the decisions taken by the board. Independent board directors are thought to be more objective in examining the performance of the management. Moreover, these independent directors play a crucial function in areas where the varying interests of the management, the shareholders and the company may differ, for example, on succession, corporate internal control system, audit function and executive remuneration.

Understanding that significance of having a high number of independent directors on the board of directors is important for a company. Indeed, as stated before, a number of researchers have found a positive link between board independence and

shareholder's interest. In addition, the proportion of independent or external directors on the board is usually used to assess the board independence.

According to Al-Matari et al. (2012) past findings have consistently reported that the number of independent directors has a positive relationship with the monitoring and financial reports. For instance, Beekes, Pope and Young (2004) in their study found that companies with a comparatively high percentage of external directors on the board, increased the conservativeness of these boards. Similar findings have been reported by Kiel and Nicholson (2003) who investigated the link between board demographics and corporate performance in selected Australian big public traded companies. Their study also revealed that there is a positive link between the number of external directors and the performance of the company.

The board of directors is responsible for overseeing the operations of the organization on behalf of the shareholders. The size of the board of directors and therefore its effectiveness has drawn a lot of argument among various scholars. When looking into the board of directors of a given company, reference is made to the total number of directors who constitute the board. In this perspective and basing on the number of directors who sit on the board, there could be a small or large board of a company. A lot of contrast has existed among various researches who have studied the effectiveness of both small and large boards of directors in minimizing the agency costs of their companies as well as the suitability of their management practices.

Researchers on one side have argued that larger boards are effective when it comes to safeguarding the interests of the shareholders because the large boards varied expertise in addition to a wide range of experience which constitutes some of the greatest assets in the synergistic governance by the board. Additionally, a large board is powerful and this is vital when it comes to advising and recommending on strategic options of the company. Some writers such as Abdul Rahman and Ali (2006) as well as Zahra and Pearce (1989) have argued that having a large board is crucial because it helps create corporate identity as well as strengthening the link between the environment and the company. To further support this stand, Forbes and Milliken (1999) have argued that the size of the board has a bearing on its



effectiveness. For instance, they say that for a large board there will be a wide range of skills and knowledge at their disposal. Additionally, cognitive conflict is enhanced by the huge perspective assembled by a large board. According to Pfeffer (1972) the resource dependency theory points to the fact that the variety of knowledge present in large boards is crucial for resource management.

On the contrary, some scholars have strongly advocated for a smaller board of directors citing various reasons. First of all, such researchers have criticized the credibility of large boards by saying that a larger number of directors frustrate decision-making, coordination and communication as these processes become increasingly complex in the large boards. In addition, in large boards it is argued that coordination of the various contributions of group members is very difficult. Proponents of this idea point to the fact that when the board is large, effective utilization of skills and knowledge is also difficult. Large boards are criticized on the basis that having strong cohesion, maintaining norms, building and maintaining trust; and personal relationships is a daunting task. According to Lipton and Lorsch (1992), a large board is dysfunctional because it is easier for top managers to control the large board that does not realistically criticize the management decisions.

After analysing various views on the size of the board, Abdellatif (2009) came to a conclusion that the performance of a corporation was negatively related to the size of the board but the size of the board was positively related to the value of the company. The scholar also said that large boards did not necessarily add value or influence the value of accounting information. Supporters of a small board say that contradiction in objectives of the company does not exist. Various reports and committees best practices in corporate governance support small size of the board of directors. For instance the Hampel Committee, Final Report (1998); Saudi Code of Corporate Governance (2006) and the Malaysian Code on Corporate Governance (Revised 2017) support a smaller size of the board. Studies by Byard, Li and Weintrop (2006), Yermack (1996) and Vafeas (2000) have found an association between disclosure and board size. The small size of the board therefore aids in quality management and better disclosure.

There may be a difficulty in pinning a responsibility or accountability to the board of governors without understanding the role this board plays in terms of each board member or based on the role generally assigned to each board member with respect to their opinion on going concern of the company. While members of the board may be appointed based on the individual's expertise, the members have to understand that the authority they have is not exercisable collectively (Al-Matari et al. 2012).

According to the Saudi Arabia corporate governance regulations (2010), there are rules and standards that control the management of joint stock companies that are listed on the Saudi Stock Exchange to guarantee that there is compliance with the best practices in governance to ensure that the rights of stakeholders are protected. According to the regulations, the board of directors is responsible for approving the corporate body's strategic plans and key objectives. In addition, the board of directors is also responsible for supervision of their implementation. This mandate implies that the board of directors is answerable if and when the company's strategic plans and objectives are not steering the company to the right direction. By and large, the board is thus culpable when a corporate body fails because it has an approval and a supervisory role in the formulation and implementation of the strategic plans as well as the objectives. Among the roles and functions of the board mandated by the Saudi Arabia corporate governance regulations, the board must lay down a comprehensive plan for the corporate body or company, detailing the main work plan and the strategy regarding management of any risk, review and revision of such policy.

Determination of capital structure is also part of what the board is mandated to take care of and this includes establishing the accompanying financial objectives and followed by approval of annual budget. This aspect of the role of board of governors shows that even financial failure of the corporate body shall ultimately cast culpability on the board. Coupled with the fact that another Saudi Arabia corporate governance regulation (2010) mandates the board of governors to supervise the main capital expenses and the acquisition or disposal of assets implies that almost everything that happens in the corporate body is in the limelight of the board and it is culpable when almost anything goes wrong.

There are a number of factors that are related to the audit committee and which have a direct impact on the company's performance. Past studies have delved into investigating the impact of various audit committee variables on company's performance. For instance, the study by Chan and Li (2008) brought out the empirical result of the relationship that exists between audit committee independence and company's performance though the results generally showed that it is ambiguous. In the same study, Chan and Li (2008) established that autonomy of the audit committee such that there are at least 50% of expert-independent directors in the audit committee has a positive impact on the performance of the company based on the measurement of Tobin's Q. In a similar light, the study by Ilona (2008) established that there is a positive correlation between audit committee independence and performance of the company when analysed from the Return on Assets (ROA) basis.

Additionally, Erickson, Park, Reising, and Shin (2005) contended that independent directors can lessen agency problems. Founded on the contention provided by Erickson et al. (2005) that the independence of a company's directors can help in reducing the agency problem, it can equally be argued that independence of audit committee can also help in reducing the agency problems. What this means is that a positive relationship between the independence of audit committee and company's performance is not only expected but also justified. Following from the above contention with reference to the agency theory, it is possible to empirically test the hypothesis that there is a positive correlation between the autonomy of the audit committee members and company's performance.

Audit committee meeting and company's performance have been highly connected to positive Auditors' Opinion. The frequency which associates the audit committee call for meetings should be considered to be an imperative attribute for the monitoring effectiveness of the audit committee (Lin, Li and Yang, 2006). Lin et al. (2006) maintain that if the audit committee meets frequently, the company stands high chances of getting positive opinion from the auditors relating to the financial health of the company since there is closer supervision.

In another study, Anderson, Sattar and Reeb et al. (2004) argued that audit committee supervises the internal control and supplies steadfast information to the shareholders providing the stockholders with vital information that includes status of financial distress and going concern. In view of that, according to Hsu (2007), audit committee reinforces the internal auditing function and keeps an eye on the management's evaluation of business risk. Xie, Davidson and Da Dalt (2003) add that the frequency of audit committee meetings is judged as a replacement for audit committee function.

The point by Xie et al. (2003) as illustrated in the above paragraph therefore implies that the audit committee that meets more frequently with the internal auditors has better information about issues that relate to auditing, accounting and financial position of the company. When a significant auditing or accounting concern comes up, the audit committee can direct the appropriate level of internal audit function to deal with the problem without any delay and hence provide a higher likelihood of having positive review on the going concern of the company. As a consequence, an audit committee that conducts meetings frequently can mitigate the likelihood of financial fraud in the company (Abbott et al., 2004) by providing an early prediction of financial distress and recommending mitigation measures. Audit committees that essentially inactive and which conduct smaller number of meetings are not likely to be effective.

In a study conducted by Beasley et al. (2000), the authors found that fraudulent companies with corrupted earnings and financial reports have smaller number of audit committee members than companies that do not experience such fraudulent cases such as misstatement of earnings. An audit committee that regularly conducts meeting has sufficient time to supervise the financial reporting practice, detect and ascertain management risks and monitor internal controls. Accordingly, company's performance is strengthened with the activities carried out by the audit committee. More outstandingly, there have not been many studies that have focused on examining the impact of audit committee meeting on performance of the company.

As a point of illustration, Hsu (2007) established that audit committee meeting has opposite relationship with company's performance. This implies that on the basis

of investigation into the subject of audit committee meetings, it is justifiable to empirically test the hypothesis that the frequency of audit committee meeting has a positive correlation with company's performance.

### **3.6.2 Audit Committee Size and Audit Committee Opinion on Company's Performance**

Studies have also identified another variable that relates to the audit committee and the auditor's type of opinion on the company's financial status, which is its size; and this is a characteristic regarded as being relevant to the audit committee's successful discharge of its duties (Al-Matari et al., 2012). In accordance with assessment carried out by Al-Matari et al. (2012), it is usually proposed that an audit committee should have no less than three audit committee members; and among the corporate governance reports that recommend this include the Capital Markets Authority and the New York Stocks Exchange (Karamanou & Vafeas, 2005).

These recommendations not only offer evidence of the vital role the size of the audit committee plays. On the one hand, it demonstrates the significance of the main argument behind the audit committee size which holds that a larger committee size has superior organizational reputation and authority (Al-Matari et al., 2012) and a far-reaching knowledge base (Karamanou & Vafeas, 2005). On the other hand, an audit committee can be confronted by process losses and dilution or dispersal of responsibility if it becomes exceedingly large. Similarly, just as the previous hypotheses that have been posited for investigation and testing, the aspect of audit committee size can also be empirically investigated by testing a hypothesis that suggests the size of the audit committee has a positive correlation with a company's performance, thus enhancing the likelihood of a positive Auditors' Opinion on the company's financial standing.

Despite the various studies that have attempted to create a link between a company's Auditors' Opinion on Going concern and its financial health, others have specifically focused on assessing the reliability of the Auditors' Opinion as a means of predicting the financial distress of the company (Carlo et al., 2014). In the study by Carlo et al., the researchers have undertaken a statistical analysis of the reliability of the

Auditors' Opinion as bankruptcy predictors. The authors have recognized the role of the auditors by asserting that the auditors have the responsibility of issuing an audit opinion with the purpose of assuring stakeholders that the financial reporting provides a true and reasonable view consistent with the financial reporting structure used for the preparation and presentation of the financial statements. The auditor might have or express some considerable doubts or reservations concerning the ability of the company to carry on as a going concern, and this might force the auditor to issue a modified going concern opinion. This modification is a vital undertaking that helps in informing stakeholders about uncertainties or disagreements relating to the accounting principles.

According to Carlo et al. (2014), the Auditors' Opinion may be modified if there are four main conditions substantial enough to cause doubt. The first condition is an indication of negative trends in the financial ratios. The second indication is the possible financial difficulties that create doubt for the auditor leading to modifying the Auditors' Opinion. The third condition that can cause doubt for the auditor and lead to the modified Auditors' Opinion is the presence of trouble-signalling internal matters. And the fourth condition involves identifying unfavourable conditions in external matters in the company's going concern.

From the existing empirical evidences besides the points highlighted above on the Auditors' Opinion and its scope of work, there are reservations on the reliability of the Auditors' Opinion on going concern. Many authors have criticized that the reliability for several reasons: (a) one reason is that the judgment made by the auditors is basically based on the perceptions they have about the company's going concern; (b) another criticism is based on the judgment the auditors that largely on the external factors affecting their audit profession (Bruynseels, Knechel and Willekens, 2013).

In so doing, the auditors stand the likelihood of making any one of the two types of errors. The first error is Type I error which involves false positive. A false positive or Type I error occurs when the auditors give a modified going concern opinion (GCO) that enables the company to continue in business (Carlo et al., 2014). Another type of error is Type II error which occurs when the company is headed for failure

yet the auditor fails to give a GCO. Type 1 error is mainly caused by a self-fulfilling prophecy effect and a deteriorated relationship with the client. Other factors that may lead to the Type 1 error are already discussed above under the various audit related variables. There is also evidence that another factor that impacts the Auditors' Opinion is whether the audit committee is external or internal. Internal auditors have a higher likelihood of encountering the Type II error due to the risk of lawsuit by creditors and the loss of reputation (Reynolds and Francis, 2000).

### **3.7 Critical Review of Literature**

Upon conducting an extensive literature review as part of preparation of this study and in forming the foundation of this study, the researcher concludes this chapter with a critical review of the current state of art. The current state of art based on the outcome of this extensive literature review is presented in the following section as part of the critical review of literature.

#### **3.7.1 Need for Financial Vigilance**

Another need for increased financial vigilance and more accurate tools and techniques for corporate financial distress prediction is identified by Outecheva (2007) who had argued that there is also need to identify and distinguish between external and internal risk factors; and also to examine the proportion of each identified risk factor within the risk group. In an early undertaking to the task of risk identification, Bibeault (1982) had examined the fraction of all risk factors, each within each risk group and uncovered five considerable sources of external risk. The first external source is economic change. Other external sources of risk identified in the literature include changes in competition or competitive balance, government constraints, social adjustments, and technological change.

#### **3.7.2 Ratio Analyses**

The review of literature related to financial distress prediction models has shown that the first models to be used in predicting financial difficulty in companies were traditional ratio analysis, which Beaver (1966) had used to come up with the

univariate technique of financial distress prediction. His work mainly comprised the univariate analysis of various bankruptcy predictors; ending with setting the stage for the multivariate endeavours that later followed the univariate attempts at predicting bankruptcy or financial distress. That initial effort led to a method in corporate distress risk assessment which mainly applied three criteria to select 30 financial ratios that were finally used in analysing 79 failed companies within a period of five years before default. The first of the three criteria is the popularity or frequency of the financial ratios in the existing literature. The second criterion Beaver relied on is the performance of the ratios in the past studies. And lastly, Beaver also relied on the use of ratios within the background of a cash-flow theory. Within the framework of the cash-flow theory, the company is conceived as a reservoir of liquid assets. The reservoir is thus filled by inflows (cash inflows) and emptied by outflows (cash outflows).

### **3.7.3 High Type 1 Error**

The literature review has revealed that due to its approach, the univariate method registers a very high Type I error, which is as high as 22% before the company failure while the Type II error stands at 5%; this fact cautions that the technique must be approached with great care. In addition, despite the meticulous work carried out to develop the univariate method, there are difficulties encountered when approaching the analysis via the classification model due to the possibility of the two types of errors. Type I error involves misclassification of a company that is in financial distress position. And Type II error involves misclassifying a non-financial distress company. The damage that can result from these two types of errors provides a rationale for extra alertness when conducting the assessment of companies via the univariate models.

There are other limitations of the univariate technique. Firstly, the single ratios worked out by Beaver did not capture time variation of financial ratios. The repercussion of this limitation is that accounting ratios have their forecasting capacity one by one, and therefore it is not possible to carry out analysis, for example, of rates of change of ratios over time. Secondly, the single ratios may generate incompatible or contradictory results if diverse ratio classifications are used for the same company.



This can be a serious problem in coming up with a conclusion since the results would be inconsistent and thus confusing. And thirdly, there is a high correlation among a number of accounting variables and it may be incorrect to embark on interpreting a single financial ratio in isolation. The overriding relationship between and among accounting variables implies that one accounting ratio does not have the capability of capturing the multidimensional interrelationships within the company being evaluated. These limitations offer ample justifications for a good and desirable model that can provide precise and clearly consistent categorical results in order to mitigate the possibility of misclassification that can produce dire outcome on the company.

#### **3.7.4 Overcoming Limitations of Univariate Models**

Among the first models to attempt to address the limitations of the univariate models is the Multivariate or Multiple Discriminant Analysis. Proposed and developed by Altman (1968), the MDA quickly attracted the interest of other professionals and it has become one of the most evaluated models for predicting the financial default or financial distress of company. Altman was interested in establishing the weights or coefficients objectively and attaching the established coefficients to the financial ratios.

The result was the Z-Score financial distress analysis model known as the Altman's Z-Score Model. In the Z-Score financial distress analysis model, Altman casts doubt on the quality of the univariate ratio model as an analytical method and goes ahead to apply the multivariate or multiple discriminant analysis to come up with a linear blend of the ratios which "best" distinguish between the financial distress and non-financial distress clusters.

The ratios include the WC/TA which has the highest weight among the liquidity ratios; the RE/TA which measures the company's cumulative profitability hence its ability to offer a picture of the company's going concern; the EBIT/TA which measures the proper productivity of the company's assets while excluding any influence of tax or leverage factors; the Market Value of Equity to Book Value of Debt ratio (MVE/BVD); and the Sales to total assets ratio which in effect is a tool for measuring the company's ability to handle competitive conditions.

### **3.7.5 Altman's Z-Score Model Review**

A critical review of the Altman's Z-Score Model revealed that the K & P judgmental model (Kundinya & Puri prediction model) is superior to the Altman's Z-Score Model in predicting companies that have a likelihood of failing or in financial distress position. Specifically, the study by Clark et al. (1997) has shown that in the Altman's Z-Score Model, a company with a score of 1.80 and below is classified as failure, i.e., in financial distress. A company with a score ranging between 1.81 and 2.99 is classified under the grey area, and any company with a score greater than 2.99 is classified as on-going, i.e., in non-financial distress. The authors have found a high possibility of misclassification of companies by the Altman's Z-Score Model, thus making it difficult for one to predict with precision the outcome of the companies in the grey area. In contrast, the K&P judgmental model has shown to be more superior in distinguishing failed or in financial distress companies and also non-financial distress ones, thereby mitigating the grey area problem experienced by the Altman's Z-Score Model.

For the same reason of accuracy and reliability, the LRA (Logit) and the Probit techniques were developed. The Altman's MDA technique has proved to be problematic due to its restrictive assumptions inherent in the MDA alongside the output of the MDA technique. While developing the Logit technique (O-Score method), Ohlson has criticized the MDA output by noting that, as a single dichotomous score, it does not provide any meaningful information about the probability of default. The O-Score technique is based on econometric techniques that make use of logistic transformations, namely, the Logit Model. The O-Score technique assigns a score to the independent variable after weighting the independent variables.

### **3.7.6 Analysis of Probit Technique**

Another technique analysed is the Probit Technique (Zmijewski -1984 Probit model), which categorizes the companies as financial distress and non-financial distress. The methodology for the technique involves calculating the Probit model for both the financial distress and non-financial distress companies, and then probing the

accuracy in categorizing the financial distress companies as financial distress and non-financial distress companies by weighing the Probit model against the shareholders' equity, net income and cash flow ratio. The classification encompasses placing each company into two zones; that is, financial distress and non-financial distress, on account of the cut-off point proposed by Zmijewski in 1984 such that for financial distress companies the cut-off is  $Z < 0.5$  while  $Z > 0.5$  is for non-financial distress companies.

### **3.7.7 Auditors' Opinion**

Besides the univariate and multivariate techniques, the Auditors' Opinion is also used for predicting financial distress of the company. Reliability of the Auditors' Opinion on going concern has been a subject of studies, with mixed findings. There are, however, various factors that affect the opinion and performance of the Auditors' Opinion on going concern of the company. The literature review has revealed that the composition, size and frequency of checks of the audit committee affect the opinion especially where the auditors are internal.

The existing literature has also recognized the role of auditors by pointing out that the auditors have the responsibility of issuing an audit opinion with the purpose of assuring stakeholders that the financial reporting provides a true and reasonable view consistent with the financial reporting structure used for the preparation and presentation of the financial statements. The auditor might express some considerable doubts concerning the ability of the company to carry on as a going concern and this might force the auditor to issue a modified going concern opinion (referred to as GCO).

The reviewed literature has also shown that Auditors' Opinion may be modified if there are four main conditions that can cause substantial doubt. The first condition is an indication of negative trends in the financial ratios. The second condition is an indication of possible financial difficulties that create doubt in the Auditors' Opinion leading to a GCO. The third condition that can cause doubt in the Auditors' Opinion and lead to a GCO is the presence of trouble-signalling internal matters. And the fourth condition is the unfavourable conditions in external matters that cause doubt

in the company's going concern assumption. There are other reasons for having doubts on the capacity of the Auditors' Opinion to be used as a reliable tool. The judgment made by the auditors is basically based on the perceptions they have about the company's going concern.

Also, the judgment the auditors make depends largely on the external factors affecting their audit profession. Auditors stand the likelihood of making any of the two types of errors. The first error is Type 1 error which involves false positive. A false positive or Type 1 error occurs when the auditors give a GCO for the company to continue in business. The second error is Type 2 error which occurs when the company is headed for failure and the auditor fails to give a GCO. Type 1 error is mainly caused by a self-fulfilling prophecy effect and a deteriorated relationship with the client. Other factors that may lead to the Type 1 error are already mentioned above under the various audit related variables. There is also evidence that another factor that impacts on the Auditors' Opinion is whether the audit committee is external or internal. Internal auditors have a higher likelihood of encountering Type 2 error due to the risk of lawsuit by creditors.

### **3.7.8 Review Conclusion**

Dimitras, Zanakis and Zopounidis (1996) have reviewed numerous literatures pertaining to financial distress prediction studies and they have concluded that the MDA method is the most frequently used method, followed by the LRA method. The authors have asserted that the current trend is to use the non-financial variables to help predict financial distress.

The Altman's Z-Score Model is the tried and tested model for financial distress prediction (Eidleman, 1995). The Altman's prediction model has stood the test of time and is used in recent research to examine the companies in various industries and different time periods (Grice and Ingram, 2001). Therefore, this research will be using the Altman's Z-Score Model as the base theory for the prediction of financial distress amongst the PLCs in Malaysia.

From the above analysis, considering the weaknesses and strengths of the Altman's Z-Score Model and the Auditors' Opinion on going concern, it is evident that the two methods can be used together in order to complement each strengths and offer an alternative direction which, in the case of using only one method, can only carry its inherent weakness. For instance, from the literature reviewed, it is shown that, on the one hand, the a company's Auditors' Opinion on going concern is basically a subjective method premised on various factors that affect the auditor's judgment while it is a good method for offering real time advice to investors where the auditors provide a GCO.

On the other hand, the Altman's Z-Score Model is an objective method but it is still dependent upon the availability of correct and factual financial information from the company's audited financial statements. As a consequence, the Auditors' Opinion of going concern is vital in ensuring that the financial information accessible to the company is not doctored as the Altman's Z-Score Model provides prediction based on accurate information provided. These two methods can therefore be effectively used for predicting financial distress amongst the PLCs in Malaysia to fill the research gaps identified in Section 1.7: Research Gaps.

### **3.8 Chapter Summary**

This chapter has evaluated the various financial distress prediction models and highlighted the merits and demerits of each of the evaluated model. However, prior to evaluating the various prediction models, the review has evaluated the need for financial controls and prediction. In this regard, there are several studies that have assessed the need for strict financial controls and prediction of financial distress to mitigate the corporate collapse such as the Enron Corporation (e.g. Abbott et al 2000; Beasley et al 2000; Abbott et al 2004; and Kirkos et al 2005).

The studies by Abbott et al. (2000) and Beasley et al. (2000) have support the need to equip the internal audit committees with the right tools and techniques to conduct frequent and objective evaluation of companies in order to mitigate corporate scandals.

In addition, the literature review has shown that there is a need to complement the internal audit committees with external and independent committees in order to ensure the objectivity and reliability of the Auditors' Opinion on the financial status of the company. This further helps in mitigating the Type I error (false positive) and the Type II error. The early studies have established that companies with audit committees comprising of autonomous auditors who meet no less than two times a year have less likelihood of being sanctioned for fraudulent reporting or doctored financial statements, and this is a way of dealing effectively with the Type II error.

Finally, based on the reviewed literature, the Altman's Z-Score Model will be used as the base theory in this study, which will also include the Auditors' Opinion on going concern as an additional variable to predict the financial distress among the PLCs in Malaysia.

## **CHAPTER FOUR**

### **4 RESEARCH METHODOLOGY AND HYPOTHESES DEVELOPMENT**

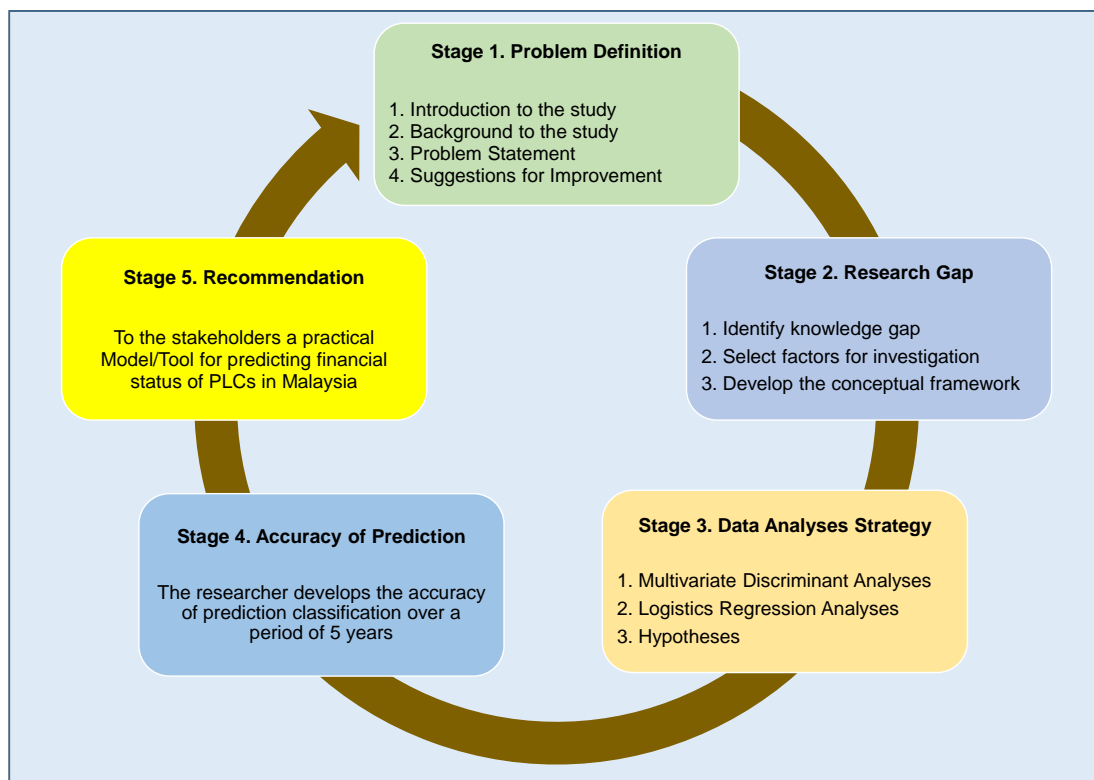
#### **4.1 Introduction**

In this chapter the researcher presents an overall bird's eye view of this study with the step-by-step action taken to complete the thesis in a structured and academic manner. This chapter, which deals with the research methodology looks into in-depth approach undertaken by the researcher to answer all the research questions while realizing the aims and objectives of the study including all procedures, processes and methods done at each and every one of the stages from the start to completion of this research.

For the purpose of this study, the research methodology includes the research philosophies, the research methods and the tools and techniques used to achieve the ultimate aims and objectives of this study (Tan, 2008).

#### **4.2 Overall Outline of the Study**

The overall outline of the study can be summarized in Figure 4-1 below.



**Figure 4-1 Overall Study in Summary**

Source: Researcher's own work

The researcher commences the investigation with an elaborate problem definition which leads the researcher to identifying the research gap, selecting variables for investigation and establishing the appropriate research framework. Next, the researcher establishes the data acquisition and data analyses strategy which leads the researcher to ascertain the accuracy of prediction. Finally, the researcher completes the study with recommendations.

This overall study summary provides a visual presentation of the study as a whole and the researcher attempts to provide the same line of thought in section 4.5 Problem Definition where the stages are described and presented in detail. This is again presented in a flow chart in the section 4.6 Research Flow of this study.



### 4.2.1 Gist of Problem Definition

The researcher presents the entire study as a whole for the clear understanding of all readers. The entire study can be summarized based on the problem definition as stated in Table 4-1 below.

**Table 4-1 Overall Gist of the Study**

Introduction to the Study	Predicting financial status of PLCs in Malaysia
Background of the study	Importance of prediction model/tool to the stakeholders of PLCs.
Literature Review	Auditors' Opinion on going concern identified as research gap
Problem Statement	Altman's Z-Score Model (based on US data) is used in predicting financial status of the PLCs in Malaysia.
Problem Solution	Auditors' Opinion on going concern with Malaysian data to improve accuracy of predicting financial status of the Malaysian PLCs.

Source: Researcher's own work

### 4.2.2 Definition of Research Methodology

Research Methodology is defined by Sekaran (2008) as follows:

“...organized, systematic, data-based, critical, objective, scientific inquiry or investigation into a specific problem, undertaken with the purpose of finding answers or solutions to it.”

However, another definition of research that is more in line with the spirit of this research, by Redman and Mory (1923), is follows:

“...systematized effort to gain new knowledge”.

With the above definitions, the researcher defines the research methodology as a scientific inquiry to gain new knowledge. For the purpose of this study, the new

knowledge is to establish a better practical tool to predict financial distress amongst PLCs in Malaysia.

#### **4.2.3 General Assumption in Research Methodology**

In conducting this study, the researcher realized that the authorities in research methodology do not concur in simultaneous or consistent meaning to every words or descriptions used. In the same line, this study do not concur with any one particular work but bears its own peculiar meaning as deem fit and necessary for the purpose of this study, to achieve the aims and objectives of the study while answering all the research questions raised at the commencement of this study.

However in completing this study, the researcher attempts to reconcile with all the established works in the field of research methodology so as to provide a clear approach to all the readers of this study.

#### **4.3 Preparation of the Study**

At this juncture of the study, the researcher establishes the function and outline of this chapter in a way that is easy to understand for the readers. The function of this chapter is to manage the research of this study which focuses on the broad scopes of data collection, data analyses, data interpretation of findings and finally comparison of findings with the literature review available.

The outline of this research methodology chapter is framed around the four main scopes of the function as highlighted above in relation to the human interaction and the manner in which these are executed in order to meet the standard academic practice in meeting the aims and objectives of the study. In addition, this is also related and tied up with the data analyses to answer the research questions and research hypotheses of the study.

#### **4.4 Literature Review**

The researcher completed an extensive literature review at the commencement of this study. The entire literature review conducted in this study is discussed and presented in chapter 3 of this study.

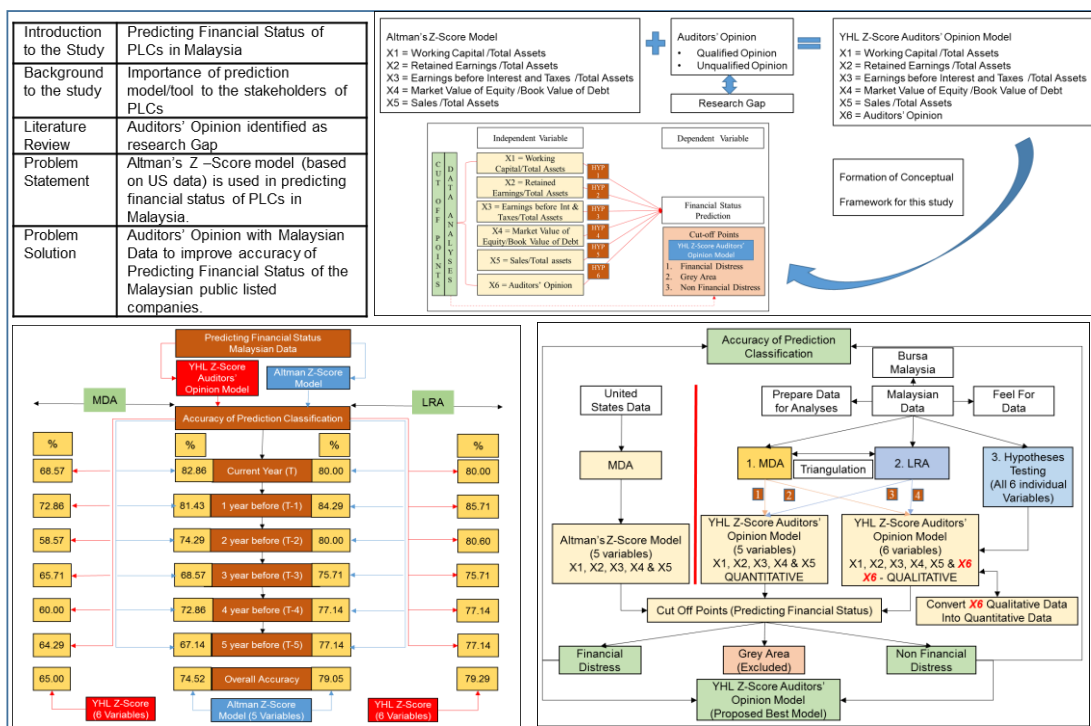
The first objective of the literature review chapter was to clearly establish the knowledge boundary in the selected topic of investigation. The second objective was to identify the knowledge gap which this study will attempt to fill. The third objective of the literature review was to identify and select the suitable variables for this investigation.

The researcher was able to present the state of art of the topic selected for investigation to the benefit of all readers. This was followed by identifying the knowledge gap related to this study. Finally the researcher also discussed in detail the variables selected for investigation in this study.

#### **4.5 Problem Definition**

The problem definition of this study is covered in a guided and structured approach for the benefit of all readers. The problem definition included the introduction of this study, the background of the study, the problem statement giving rise to this study and finally the proposed solution by the researcher. This is discussed and well presented in chapter 1 of this study.

The research flow of this study is an additional part of the problem definition of this study. Alongside with the research flow, the “Big picture” of this study is also part of the problem definition of this study. The research flow and the “Big picture” are expected to provide a holistic picture of the study to all readers in understanding the study.



**Figure 4-2 Big Picture of the Entire Study and Proposed Solution**

Source: Researcher's own work

The proposed study can be presented and seen in the following 5 stages of the investigation.

In the first stage, the researcher identifies the problem definition which includes the introduction to the study, background to the study, the problem statement identification and the proposed solution to the problem in hand. The problem is highlighted and quantified in the best possible manner.

In the next stage, the researcher identifies the knowledge gap and proceeds to gather the relevant variables for the study. The Altman's Z-Score Model is selected to be the base model with an additional variable in the form of the Auditors' Opinion on going concern. With this, the researcher is able to form a suitable conceptual framework for the study. With the conceptual framework established, the researcher is able to synthesize the research questions, research hypotheses, research aims and objectives of the study and the research scope too. The foundation for the study is formed at this stage.

In the third stage, the researcher designs the data analyses strategy. The idea to have 3 different statistical analyses is formed at this stage. The MDA, LRA and the Hypotheses testing are formed at this stage. The MDA and LRA will be tested and checked between the 5 variables and 6 variables highlighted in the research design. Triangulation will be done between the MDA and LRA.

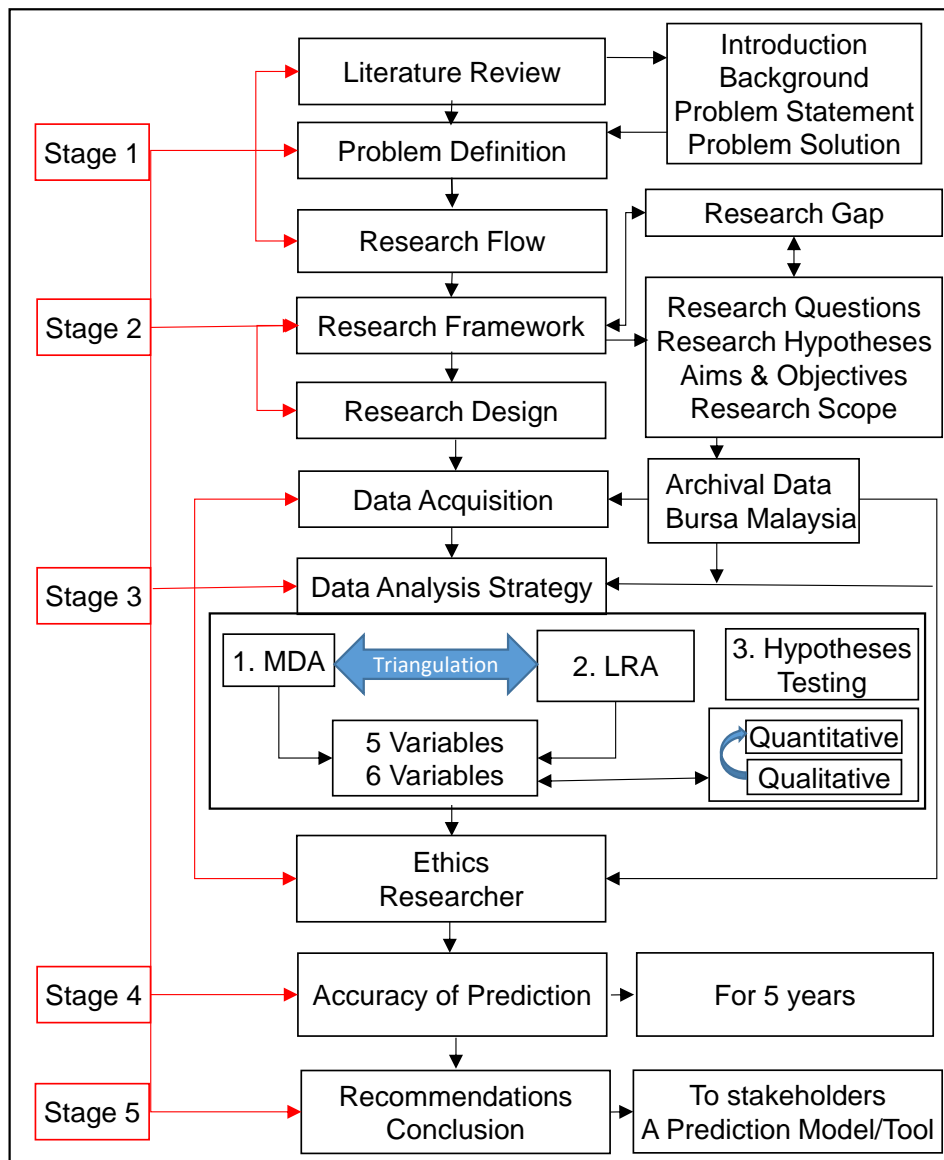
In the following stage 4, the researcher proceeds to develop the accuracy of prediction classification of the financial distress of PLCs in Malaysia. The findings of the data analyses will be used to measure the level of accuracy of the predictions which is the main objective of this study.

In the final stage of this study, the researcher is interested to provide recommendations for the relevant authorities, PLCs and major stakeholders. The recommendations will be useful for the major stakeholders to have a useful tool and technique for better prediction of the financial status of the PLCs in Malaysia. The findings will also be compared academically to match the literature review related to the study.

This study will be presented and discussed along all the 5 stages of this proposed “Big picture”.

#### **4.6 Research Flow**

The research flow of this study is developed to present in an academic manner in which the researcher forms the foundation of this study and develops it into a full fledged research. The research flow shows the readers every step taken into completing this study in a reasonable and easy to follow steps as presented in the following research flow summary in Figure 4-3 below.



**Figure 4-3 Research Flow Developed for the Study**

Source: Researcher's own work

#### 4.6.1 Research Preparation

The research preparation involves a lot of commitment from the researcher in identifying and highlighting the research problem. This was done with an extensive literature review to establish a strong foundation for the study. Further the researcher develops a viable set of aims and objectives to guide the study which are all discussed and presented in this study at the relevant chapter and within the respective chapters accordingly (Sekaran, 2008).

#### **4.6.2 Public Listed Companies**

The researcher has taken great effort in introducing and presenting the details of PLCs in Malaysia to the readers for better understanding. This was done in chapter 2 of this study.

#### **4.7 Research Framework**

The research framework for this study was formed in chapter 1 of this study. The researcher systematically established the independent and dependent variables for this study and introduced the cut-off points to facilitate the investigation into grouping and classifying the findings into financial distress, grey area and non-financial distress.

Theories are general principles that are plausible or scientifically acceptable general principles offered to explain observed facts; a model represents a structural design of theories (Merriam-Webmaster Dictionary, 1995). According to Ball and Foster (1982), Scott (1981) and Jones (1987), most bankruptcy or financial distress prediction theories are not based on the practical application of empirical research but on published data in mathematical and statistical literature. The dominating theory used in this research is based on the use of financial ratios.

#### **4.8 Research Hypotheses**

The research hypotheses for this study are formed systematically in a step by step approach cascading from the research questions (see section 1.9 Research Matrix). The detail of each study is given in the respective sections indicated below.

##### **4.8.1 Hypotheses Formulated Corresponding to the Preliminary Tests**

1. Preliminary data
  - a. There is no difference in the X Variables between NPN17 and PN17 (section 5.4).
  - b. There is no difference in the Z Score for the periods (section 5.5).

#### **4.8.2 Hypotheses Formulated Corresponding to the First Aim**

1. What is the prediction accuracy of the 5-Variable Altman's Z-Score Model in predicting financial distress amongst PLCs in Malaysia?
  - a. Prediction accuracy of the 5-Variable Altman's Z-Score Model (section 5.7.1).
2. Can the prediction accuracy of the 5-Variable Altman's Z-Score Model be improved by using data of PLCs in Malaysia?
  - a. Prediction accuracy of the MDA 5-Variable Model (section 5.7.2).
  - b. Prediction accuracy of the LRA 5-Variable Model (section 5.7.3).
3. Can the prediction accuracy of the 5-Variable Altman's Z-Score Model be improved by incorporating another variable, the Auditors' Opinion on going concern as 6-Variable model using data of PLCs in Malaysia?
  - a. Prediction accuracy of the MDA 6-Variable Model (section 5.8.1).
  - b. Prediction accuracy of the LRA 6-Variable Model (section 5.8.2).

#### **4.8.3 Hypotheses Formulated Corresponding to the Second Aim**

4. What is the best revised model that can be used with the highest prediction accuracy for financial distress amongst PLCs in Malaysia?
  - a. Select on Best Trend (section 5.9.1).
  - b. Comparison of Alpha Error (section 5.9.2).
  - c. Comparison of Beta Error (section 5.9.3).
  - d. Comparison of Accuracy (section 5.9.4).
  - e. Predictability – Next Two Years (section 5.9.5).
  - f. Predictability – 5- and 6-Variable (section 5.9.6).



#### 4.9 Research Design

The researcher believes it will be of great importance to understand the definition of research design before embarking on it. Research design is attempted to be defined by Yin, (2003) as:

*“... the logical sequence that connects the empirical data to a study’s initial research questions and, ultimately, to its conclusions.”*

In conducting a research, the researcher can depend on the research design to be treated as a guiding principle towards completing the processes, procedures and methods set out to be carried out towards data acquisition and data analyses. In order to ascertain good findings which have a high credibility, validity and reliability, the researcher must comply with the standard philosophy, paradigm, and the entire research methodology including good data analyses strategy to develop a sound research design (Bryman & Bell, 2007).

In working towards the research design for this study, the researcher considered the works of Sekaran, (2008) and Saunders et. al, (2009) as the guiding light house supported by the university’s guide and format and also by referring to peer works in the university.

In developing the suitable and relevant research design for this study, the researcher has very carefully thought and considered all the research questions and research hypotheses as guided by the conceptual framework to achieve the aims and objectives of the study.

The gist of the research design developed to complete the investigation is summarized in Table 4-2 below.

**Table 4-2 Research Design Developed for the Study**

Research Philosophy	Pragmatism
Research Purpose	Exploratory
	Descriptive
	Hypotheses Testing
Research Approach	Deductive
Research Choice	Mixed method
Research Method	Quantitative
	Qualitative
Research Strategies	Archival Research
Types of Data	Secondary Data
Data Source	Bursa Malaysia

Source: Researcher's own work

#### **4.9.1 Research Philosophy**

In the subject matter of research philosophy, the researcher presents the general discussion, namely the general research philosophy. This is usually discussed in a research work like this study. This is presented to establish the line of thinking based on a particular school of thought to associate the line of thinking of the researcher.

Research philosophy is mainly concerned with the Ontology and Epistemology of research. These are important to ascertain the process of knowledge acquisition is credible based on the well-established principles of philosophy which forms the foundation of knowledge.

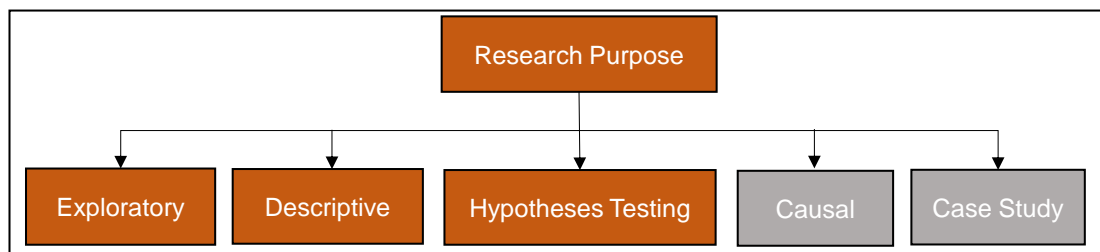
Ontology is concerned on the nature of reality of things which one is interested in. This could be the phenomenon the researcher is interested to investigate and have a better understanding of the issues in hand (Reich, 1994). In another word ontology is the sum of norms, beliefs, values and assumptions of what stands as the “world-view” in the eyes of the researcher. This sum of nature is what the researcher sees as a whole (Tan, 2008).

The next research philosophy the researchers are interested is the epistemology which is concerned about the nature of knowledge (Love, 2001). Another researcher, Tan (2008), suggests that epistemology is the process of how one gets to know what one knows which forms the sum of knowledge in one's mind.

#### 4.9.2 Research Purpose

The purpose of research can be divided into 5 different purposes as shown in Figure 4-4 below. The purposes can be classified as follows:

- Exploratory
- Descriptive
- Hypotheses testing
- Causal
- Case study



**Figure 4-4 Research Purpose Deployed in the Study**

Source: Researcher's own work

The research purpose for this study are exploratory, descriptive and hypotheses testing. These 3 different purposes are invoked at different stages of the study which are discussed and presented in the following sections below. The causal and case study purpose are excluded for the purpose of this study.

#### **4.9.2.1 Exploratory**

At the initial stage of the study, the researcher compiles foundation information and details to form the case for investigation (Burns & Bush, 2000). The exploratory purpose of a study is generally an unstructured and a random gathering of detailed information which forms the outline information of a given study (McDonough and McDonough, 1997). This represents the exploratory nature of the study.

The ground breaking preparation helped the researcher to systematically design and develop the research problem definition to include the introduction, background, problem statement and a set of proposed solutions for this study. As a continuation of this, the researcher was also able to identify the factors for this study including the formation of research questions, research hypotheses, aims and objectives of this study (Malhotra, 1999).

#### **4.9.2.2 Descriptive**

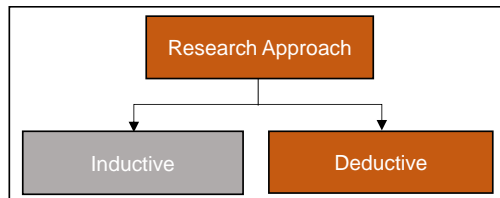
The next stage of data analyses leads into the descriptive nature of the study when the researcher attempts to explain the findings of the data. The explanation of the phenomenon, processes and procedures as it transpires is the function of descriptive data which is usually described based on the data analyses (Pyecha, 1988). This is a stage where the researcher expresses the understanding of the case being investigated in terms of measurement and units of measure in a way the readers can understand and appreciate the case in discussion (Cooper & Emory, 1995).

#### **4.9.2.3 Hypotheses Testing**

The hypotheses testing become necessary when the researcher attempts to establish and prove the beliefs rose at the commencement of the study. The researcher attempts to explain the phenomenon being investigation with the statistician's decision based on empirical data collected in the study. The significance test provides a sound statistical finding based on well-established statistical rules to determine if an observation relevant to the study is purely attributed to chance alone. This provides the researcher to prove ones belief with sufficient statistical evidence (Cooper and Emory, 1995).

### 4.9.3 Research Approach

The researcher can take either the inductive or deductive approach in conducting a study of this nature as shown in Figure 4-5 below.



**Figure 4-5 Research Approach Deployed in the Study**

Source: Researcher's own work

Research approach can be defined as,

*“An inductive research approach is typically qualitative in nature, while a deductive research approach is typically quantitative in nature”*. Gay and Airasian (2003).

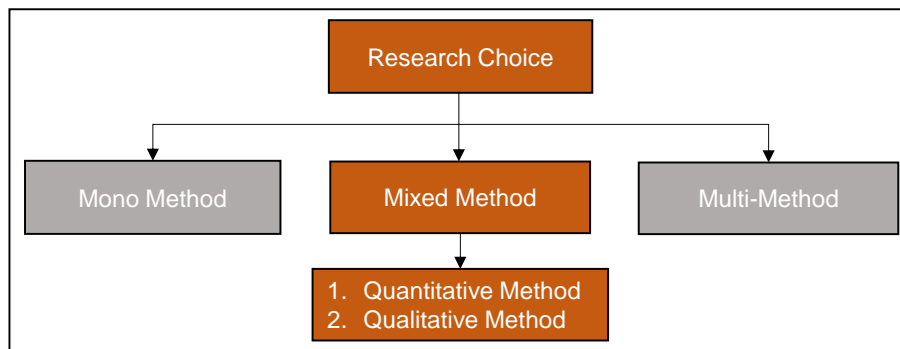
While this can be generally accepted as a general guide, the researcher is of the opinion that the inductive approach can possibly include some elements of the qualitative method while the deductive can also include some elements of the qualitative method depending on the aims and objectives of the individual case in hand (Onwuegbuzie & Leech, 2005).

The researcher takes the deductive approach to complete this study. In undertaking a deductive approach in conducting the research, the researcher conducts an extensive literature review to identify the relevant independent variables for the study. With the variables selected, the researcher then synthesizes the independent and dependent variables of the study to form the model for the study. With this established, the researcher is able to develop the hypotheses to be tested for the study. Developing to the next level, the researcher is able to collect data and analyses the data to get the findings of the study (Burney & Mahmood, 2006). This is in view to establish the

reality of the accuracy of prediction of financial status of the PLCs in Malaysia, (Cooper and Emory, 1995).

#### 4.9.4 Research Choice

Research choices can be classified as mono method, mixed method or multi-method (Saunders et al, 2009). These can be summarized as shown in Figure 4-6 below.



**Figure 4-6 Research Choice Deployed in the Study**

Source: Researcher's own work

Traditionally researchers used one method of data enquiry while excluding the other (Tashakkori and Teddlie, 1998). However, in the current day research, most researchers use a mixed method approach whereby the different methods are used to complement and support each one of the other method. (Creswell, 2003). The usage of mixed methods are seeing an increase among the researchers in order to answer the research aims and objectives (Curran & Bllackburn, 2001).

In this study, the researcher decided to use the mixed method to complete this investigation. The mixed method in this study invoked both the quantitative and qualitative methods.

An additional benefit of using this mixed method of data analyses is that it allows the researcher to proceed to conduct triangulation which is discussed in this study (Campbell & Fiske, 1959).

#### 4.9.5 Research Method

In this study, the researcher uses both the quantitative and qualitative data in data acquisition and data analyses for achieving the aims and objectives of the study. The classification of methods used in this study is summarized in Table 4-3 below.

**Table 4-3 Mixed Method Deployed in the Study**

<b>Z-Score Model</b>		
<b>Item No</b>	<b>Variable Descriptions</b>	<b>Method</b>
X1	Working Capital / Total Assets	Quantitative
X2	Retained Earnings / Total Assets	
X3	Earnings before Interest and Taxes / Total Assets	
X4	Market Value of Equity / Book Value of Debt	
X5	Sales / Total Assets	
X6	Auditors' Opinion	Qualitative

Source: Researcher's own work

The data is explained in the following sections.

##### 4.9.5.1 Quantitative Data

Quantitative data are hard numerical data which fits measuring, counting and summarizing perfectly well. Further, the quantitative data has statistical significance upon analyses.

For the purpose of this study, the quantitative data are the data set collected from the audited financial statements available at Bursa Malaysia. These are identified as independent variables X1, X2, X3, X4 and X5. Existing data can also be considered as part of useful data which is used for data analyses (Babbie, 1990).

The quantitative data analyses is also otherwise referred as hypotheses testing (Kerlinger, 1964). In this study, the researcher uses the quantitative data and is

conducting the hypotheses testing as usually done with quantitative data in similar studies.

#### **4.9.5.2 Qualitative Data**

Qualitative data has softer approach to data where it has a more descriptive touch and goes to the bottom of the issue. Usually this has personal issues in great detail.

In this study, the researcher gathers the Auditors' Opinion data from the audited financial statements available at Bursa Malaysia which forms the qualitative data for the purpose of this investigation. This is identified as independent variable X6 in this study.

In order to conduct the proposed analyses, the researcher needs to transform the qualitative data into quantifiable data. For this reason the researcher relies on Trochim, (2006) in which it is put forward that,

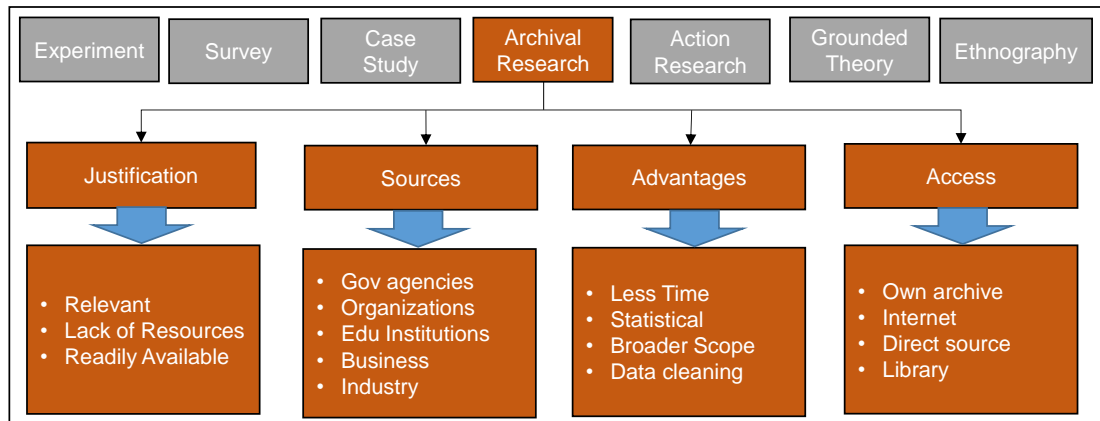
*“all qualitative data can be coded quantitatively”.*

As such the Auditors' Opinion which is in the form of qualitative data will be transformed into a quantitative data to facilitate the data analyses in this study.

#### **4.9.6 Research Strategies**

There are numerous research strategies which can be used to conduct a study of this nature. The strategies are namely experiment, survey, case study, archival research, action research, grounded theory and ethnography as highlighted in Saunders et al. (2009). All the research strategies are summarized in Figure 4-7 below.





**Figure 4-7 Research Strategies Developed for the Study**

Source: Researcher's own work

All the individual research strategies can be used to meet different research aims and objectives of a given study (Yin, 2003).

For the purpose of this study, the researcher decided to use the archival research. This refers to the data used for analyses in this study.

For the purpose of this study, the researcher decided to use the archival research which refers to the data used for analyses in this study, with sufficient grounds for selecting the archival research. This is then discussed and presented under four major broad areas as follows:

- Justification
- Sources
- Advantages
- Access

#### **4.9.6.1 Justification**

The justification for the researcher to select archival research for this study is due to the relevancy of the data available for analyses and interpretation.

This is coupled with the fact that the researcher does not have ample resources to conduct such an extensive data collection to gather all the data needed for the study.

The researcher chose to do archival research to capitalize on the readily available data set to be converted to useful meaning in the selected area of study.

#### **4.9.6.2 Sources**

The sources of archival data are numerous. This can be obtained from the government agencies, organizations, educational institutions, businesses and industry. For the purpose of this study the researcher obtained the archival data from Bursa Malaysia.

#### **4.9.6.3 Advantages**

By selecting to do archival research, the researcher is able to enjoy certain advantages namely less time taken to complete the study, be more focused on statistical analyses, broader scope of research and clean data set.

The researcher can capitalize on the readily available data from the Bursa Malaysia which means less time taken for completion of the study.

With the readily available data set for analyses, the researcher can spend more time and attention to be focused on the statistical analyses.

The readily available data set allows the researcher to concentrate on a broader scope of study without the additional burden of data collection which is time consuming and requires more resources.

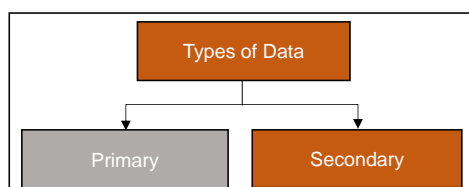
The data set from Bursa Malaysia can be taken as it is without having to clean the data to ensure fitness for use and also goodness for use.

#### **4.9.6.4 Access**

The access of archival data can be from a wide source like own archive, internet, direct source and library. However for the purpose of this study, the researcher obtained the data from internet source published by Bursa Malaysia.

### 4.9.7 Types of Data

There are two types of data which are commonly used to determine a study. Data are needed to achieve the aims and objectives of a study. Primary and secondary data are the common types of data available for researchers to complete their study as shown in Figure 4-8 below.



**Figure 4-8** Types of Data Deployed in the Study

Source: Researcher's own work

For the purpose of this study, the researcher decided to use only the secondary data to achieve the aims and objectives of the study.

#### 4.9.7.1 Primary Data

There is no primary data being collected or used in this study. This is in line with the research design of the study.

#### 4.9.7.2 Secondary Data

As it is a statutory requirement for both private and PLCs to be audited in Malaysia, audited financial statements would be readily available for research purpose. The audited financial statements for PLCs are used due to dependability of the data as they are examined by approved auditors licensed by the Ministry of Finance, Malaysia and in compliance with the applicable approved accounting standards, tax legislations, Companies Act, 1965 and the requirements of regulatory bodies in Malaysia such as Securities Commission and Bursa Malaysia.

As at 1<sup>st</sup> September 2010, 36 PLCs were classified as under PN17 by Bursa Malaysia. 35 PN17 companies are selected due to the availability of data required for this study. The 35 PN17 companies are matched with 35 non-PN17 companies as

paired samples with similar industry and size (measured by closest asset); and same financial period to minimize bias in selecting the control group or holdout sample.

Nam and Jinn (2000) had suggested that the construction of a matched sample will enhance the validity and reliability of the analysis as any sample bias associated with the characteristics of large companies will be eliminated. Piatt and Piatt (2002) supported the use of such a basis for comparing companies during the same time period to control the impact of varying macroeconomic environments. In addition, matching the industry is used to account for the possibility that there are systematic differences in the reporting behavior of companies across industries (Whittred and Zimmer, 1984).

The selected data samples are summarized as shown in the following Table 4-4 below:

**Table 4-4 Selected Data Samples for Analysis**

Samples selected (PN17)	Frequency	Percentage	Paired Samples selected (Non-PN17)	Frequency	Percentage
Consumer products	16	45.7%	Consumer products	16	45.7%
Construction	8	22.9%	Construction	8	22.9%
Services	5	14.3%	Services	5	14.3%
Property	3	8.6%	Property	3	8.6%
Plantation	1	2.9%	Plantation	1	2.9%
Mining	1	2.9%	Mining	1	2.9%
Technology	1	2.9%	Technology	1	2.9%
Total	35	100.0%	Total	35	100.0%

Source: Compiled by the researcher from the archival databases in Bursa Malaysia

The name of the PN17 and non-PN17 companies are not disclosed as reporting and publishing of the samples selected are not in reference to a particular company. This is done in aggregate as a representation of the industry and due to non-disclosure of the details of the companies.

Audited financial statements for six (6) years and the required data of each PLC are obtained from the Bursa Malaysia; they comprise five (5) years preceding to the financial distress and the year the company is classified as financial distress. The accuracy of the financial predictions will be assessed up to five (5) years prior to financial distress, namely, before the classification as PN17 companies.

#### **4.9.8 Data Source**

The data sources for this study are from the literature review and the annual audited financial statements.

The literature review has provided information and details for the researcher to form the foundation for this study. The extensive problem definition for this study is developed based on the materials in the literature review.

The data used for data analyses were obtained from the annual audited financial statements from the Bursa Malaysia.

#### **4.10 Data Acquisition**

In this study, the researcher has collected secondary data from the archival data in the Bursa Malaysia which carries the data of all the PLCs. The Bursa Malaysia data was gathered in the following format for the purpose of data analyses in order to facilitate subsequent data analyses.

**Table 4-5 Data Collection Format for One Year**

Sample Code	Sales	EBIT	Total Assets	Current Assets	Current Liabilities	Total Liabilities	Retained Earnings	Market Value of Equity
FD1	143190	-277369	63422334	34911512	197645	257343	23165991	102397440
FD2	1053000	1923000	280567000	84352000	57272000	101447000	14358000	402806520
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
FD35	0	-2684	15997	15997	14794	14794	-10797	19320

Sample Code	Sales	EBIT	Total Assets	Current Assets	Current Liabilities	Total Liabilities	Retained Earnings	Market Value of Equity
NFD1	5119371	790760	108837899	47976593	208318	208318	1399312	83977293.64
NFD2	25558303	25203319	145880011	148243200	62172167	64545652	9678639	2081505614
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
NFD35	0	7482324	93356776	54006959	11896498	16929554	2260475	29296800

Source: Compiled by the researcher from archival databases in the Bursa Malaysia

#### 4.10.1 Data Collection of Companies

Note that 35 companies were included in each of PN17 and NPN17, so that a total of 70 companies were studied. The raw data collected were as follows:

- Sales
- Earnings before Interest and Taxes
- Total Assets
- Current Assets
- Current Liabilities
- Total Liabilities (Book Value of Debt)
- Retained Earnings, and
- Market Value of Equity

This format of data collection was then used to collect data for a six-year period. The periods are labeled as:

- T-5, for five years ago

- T-4, for four years ago
- T-3, for three years ago
- T-2, for two years ago
- T-1, for the last year
- T-0, for the current year

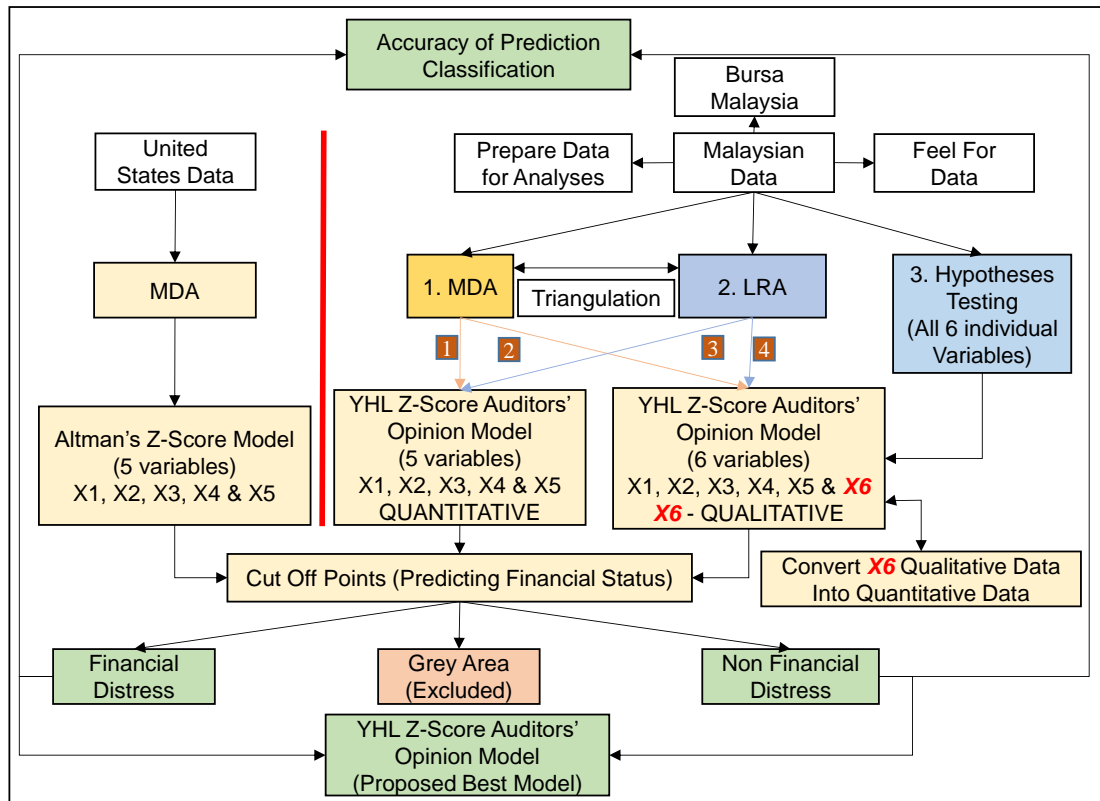
#### **4.10.2 Derived Data**

From the raw data collected, several metrics were derived so that the company information can be made comparable. The followings are the metric commonly used in the industry:

- $X1 = \text{Working Capital} / \text{Total Assets}$
- $X2 = \text{Retained Earnings} / \text{Total Assets}$
- $X3 = \text{Earnings before Interest and taxes} / \text{Total Assets}$
- $X4 = \text{Market Value of Equity} / \text{Book Value of Debt}$
- $X5 = \text{Sales} / \text{Total Assets}$

#### **4.11 Data Analyses Strategy**

The data analyses strategy for this study can be summarized as shown in Figure 4-9 below:



**Figure 4-9 Data Analyses Strategy**

Source: Researcher's own work

The researcher will use Malaysian data obtained from Bursa Malaysia to conduct the proposed analyses in this study. The researcher will conduct MDA, LRA and Hypotheses Testing.

The MDA will be conducted with both the 5 variables and also 6 variables model.

Likewise, the LRA will also be conducted with the 5 variables and 6 variables model.

The hypotheses testing will be conducted based on all the 6 variables selected for this study.

The results will be used to identify the cut-off points which will be relied for the financial status prediction. The cut-off points will be relied to determine the financial



distress and non-financial distress classification of the companies while the grey area will be excluded from the study.

The YHL Z-Score Auditors' Opinion Model is proposed as the best model by the researcher because it is ideal for increasing the accuracy of financial distress prediction classification.

#### 4.11.1 United States Data

The United States data forms the baseline study for this research. The United States Data uses the MDA with 5 variables namely X1, X2, X3, X4 and X5 as defined in section 4.10 above. These variables were used to multiply the coefficients from the MDA. The coefficients for the Altman's Z-Score Model are given in Table 4-6.

**Table 4-6 Coefficients of the Altman's Z-Score Model**

X1	X2	X3	X4	X5	LC	UC
1.200	1.400	3.300	0.600	0.999	1.810	2.990

Using this model, a pair of cut-off points is used to determine for the financial status of the companies. The cut-off points are then used to classify companies into

- Financial distress; if the metric falls below the Lower Cut-Off Point;
- Grey area; if the metric falls between the Lower and Upper Cut-Off Points;  
and
- Non-financial distress; if the metric falls above the Upper Cut-Off Point.

A classification table is then drawn to determine the number of correct and incorrect classification. Statistical measures such as the False Positive Rate, False Negative Rate and Accuracy can then be calculated to compare the model. A model is deemed better if its classification has lower False Positive Rate, lower False Negative Rate and higher Accuracy.

**Table 4-7 Example of a Classification for Prediction Counts**

	Predicted Fail	Uncertain	Predicted Pass	Total
Fail	19	0	16	35
Pass	9	0	26	35
Total	28	0	42	70

#### 4.11.2 Malaysian Data

In principle, the Altman's Z-Score Model could be used to predict the financial status of the PLCs in Malaysia using the same classification in that model and this is frequently done in practice. However, the researcher proposed that such a simplistic application neglects characteristics within countries which are vastly dissimilar. Such characteristics could easily include business culture, ethics and etiquette that are hugely different between the United States and Malaysia.

The researcher proposed to use the Malaysian data set to conduct a study similar to the Altman's Z-Score Model using the Malaysia data as the original data source. It is highly possible that such a study could result in a model that is better fitted to the Malaysian business environment. This then should result in better classification, i.e. lower False Positive Rate, lower False Negative Rate and higher Accuracy.

Further description of data analyses undertaken in this study is explained in detail in Table 4-8 below.

**Table 4-8 Data Analyses Strategy for the Study**

Item	Data Analyses	Analysis
1.	Hypotheses Testing X-Variables	Variables (X1 through X6) of the study are tested for significance
2.	Hypotheses Testing Z-Scores	The Z-Score (T-5 through T-0) of the study are tested for significance
3.	Multiple Discriminant Analyses	5-Variables model development
4.	Logistics Regression Analyses	5-Variables model development
5.	Multiple Discriminant Analyses	6-Variables model development
6.	Logistics Regression Analyses	6-Variables model development

Item	Data Analyses	Analysis
7.	Selection of the Best Model	Alpha Error, Beta Error, Accuracy, Next Two Years, 5- and 6-Variable

#### 4.11.2.1 Hypotheses Testing of X-Variables

Inferential statistics is used to test that the hypotheses of the X-Variables for PN17 and NPN17 are indeed different. This difference is tested using a standard anova test with a significance level of alpha equal to 0.05. If the test was not significant, then the PN17 and NPN17 data are the same and no further analysis can be made. For ease of understanding, the researcher has summarized the six hypotheses for studying the X-Variables.

**Table 4-9 Hypotheses Testing for X-Variables**

Hyp No.	Variable	Hypotheses Test Used
Hyp1	X1	A parametric equality of means anova test at a significance level of 0.05 will be used
Hyp 2	X2	A parametric equality of means anova test at a significance level of 0.05 will be used
Hyp 3	X3	A parametric equality of means anova test at a significance level of 0.05 will be used
Hyp 4	X4	A parametric equality of means anova test at a significance level of 0.05 will be used
Hyp 5	X5	A parametric equality of means anova test at a significance level of 0.05 will be used
Hyp 6	X6	A parametric equality of means anova test at a significance level of 0.05 will be used

#### 4.11.2.2 Hypotheses Testing of Z-Scores

Inferential statistics is also used to test that the hypotheses the Z-Scores for the PN17 and NPN17 are indeed different. This difference is tested using a standard anova test with a significance level of alpha equal to 0.05. If the test was not significant, then the PN17 and NPN17 data are the same and no further analysis can be made. For

ease of understanding, the researcher has summarized the six hypotheses for studying the Z-Scores for the periods: T-5, T-4, T-3, T-2, T-1 and T-0.

**Table 4-10 Hypotheses Testing of Z-Scores**

Hyp No.	Variable	Hypotheses Test Used
Hyp1	T-5	A parametric equality of means anova test at a significance level of 0.05 will be used
Hyp 2	T-4	A parametric equality of means anova test at a significance level of 0.05 will be used
Hyp 3	T-3	A parametric equality of means anova test at a significance level of 0.05 will be used
Hyp 4	T-2	A parametric equality of means anova test at a significance level of 0.05 will be used
Hyp 5	T-1	A parametric equality of means anova test at a significance level of 0.05 will be used
Hyp 6	T-0	A parametric equality of means anova test at a significance level of 0.05 will be used

#### 4.11.2.3 Multiple Discriminant Analysis

In this step, the researcher will conduct MDA using the Malaysian data to develop a Malaysian financial distress prediction model. The 5-Variable model uses the variables X1, X2, X3, X4 and X5 as defined previously.

In addition to the 5-Variable model, the researcher proposes that a model with a sixth variable, X6, namely the Auditors' Opinion to be included for added classification accuracy. When an Auditors' Opinion agrees with the non-financial distress condition of a company then the opinion is labeled as unqualified (clean report) and coded as a 1. When an Auditors' Opinion disagrees with the non-financial distressed condition of a company then the opinion is labeled as qualified (modified report) and coded as a 0.

Thus, the MDA would be conducted using two models i.e. based on a 5-Variable model and a 6-Variable model. Note that in the 6-Variable model, the researcher extends the 5-Variable model to include the 6-Variable, the Auditors' Opinion. The

researcher anticipates that the 6-Variable model prediction would be better than the 5-Variable model prediction.

In either case, the classification accuracy will be compared with the Altman's Z-Score Model as the baseline. It would be particularly noteworthy to see if the 6-Variable model was better than the 5-Variable original US data study. If indeed the 6-Variable model was better than the 5-Variable original US data study, the researcher would have successfully developed a better model with higher accuracy for financial distress prediction based on the Malaysian data. The model would in fact be better on two counts. First, the model would be intrinsically different from the US data model on account of using a sixth model and second, it would facilitate higher classification accuracy with respect to the Malaysian data on account of being based on the Malaysian data.

MDA derives an equation as a linear combination of the independent variables that will best discriminate the groups in the dependent variable. This linear combination is known as the discriminant function where each independent variable is assigned a discriminant coefficient. The discriminant equation is of the form

$F = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \varepsilon$  where, F is a latent variable formed by the linear combination of the independent variables,  $X_1, X_2, \dots, X_n$  with  $n$  independent variables,  $\beta_0, \beta_1 X_1, \beta_2, \dots, \beta_n$  are the discriminant coefficients and  $\varepsilon$  is the error term.

The objective of the discriminant analysis is to test if the classification of groups in variable Y depends on at least one of the X's. The corresponding hypothesis can be written as:

- Ho: Y does not depend on any of the Xi's.
- Ha: Y depends on at least one of the Xi's.

Another more statistical way of writing this is

- Ho:  $\beta_i = 0$ , for  $i = 1, 2, \dots, n$
- Ho:  $H_a: \beta_i \neq 0$ , for at least one  $i$

#### 4.11.2.4 Logistic Regression Analysis

The LRA is another form of classification method. Some studies indicate that the LRA gives better results. Consequently, in this study, the researcher investigates the LRA method to develop models similar and very importantly alongside the MDA. In this sense, MDA will be triangulated with LRA to see if there is any better outcome in comparison with the MDA. These analyses will also be twofold. Like the MDA, the first analysis would be based on the 5-Variables model and the second would be based on the 6-Variables model (i.e. that which includes the Auditors' Opinion).

The LRA is based on the binary Dependent Variable. Thus, if  $F(X)$  represents the likelihood of success, then  $1 - F(X)$  represents the likelihood of failure. Hence,

$F(x) = \frac{1}{1 + \exp(-(\beta_0 + \beta_1 x_1 + \dots + \beta_n x_n))}$  where the  $\beta$ 's are the coefficients of  $X$ . The

logit function can be expressed as the ratio of Success to Failure,

$$\frac{F(x)}{1 - F(x)} = \exp(\beta_0 + \beta_1 x_1 + \dots + \beta_n x_n).$$

Unlike regression where the Ordinary Least Squares method is used minimize the sum of the square distances of the data points to the regression line, the LRA use the Maximum Likelihood Estimation (MLE) to maximize the log likelihood (LL). This reflects how likely it is the odds that the observed values of the dependent may be predicted from the observed values of the independents.

In LRA, the cut-off points corresponding to the LRA is always 0.50. Using this model, the cut-off point is then used to classify companies into:

- Financial Distress; if their metric falls below 0.50 and
- Non-Financial Distress; if their metric falls above 0.50.

An additional feature of the LRA is that there is no Grey Area as in the MDA. A classification table is then drawn to determine the number of correct classification as follows.

**Table 4-11 Classification Table for Correct Predictions**

	Predicted Fail	Predicted Pass	Total
Fail	19	16	35
Pass	9	26	35
Total	28	42	70

The total number of correct classification is used as a measure of accuracy for the model that is investigated for the classification. Note that several models can be fitted to a given set of data. Each model statistical measures such as the False Positive Rate, False Negative Rate and Accuracy can be calculated to compare the models. A model is deemed better if its classification has lower False Positive Rate, lower False Negative Rate and higher Accuracy.

The objective of the LRA is to test if the classification of groups in variable Y depends on at least one of the X's. The corresponding hypothesis can be written as:

- $H_0$ : Y does not depend on any of the  $X_i$ 's.
- $H_a$ : Y depends on at least one of the  $X_i$ 's.

Another more statistical way of writing this is

- $H_0: \beta_i = 0, \text{ for } i = 1, 2, \dots, n$
- $H_a: \beta_i \neq 0, \text{ for at least one } i$

Note that the hypothesis for the MDA and the LRA are essentially the same. This is the important statistical property that allows both the models to be treated the same for analytical properties.

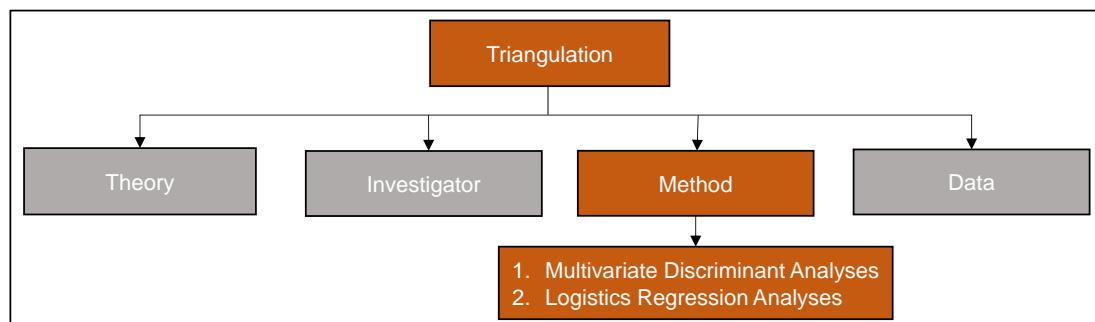
#### 4.11.2.5 Triangulation

Triangulation is used to establish an improved credibility of the findings. Triangulation is defined as different ways in which data collection, from different sources, varied analyses and varying source or theories put together to evaluate the credibility and validity of the data analyses findings (Leedy, 1997). There are a number of ways for a researcher to increase and improve credibility of a study.

Triangulation can be done using different theories to formulate the study in the first place (Veal, 2005). Next the researcher could use different investigators to see if the results are complementing each other. Otherwise the data could also be triangulated to see if it results in the same finding (Denzin, 1989).

However, in this study, the researcher used different method of data analyses to establish triangulation (Bryman, 2004). Different types of data analyses method is believed to produce better and improved reliability and validity to the study in comparison to one particular data analyses method (Creswell, 1994).

The entire scope of triangulation is summarized for the benefit of readers as shown in Figure 4-10 below.



**Figure 4-10 Triangulation**

Source: Researcher's own work

The method triangulation in this study is established between the two different methods, namely, the MDA and LRA. The analyses findings from the MDA and LRA will be compared with the original model to see which one of this presented a better model of prediction in financial status amongst the PLCs in Malaysia.



### 4.11.3 Modeling

MDA starts from the premise that a company's financial statements are multivariate documents that measure several aspects of the company's financial results and position simultaneously. MDA was developed mainly in response to the shortcomings of univariate financial ratio analysis. The first attempt to use MDA for bankruptcy or financial distress prediction purpose was developed by Edward Altman in the United States in 1968. By utilizing 33 bankrupt companies and 33 non-bankrupt companies in the United States, Altman's Z-Score Model was developed.

Altman's Z-Score Model adheres to the criteria necessary to generate reliability and validity in evaluating the financial status of business entities. The necessary criteria are as follows:

1. The sample of financial distressed companies should include a minimum of 30 companies.
2. The non-financial distress companies should be comparable in size and industry.
3. The differences of financial distress and non-financial distress companies should be analyzed.
4. A scoring system for the identified significant ratio should be derived.

(Eidleman, 1995)

Within the framework of Altman's Z-Score Model, the five dependent variables are set out below:

- X1 = Working Capital / Total Assets
- X2 = Retained Earnings / Total Assets
- X3 = Earnings before Interest and Taxes / Total Assets
- X4 = Market Value of Equity / Book Value of Debt
- X5 = Sales / Total Assets

The ratios will be computed based on data collected from the audited financial statements of the PN17 and NPN17 (as paired sample) companies as at 1<sup>st</sup> September 2010. The dependent variable is represented by Z-Score and sum of the ratios with applied MDA, indicating the financial status of the company as set out below:

$$Z = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 0.999X5$$

Z-Scores calculated will be classified as financial distress, uncertain or non-financial distress based on the followings:

**Table 4-12 Z-Scores Classification**

No.	Z-Score	Classification
1.	< 1.81	indicates financial distress
2.	between 1.81 and 2.99	indicates uncertain or grey area
3.	> 2.99	indicates non-financial distress

The accuracy of the predictions will be analyzed up to 5 years prior to financial distress.

The empirical data collected from the audited financial statements and Auditors' Opinion on going concern will be incorporated into the Altman's Z-Score Model. A new model known as YHL Z-Score Auditors' Opinion Model will be created to improve the accuracy of financial distress prediction amongst PLCs in Malaysia.

#### **4.11.4 Multiple Discriminant Analysis (MDA)**

The literature exercise provides a sound rationale for choosing MDA as an appropriate tool for investigating and predicting financial difficulties among PLCs in Malaysia. Firstly, the MDA provided a solution to the myriad of demerits that were associated with the univariate technique throughout the univariate method's gradual development alongside the various limitations inherent in the model, especially considering the classification model developed and adopted by Beaver (1966). MDA is a necessary solution to help in mitigating the problems identified in the literature

review. Secondly, since its proposal and development by Altman (1968), the MDA approach quickly attracted the interest of other professionals and it became one of the greatly evaluated models for predicting financial distress of companies and hence it has sufficient past literature that support its use as a prediction tool.

Another basis for choosing MDA is hinged on the fact that during its course of development, the main idea was to come up with a more efficient tool for financial distress risk prediction by mitigating inadequacies of the previous approaches. That process led to elimination of the identified weaknesses in the univariate model, through formulation of a number of questions to help in development and successful extension of the prior models. Based on that undertaking, MDA provides an appropriate avenue designed to pinpoint the financial ratios that are the most vital in detecting probability of financial distress. Moreover, MDA has another question that seeks to find out what weights or coefficients that ought to be attached to the identified financial ratios. Lastly, still in respect to its procedure, MDA poses the question of how the coefficients are supposed to be established objectively. These questions asked by MDA technique incorporate objectivity that is a vital requirement for scientific undertaking such as the current research study.

Yet, MDA offers an appropriate blend analytical method and goes ahead to apply MDA to come up with a linear blend of the ratios which “best” distinguish between financial distress and non-financial distress groups and classifications. After disputing the effectiveness and accuracy of the univariate ratio model as an analytical method while developing the Z-Score financial distress analysis model, the blend of ratios was achieved through MDA.

Justification for MDA is also based on the rationales provided by other past studies including that by Nur Adiana et al. (2008) which was carried out to fill the gap of comparing the predictive accuracy of MDA, LRA (Logit analysis) and hazard model and to examine which among the variables were essential in predicting companies in financial distress. The predictive accuracy of these three models is not conclusive. Among the ten determinants of corporate performance examined, the ratio of debt to total assets was a significant predictor of financial distress regardless of the methodology used.

Altman (1968) applied MDA to determine a cut-off value he used to establish the criteria determining companies going through financial problems or those in strong financial position. Using this model Altman (1968) prediction was 95% accurate. That accuracy level is appropriate given that majority of scientific undertakings hinged on statistical significance are based on an error level of 5% (or  $p = 0.05$ ).

Moreover, MDA Model developed by Altman is more precise than the univariate model developed earlier. In addition, while the level of Type I error was up to 33% in the Beaver's univariate model, Altman's Z-Score Model reduced the Type I error to 6% while the Type II error reduced from 5% to 3% as the overall accuracy of the Z-Score in Altman's Z-Score Model stood at 95% and this boosts the justification for choosing MDA as part of the tools for financial distress prediction.

#### **4.11.5 Logistics Regression Analysis (LRA)**

The choice of LRA is based on its ability to take care of the weaknesses inherent with the MDA method. This means that the two methods form an appropriate pair of prediction models that take care of the inherent weaknesses and demerits. The observation by Mutchler et al. (1997) strengthens this stand where they noted that LRA is a better model to address the limitations associated with MDA Model. Besides that observation, LRA has also been subjected to rigorous use in the past as a financial distress prediction technique. For instance, in the study by Ohlson (1980), it examined 105 companies facing financial distress and 2,058 companies not in financial distress. Ohlson (1980) established that it was possible to predict financial distress with similar accuracy as that of Altman's Z-Score Model using seven financial ratios through the LRA model.

An early study by Abbott et al. (2000) helps in strengthening the rationale for choosing LRA. In that study, the authors (Abbott et al., 2000) had conducted an investigative study using statistical regression examining if the presence of an independent audit committee alleviates the possibility of fraud in the company. That early study established that companies that have audit committees comprising of autonomous managers that meet no less than two times a year have less likelihood of

being sanctioned for fraudulent reporting or doctored financial statements (Abbott et al. 2000).

Another important issue is the choice of the two methods to be used together for the prediction exercise is hinged on the limitations and abilities of each of the two methods. First, after Altman had developed the Z-Score Model and established it as a better alternative for mitigating the weaknesses identified in the earlier models, a number of researchers directly put the technique's classification under rigorous test for accuracy of Altman's Z-Score Model. For instance, Outecheva (2007) observes that Altman's approach in selection of variables may bring about a search bias if a selected set of extrapolative variables is used for companies in time periods dissimilar to those used in the original model. Begley et al. (1996) express their doubt in the performance of the model in periods corresponding to a different economic situation. For example, changes in bankruptcy laws or buyout actions in the 1980s transformed the likelihood of bankruptcy or financial distress.

Consequently, the application of the MDA Model built before the alterations may amplify the number of errors related to variable classification. Lastly, Grice and Ingram (2001) demonstrate that the accuracy of the original Altman's Z-Score Model is considerably lesser in recent times and propose re-estimating the coefficients of the discriminant function by means of estimation samples near to the periods under consideration in the test.

Mohamed et al. (2001) compared MDA and the LRA Model in the analysis of financial distress. Their sample consisted of 26 companies that have sought protection under Section 176 of Malaysian Companies Act, 1965 (company under financial distress) and 79 non-financial distress companies. Their results showed that when using MDA, debt ratio and total assets turnover were found to be significant but when LRA was used, an additional variable, interest coverage was also found to be significant. In conclusion, those results show importance of using the two methods together.

## **4.12 Data Presentation**

In this study, the researcher took great care to select suitable data set to answer all the research aims, objectives and questions of the study. Together with these, the researcher was conscious all along to present the raw data and data analyses in a way to create clear visibility to the readers. This was achieved through the use of presentation aides and also selection of tables, figures and charts to represent the data as clear as possible. The researcher used the following data presentation tools and techniques to complement the extensive data analyses conducted in this study:

- Raw data
- Summary data
- Bar graphs
- Charts
- Diagrams
- Figures
- Tables

### **4.12.1 Software Used**

Statistical Packages for Social Sciences (SPSS version 21) software will be used for preparing, describing, visualizing, analyzing and modeling data for the entire study and also for performing correlation or association tests as highlighted in this study.

The researcher will use Microsoft Office Word 2010 for managing the word processing of this study.

Microsoft Office Excel 2010 is used to conduct spreadsheet analysis, data management, data calculation and layout of results.

Microsoft Chart Wizard 2010 is used for generating graphs, tables, figures and charts for presentation in the word document.

The Microsoft Office Power Point 2010 is used to draw tables, charts and figures to aide visual presentation of this study.

#### **4.12.2 Statistical Findings – Descriptive Analyses**

The data analyses findings are usually presented using statistical interpretations which is commonly referred to as descriptive analyses. The descriptive analyses is defined by Zikmund, (2012) as,

*“the transformation of raw data into a form that would provide information to describe a set of factors in a situation that will make them easy to understand and interpret”.*

The findings are commonly presented in the distribution, the central tendency and the dispersion.

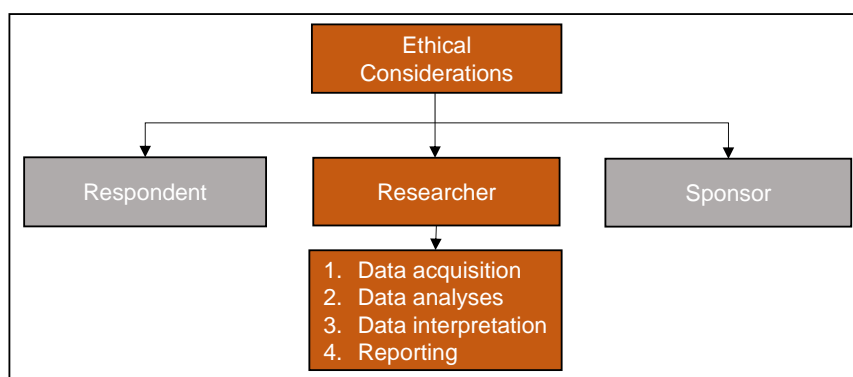
The distribution are usually measured and presented in frequency and percentage. In this study, the researcher widely used frequency and percentage to present the distribution of the findings in the study.

The central tendency is another commonly used statistical descriptive analyses of the findings. The central tendency comprises of mean, median and mode which are used in this study.

The dispersion is usually used to measure the spread values around the central tendency. The usual measures are range and standard deviation which are widely used in this study. The standard deviation is used extensively in making the statistical decision to reject or not to reject the null hypotheses.

#### **4.13 Ethical Consideration**

In conducting a study of this nature, the researcher has to be conscious and be aware of the ethical considerations so as not breach the standard observable ethics to make the findings credible and acceptable. The general ethical considerations can be summarized as shown in Figure 4-11 below.



**Figure 4-11 Ethical Considerations of the Study**

Source: Researcher's own work

There are three main areas of ethical considerations to be observed by the researcher. Firstly, the respondents in a given study; secondly, the researcher; and thirdly, the sponsors. In this study, there are no respondents involved in data collection, likewise there is also no sponsor involved in this study. As such, the researcher will declare and observe the ethics in relation to a researcher in the absence of the respondents and sponsors related ethical issues

The ethical issues involving a researcher, according to McNamara (1994), can be summarized to include an unbiased analyses and reporting without fear or favor of the emerging findings of the investigation. In this case, the researcher being a chartered accountant took all reasonable and possible actions to adhere to the unbiased data acquisition, data analyses, interpretation of findings and reporting of the findings. In addition, the researcher also complied with the code of ethics of the professional bodies, namely the Malaysian Institute of Accountants (MIA) and the Association of Chartered Certified Accountants (ACCA), United Kingdom where he is a member for both of the professional accountancy bodies. Furthermore, the researcher has also complied with the code of ethics for a researcher of Curtin University when conducting this study.

Archival data acquisition from the Bursa Malaysia was done to obtain and achieve the aims and objectives of the study. The data analyses were conducted by the researcher as an academic advancement and personal career development without concealing the true purpose of the research. The interpretation of the data analyses



was carried out without any misrepresentation of the data and findings of the analyses. The interpretation of the study data was done as it transpired in the spirit of research. And the findings were reported with no deception at all and only to reflect the true findings of the study without hiding the original and true purpose of the research.

The researcher vows and affirms that all the ethics of a researcher has been fully observed positively at the highest standard expected of a researcher without having the need to resort to unethical and biased means of data acquisition, analyses, interpretation or reporting with fear or favor. The researcher further declares there is no gain in any form to the researcher or any other individual in relation to this study apart from the academic achievement.

#### **4.14 Prediction Classification**

Several metric will be used to compare the desirability of the models. These include:

1. False Positive Rate
2. False Negative Rate
3. Accuracy

The False Positive Rate is the error of classifying a PN17 company as a NPN17. This would cause an investor to invest in a financial distress company thinking it would be a non-financial distress company. This would very likely result in the investor to incur a loss due to incorrect investment decision.

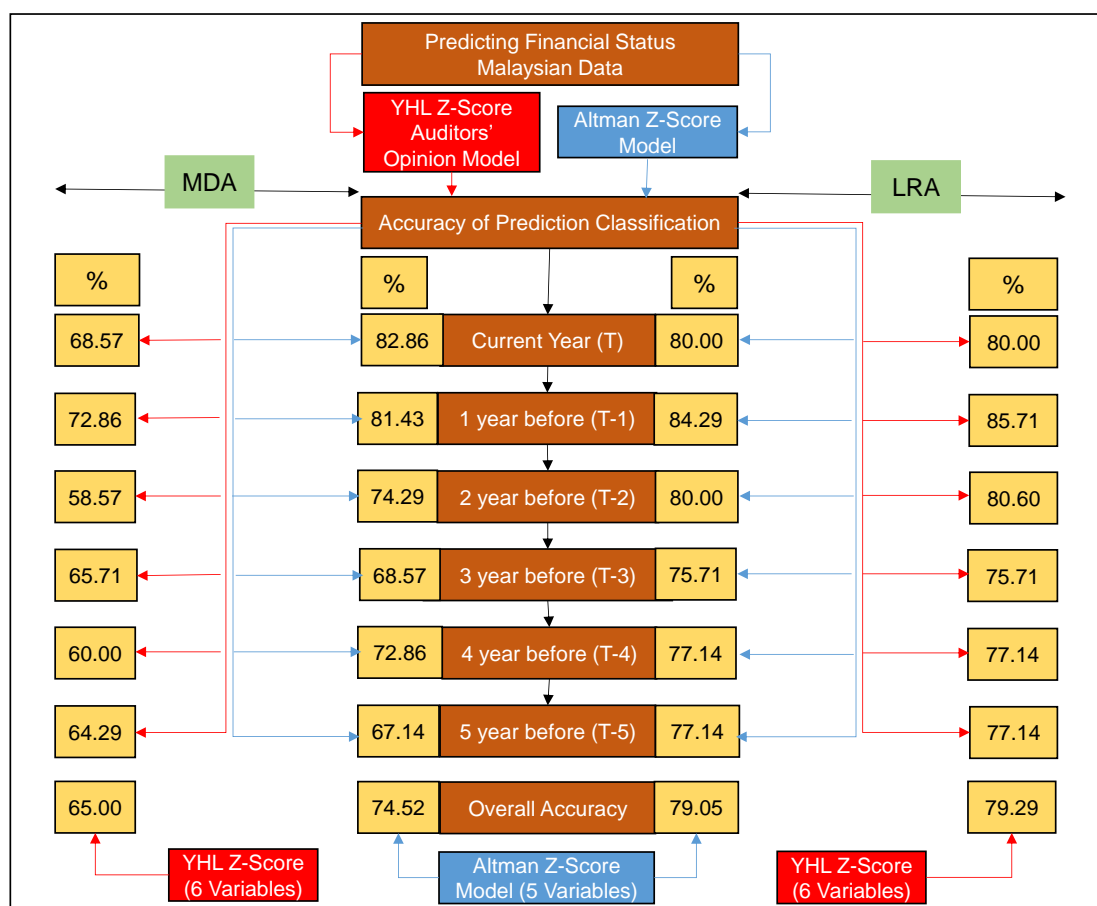
The False Negative Rate is the error of classifying a NPN17 company as a PN17. This would cause an investor to not invest in a non-financial distress company thinking it would be a financial distress company. This would very likely discourage the investor to invest and hence the loss would be a lost opportunity.

The accuracy is the ratio of the total number of correct predictions to the actual classification. Hence,

$$\begin{aligned}
 \text{Accuracy} &= \frac{\text{Total number of correct predictions}}{\text{Number of PN17 and NPN17 companies}} \\
 &= \frac{\text{True Positive} + \text{True Negative}}{\text{Number in PN17} + \text{Number in NPN17}} \\
 &= \frac{\text{True Positive} + \text{True Negative}}{35 + 35} \\
 &= \frac{\text{True Positive} + \text{True Negative}}{70}
 \end{aligned}$$

Of the two types of errors, False Positive Rate and False Negative Rate, the former would be more unacceptable to the investor since it involves a definite loss of money.

The studies that will be conducted in this research are represented by Figure 4-12.



**Figure 4-12 Accuracy of Prediction Classification**

Source: Researcher's own work

#### **4.15 Chapter Summary**

In this chapter, the researcher has presented and discussed all the relevant steps to be undertaken to execute this study to meet the required academic standards expected of a PhD-level thesis. The relevant steps were presented in a guided step-by-step approach for ease of understanding and also for following through the entire process and procedures used in completing this study. Every step of the proposed investigation has been considered very carefully and systematically presented for the benefit of all readers.

The problem definition provided a strong basis for the study. The research flow cleared the path for the study. The research framework established the variables selected for the study, providing the bases for the development of the research hypotheses. The research design, extensively used to clarify the why, how and what of the entire study, was followed by the data acquisition and the data analyses strategy. The ethical considerations were presented to remove any biasness that may doubt the researcher's capability in reporting the findings of this study objectively. Finally, the data analyses and findings in relation to the accuracy of prediction classification concluded the chapter.

## CHAPTER FIVE

### 5 RESULTS, ANALYSIS AND DISCUSSION

#### 5.1 Introduction

The aim of this research was to determine the best statistical model that would best predict the financial distress of PLCs in Malaysia.

The objective of this research was to collect Malaysian data for PLCs in Malaysia and compare its financial results and position against the Altman's Z-Score Model and determines its financial distress prediction accuracy. Then, several models (5-Variable and 6-Variable) were developed using different statistical analyses and strategies (Multiple Discriminant Analysis and Logistic Regression Analysis) as outline below.

#### 5.2 Models Tested

The researcher advocates the following strategy of test to elucidate the best model for predicting financial distress of the company's financial status, namely financial distress or non-financial distress.

**Table 5-1 Elucidate Best Model for Prediction of Company's Financial Status**

No.	Aspect	Type of Test	Section, Header, Page
1	Data cleaning	Outlier	5.3 Data collection, page 137
2	Data Variables	ANOVA	5.4 Hypothesis Testing of X-Variables, page 142
3	Data Z-Score	ANOVA	5.5 Hypotheses Testing of Z-Score of Periods, page 148
4	Altman's Z-Score Model	MDA	5.7.1 Altman's Z-Score Model, page 157
5	5-Variable model	MDA	5.7.2 MDA 5V Model, page 163

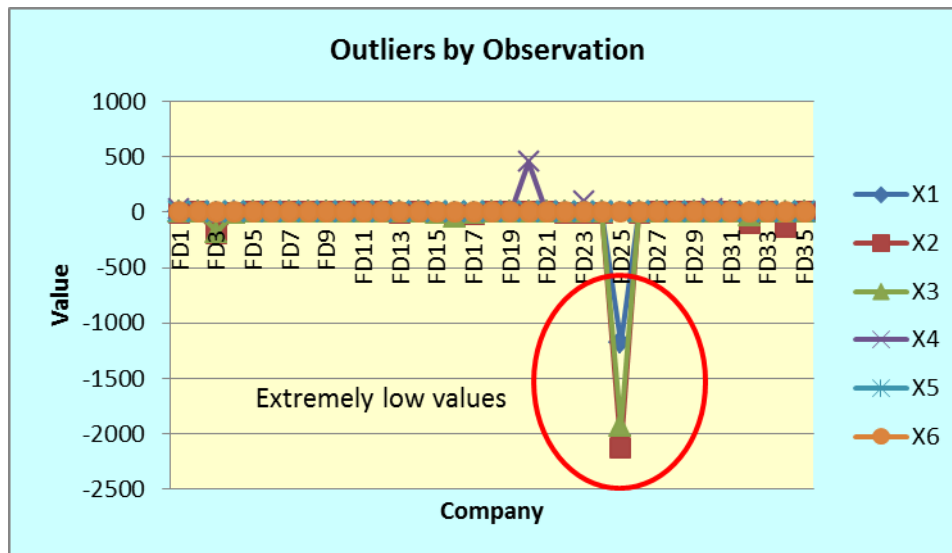
6	5-Variable model	LRA	5.7.3 LRA 5V Model, page 175
7	6-Variable model	MDA	5.8.1 MDA 6V Model, page 183
8	6-Variable model	LRA	5.8.2 LRA 6V Model, page 194

This strategy is explained as follows:

1. The data is cleaned of outliers.
2. The Variables (X1 through X6) are tested to ensure there is a significant difference between PN17 and NPN17 at alpha equal to 0.05.
3. The Z-Score values for T-5 through T-0 are tested to ensure there is a significant difference between PN17 and NPN17 at alpha equal to 0.05.
4. The Altman's Z-Score Model is characterized using the Multiple Discriminant Analysis for comparison.
5. The 5-Variable model is characterized using the Multiple Discriminant Analysis.
6. The 5-Variable model is characterized using the Logistic Regression Analysis.
7. The 6-Variable model is characterized using the Multiple Discriminant Analysis.
8. The 6-Variable model is characterized using the Logistic Regression Analysis.

### 5.3 Data collection

The original data was collected for 35 companies in PN17 and 35 companies in NPN17 over a period of 6 years. A visual observation showed that there appeared to be very high variability in the data variables. Figure 5-1 below shows a representative case for 35 PN17 companies for the T-0 year.



**Figure 5-1 Data for 35 PN17 Companies in the T-0 Year**

Source: Researcher's own work

Although it could be suggested that normalization of the data would reduce this outlier values, this is clearly not feasible as the data points appear not to belong to the data set. Additionally, data points for a company in one period may be an outlier but it may not be in another period. Hence, so as not to discard useful data, it was imperative to remove only “true” outliers for a company, in a given time period. Also, another consideration was that normalization on a variable would simply amount to a univariate manipulation and this was clearly not acceptable.

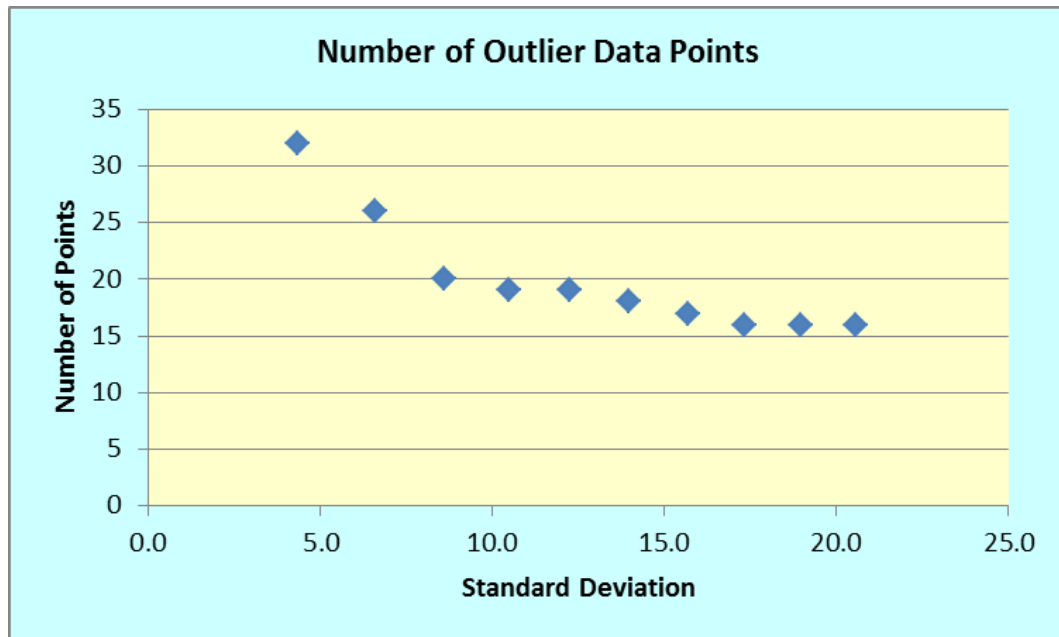
Thus, it was decided to use a multivariable outlier check to identify records that were clearly outliers. The multivariate outlier check proposed is based on the Mahalanobis distance. The Mahalanobis distance is defined as  $D(X) = \sqrt{(X - \mu)^T \Sigma^{-1} (X - \mu)}$  where  $X$  is the matrix of variables,  $\mu$  is the matrix of means or center of the variable

and  $\Sigma$  is the covariance of the X matrix. More importantly, the Mahalanobis distance squared,  $D^2$  is the squared distance of  $x$  from the mean in standard deviations in the direction of  $x$ . Therefore, it would be easy to identify a cut-off point based on the standard deviation. Since,  $D^2$  follows a Chi-squared distribution with  $n$  degrees of freedom, the Chi-squared value at a stated value of  $\alpha$  would provide a convenient cut-off point corresponding to the error. For example, for 5 variables ( $n = 5$ ), and  $\alpha = 0.05$ , and  $\chi^2 = 11.070$ . Any  $D^2$  value above this would have a probability of less than 5% and hence discarded as an outlier.

However, the choice of  $\alpha$  was determined empirically as follows. A program was created that would calculate the number of data points that would be removed at a given value of  $D^2$  corresponding to a  $\alpha$  value. The calculated values are tabulated in Table 5-2 and shown graphically in Figure 5-2 below.

**Table 5-2 Count of Outlier Data Points by Alpha Value**

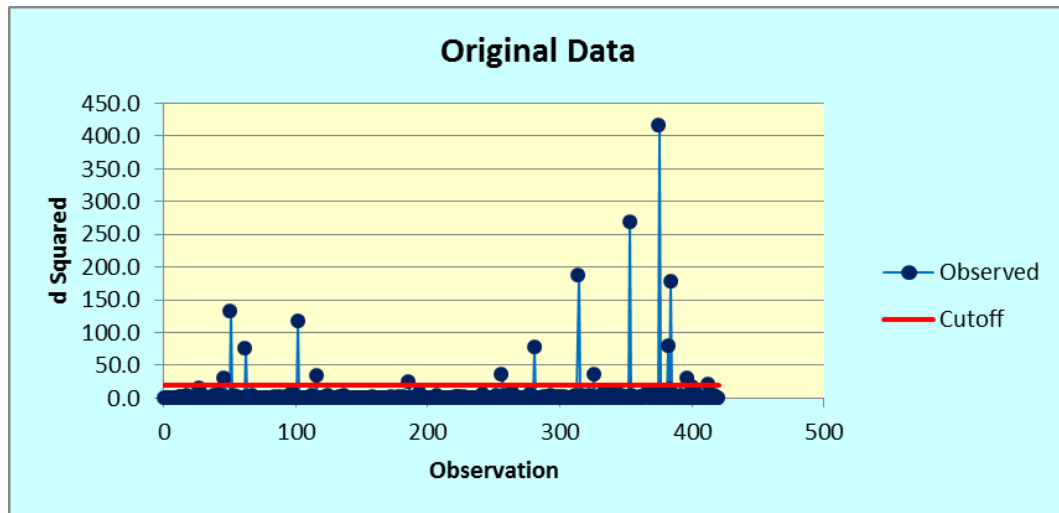
No.	Alpha	$D^2$	Count
1	0.500	4.351	32
2	0.250	6.626	26
3	0.125	8.625	20
4	0.063	10.489	19
5	0.031	12.272	19
6	0.016	13.998	18
7	0.008	15.682	17
8	0.004	17.335	16
9	0.002	18.963	16
10	0.001	20.570	16



**Figure 5-2** Number of Outlier Points at Different Distances

Based on this finding, an  $\alpha$  value of 0.001 was used, corresponding to  $D^2$  value of 20.0, to identify outliers more than 20 standard deviations away from the mean. A total of 16 pairs of data points were eliminated from the data. In other words, if an outlier was removed, the corresponding pair of the data was also removed. This was necessary to maintain the balance of matched pairs in the dataset. This reduced data was then used in subsequent modeling. Figure 5-3 shows the original data before removing outliers.



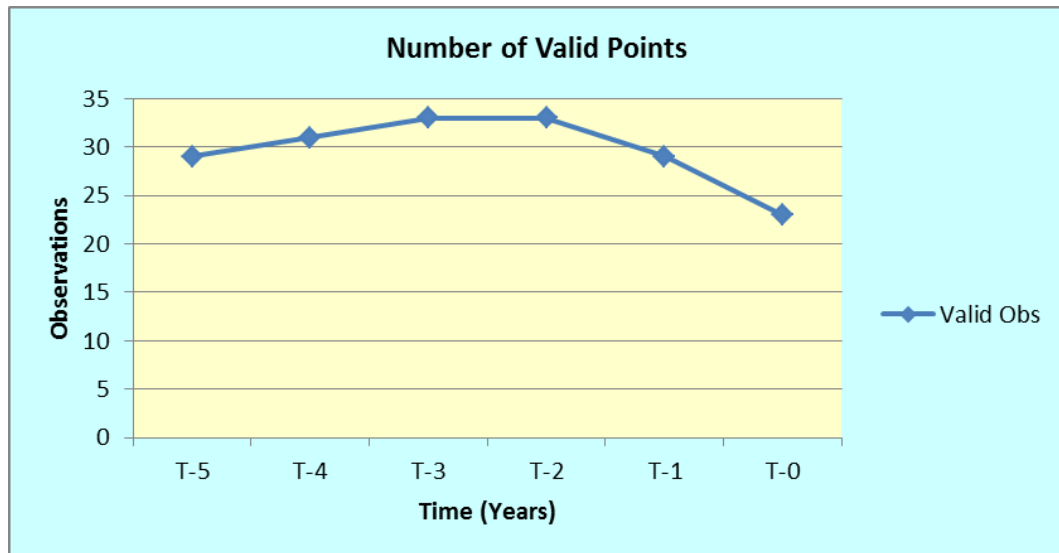


**Figure 5-3 Scatter Graph of Original Data**

Table 5-3 shows the number of outliers removed from each data set. Figure 5-4 shows the number of valid points in dataset.

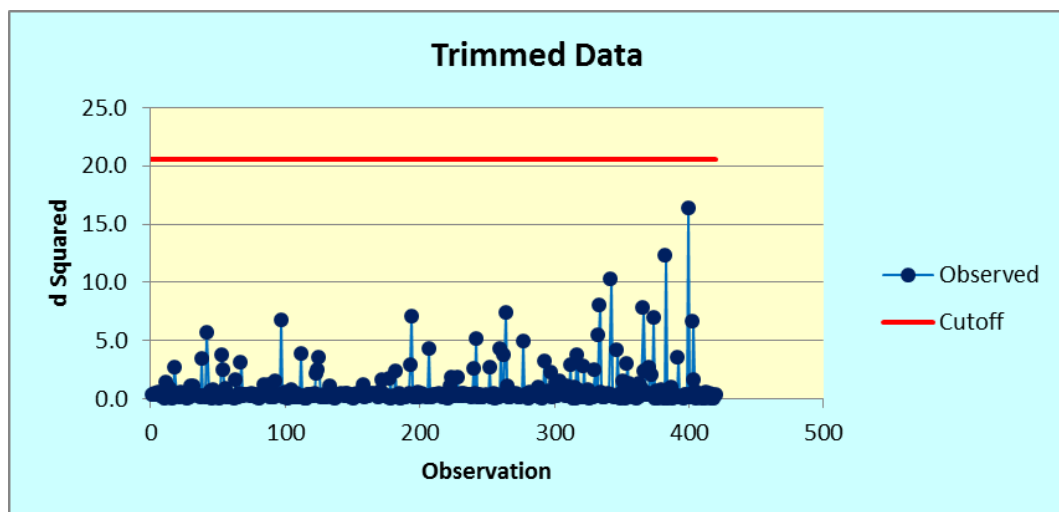
**Table 5-3 Number of Data Points Removed in Data Sets**

	T-5	T-4	T-3	T-2	T-1	T-0
PN17	3	2	1	1	3	6
NPN17	3	2	1	1	3	6
Removed	6	4	2	2	6	12
Valid Obs	29	31	33	33	29	23



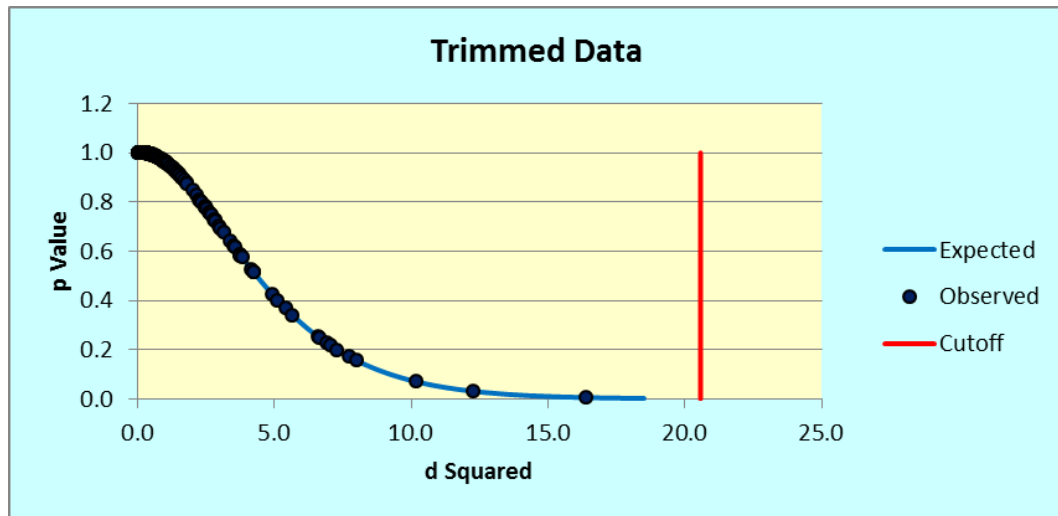
**Figure 5-4** Number of Valid Points in Dataset

Figure 5-5 below shows the data after outlier removal.



**Figure 5-5** Scatter Graph of Data after Removing Outliers

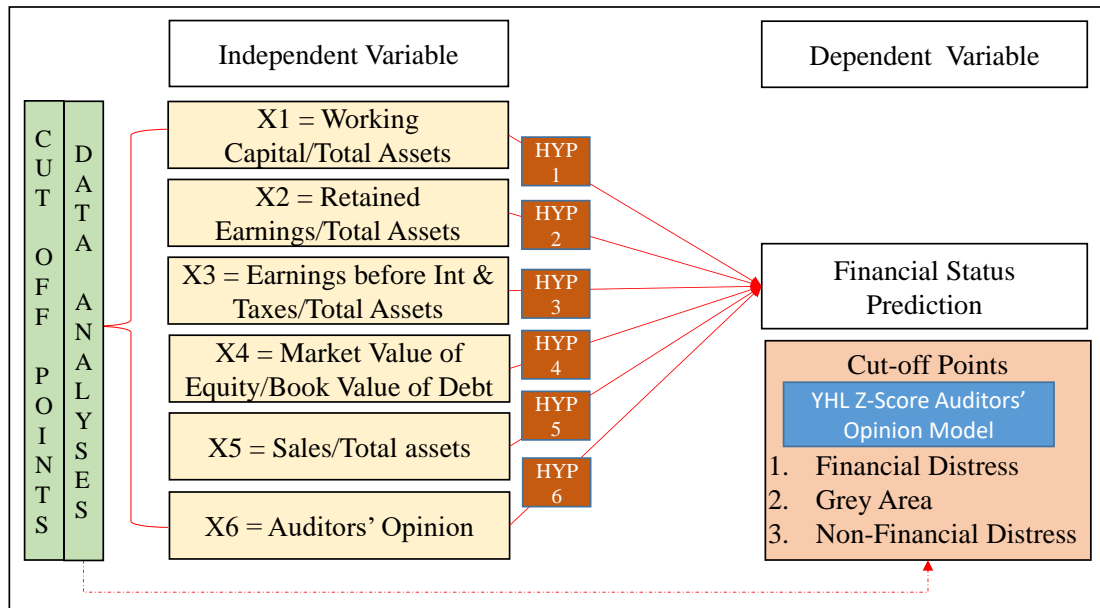
Figure 5-6 below shows the fit of Expected data (line) and Observed data (points).



**Figure 5-6 Expected and Observed Data fitting after Outlier Removal**

#### 5.4 Hypothesis Testing of X-Variables

When considering the Altman's Z-Score Model, it is essential that the PN17 data was different from the NPN17 data. In particular, it would be expected that the Z-Score mean of NPN17 was greater than the mean of PN17 data, allowing for differences in variances. This enabled the researcher to test individual discriminating ability of the variables using the F-test. The F-test relates the difference between the average values of the ratios in each group to the variability of values within each group. The hypothesis tests are completed for each variable and then consolidated at the end of this section. The syntheses of the hypotheses are summarized in Figure 5-7 below for the benefit of the reader.



**Figure 5-7 Research Hypotheses for X-Variable**

Source: Researcher's own work

### 5.4.1 Hypothesis 1: X1

Ho: The mean Z-Score of X1 for NPN17  $\leq$  PN17

Ha: The mean Z-Score of X1 for NPN17  $>$  PN17

The mean NPN17 = 0.394 and the mean PN17 = -639. Using analysis of variance, the results for this test is as follows:

**Table 5-4 Hypothesis 1: X1**

X1	Ssq	Dof	Var	F-Ratio	P-Value
M	111.969	1	111.969	4.428	0.036
Err	10543.291	417	25.284		
St	10655.259	418			
Sm	6.160	1			
ST	10661.419	419			

The p-value obtained is 0.036. Therefore, Ho is rejected in favor of Ha, and it can be said that the mean Z-Score of X1 for NPN17  $>$  PN17 at  $\alpha = 0.05$ .

In the table, M is the mean of X1, Err is the error, St is the corrected sum of squares due to X1, Sm is the sum of squares due to the mean, ST is the total sum of squares, Ssq is the sum of squares, Dof is the degrees of freedom and Var is the variance. Note that these abbreviations are used for all analyses of variance in this thesis.

### 5.4.2 Hypothesis 2: X2

Ho: The mean Z-Score of X2 for NPN17  $\leq$  PN17

Ha: The mean Z-Score of X2 for NPN17  $>$  PN17

The mean NPN17 = 0.124 and the mean PN17 = -0.968. Using analysis of variance, the results for this test is as follows:

**Table 5-5 Hypothesis 2: X2**

X2	Ssq	Dof	Var	F-Ratio	P-Value
M	123.675	1	123.675	19.139	0.000
Err	2668.756	413	6.462		
St	2792.432	414			
Sm	71.587	1			
ST	2864.019	415			

The p-value obtained is 0.000. Therefore,  $H_0$  is rejected in favor of  $H_a$ , and it can be said that the mean Z-Score of X2 for NPN17 > PN17 at  $\alpha = 0.05$ .

### 5.4.3 Hypothesis 3: X3

$H_0$ : The mean Z-Score of X3 for NPN17  $\leq$  PN17

$H_a$ : The mean Z-Score of X3 for NPN17 > PN17

The mean NPN17 = 0.081 and the mean PN17 = -0.597. Using analysis of variance, the results for this test is as follows:

**Table 5-6 Hypothesis 3: X3**

X3	Ssq	Dof	Var	F-Ratio	P-Value
M	48.085	1	48.085	8.110	0.005
Err	2466.514	416	5.929		
St	2514.598	417			
Sm	27.419	1			
ST	2542.018	418			

The p-value obtained is 0.005. Therefore,  $H_0$  is rejected in favor of  $H_a$ , and it can be said that the mean Z-Score of X3 for NPN17 > PN17 at  $\alpha = 0.05$ .

### 5.4.4 Hypothesis 4: X4

$H_0$ : The mean Z-Score of X4 for NPN17  $\leq$  PN17

$H_a$ : The mean Z-Score of X4 for NPN17 > PN17

The mean NPN17 = 14.371 and the mean PN17 = 5.900. Using analysis of variance, the results for this test is as follows:

**Table 5-7 Hypothesis 4: X4**

X4	Ssq	Dof	Var	F-Ratio	P-Value
M	6211.698	1	6211.698	19.281	0.000
Err	111793.483	347	322.171		
St	118005.181	348			
Sm	33240.563	1			
ST	151245.743	349			

The p-value obtained is 0.000. Therefore, Ho is rejected in favor of Ha, and it can be said that the mean Z-Score of X4 for NPN17 > PN17 at alpha = 0.05.

#### 5.4.5 Hypothesis 5: X5

Ho: The mean Z-Score of X5 for NPN17 <= PN17

Ha: The mean Z-Score of X5 for NPN17 > PN17

The mean NPN17 = 0.256 and the mean PN17 = 0.152. Using analysis of variance, the results for this test is as follows:

**Table 5-8 Hypothesis 5: X5**

X5	Ssq	Dof	Var	F-Ratio	P-Value
M	1.140	1	1.140	6.368	0.012
Err	74.835	418	0.179		
St	75.975	419			
Sm	17.481	1			
ST	93.457	420			

The p-value obtained is 0.012. Therefore, Ho is rejected in favor of Ha, and it can be said that the mean Z-Score of X5 for NPN17 > PN17 at alpha = 0.05.

#### 5.4.6 Hypothesis 6: X6

Ho: The mean Z-Score of X6 for NPN17 <= PN17

Ha: The mean Z-Score of X6 for NPN17 > PN17

The mean NPN17 = 1.000 and the mean PN17 = 0.876. Using analysis of variance, the results for this test is as follows:

**Table 5-9 Hypothesis 6: X6**

X6	Ssq	Dof	Var	F-Ratio	P-Value
M	1.610	1	1.610	29.533	0.000
Err	22.781	418	0.054		
St	24.390	419			
Sm	369.610	1			
ST	394.000	420			

The p-value obtained is 0.000. Therefore,  $H_0$  is rejected in favor of  $H_a$ , and it can be said that the mean Z-Score of X6 for NPN17 > PN17 at  $\alpha = 0.05$ .

#### 5.4.7 Summary of Hypotheses

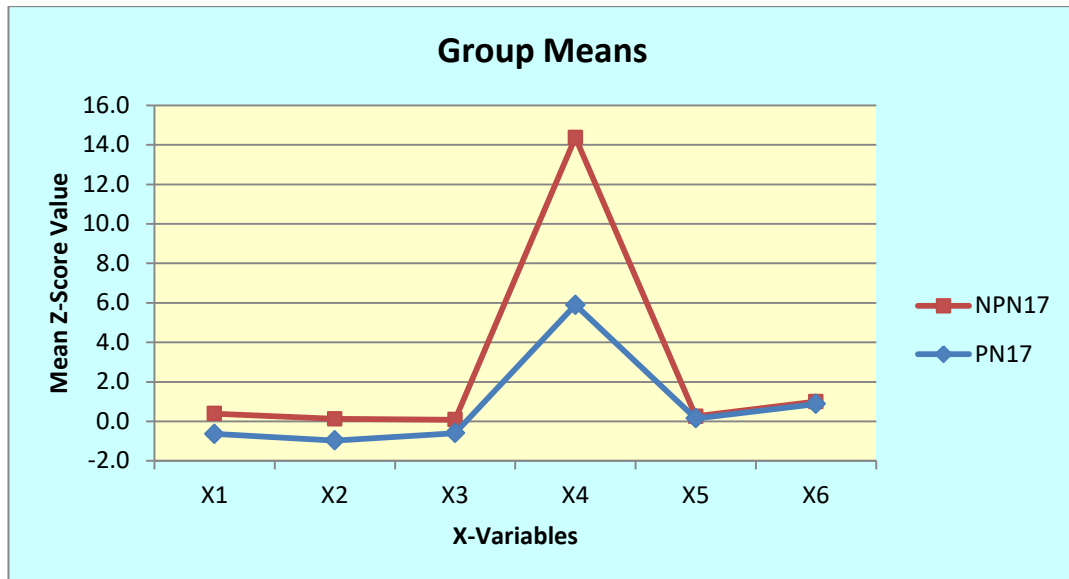
The overall summary is given in Table 5-10. Note that the sample sizes having varying observations due to the removal of outliers as indicated earlier in this study with observations of Z-Scores values above 100 standard deviations. In all cases,  $H_0$  is rejected and data is consistently in favor of  $H_a$ . This implies that the Z-Score mean of NPN17 is greater than the mean of PN17 and therefore permits subsequent analysis of MDA and LRA.

**Table 5-10 Collation of Hypotheses X1 – X6**

	X1	X2	X3	X4	X5	X6
PN17	-0.639	-0.968	-0.597	5.900	0.152	0.876
NPN17	0.394	0.124	0.081	14.371	0.256	1.000
F-Ratio	4.428	19.139	8.110	19.281	6.368	29.533
P-Value	0.036	0.000	0.005	0.000	0.012	0.000
Count	419	415	418	349	420	420

The mean values for PN17 and NPN17 are shown diagrammatically Figure 5-8.





**Figure 5-8 Collation of Hypotheses X1 – X6**

### 5.5 Hypotheses Testing of Z-Score of Periods

When considering the Z-Score Model, it is essential that the PN17 data was different from the NPN17 data. In particular, it would be expected that the Z-Score mean of NPN17 was greater than the mean of PN17 data, allowing for differences in variances. This enables the researcher to test individual discriminating ability of the variables using the F-test. The F-test relates the difference between the average values of the ratios in each group to the variability of values within each group. The hypothesis test is completed for each variable and then consolidated at the end of this section.

#### 5.5.1 Hypothesis 1: Z-Score T-5

Ho: The mean Z-Score of T-5 for NPN17  $\leq$  PN17

Ha: The mean Z-Score of T-5 for NPN17  $>$  PN17

The mean NPN17 = 3.489 and the mean PN17 = -3.6777. Using analysis of variance, the results for this test is as follows:

**Table 5-11 Hypothesis 1: T-5**

Z-Score	Ssq	Dof	Var	F-Ratio	P-Value
M	898.682	1	898.682	10.337	0.002
Err	5911.920	68	86.940		
St	6810.602	69	98.704		
Sm	0.621	1		3.215	0.002
ST	6811.222	70			

The p-value obtained is 0.001. Therefore,  $H_0$  is rejected in favor of  $H_a$ , and it can be said that the mean Z-Score of T-5 for NPN17 > PN17 at  $\alpha = 0.05$ .

### 5.5.2 Hypothesis 2: Z-Score T-4

$H_0$ : The mean Z-Score of T-4 for NPN17  $\leq$  PN17

$H_a$ : The mean Z-Score of T-4 for NPN17 > PN17

The mean NPN17 = 1.347 and the mean PN17 = -1.968. Using analysis of variance, the results for this test is as follows:

**Table 5-12 Hypothesis 2: T-4**

Z-Score	Ssq	Dof	Var	F-Ratio	P-Value
M	192.374	1	192.374	7.853	0.007
Err	1665.759	68	24.496		
St	1858.133	69	26.929		
Sm	6.739	1		2.802	0.007
ST	1864.872	70			

The p-value obtained is 0.007. Therefore,  $H_0$  is rejected in favor of  $H_a$ , and it can be said that the mean Z-Score of T-4 for NPN17 > PN17 at  $\alpha = 0.05$ .

### 5.5.3 Hypothesis 3: Z-Score T-3

$H_0$ : The mean Z-Score of T-3 for NPN17  $\leq$  PN17

$H_a$ : The mean Z-Score of T-3 for NPN17 > PN17

The mean NPN17 = 1.418 and the mean PN17 = -2.085. Using analysis of variance, the results for this test is as follows:

**Table 5-13 Hypothesis 3: T-3**

Z-Score	Ssq	Dof	Var	F-Ratio	P-Value
M	214.707	1	214.707	30.619	0.000
Err	476.831	68	7.012		
St	691.538	69	10.022		
Sm	7.776	1		5.533	0.000
ST	699.314	70			

The p-value obtained is 0.000. Therefore,  $H_0$  is rejected in favor of  $H_a$ , and it can be said that the mean Z-Score of T-3 for  $NPN17 > PN17$  at  $\alpha = 0.05$ .

#### 5.5.4 Hypothesis 4: Z-Score T-2

$H_0$ : The mean Z-Score of T-2 for  $NPN17 \leq PN17$

$H_a$ : The mean Z-Score of T-2 for  $NPN17 > PN17$

The mean  $NPN17 = 1.662$  and the mean  $PN17 = -3.426$ . Using analysis of variance, the results for this test is as follows:

**Table 5-14 Hypothesis 4: T-2**

Z-Score	Ssq	Dof	Var	F-Ratio	P-Value
M	453.010	1	453.010	17.736	0.000
Err	1736.837	68	25.542		
St	2189.847	69	31.737		
Sm	54.466	1		4.211	0.000
ST	2244.314	70			

The p-value obtained is 0.000. Therefore,  $H_0$  is rejected in favor of  $H_a$ , and it can be said that the mean Z-Score of T-2 for  $NPN17 > PN17$  at  $\alpha = 0.05$ .

#### 5.5.5 Hypothesis 5: Z-Score T-1

$H_0$ : The mean Z-Score of T-1 for  $NPN17 \leq PN17$

$H_a$ : The mean Z-Score of T-1 for  $NPN17 > PN17$

The mean  $NPN17 = 1.955$  and the mean  $PN17 = -9.704$ . Using analysis of variance, the results for this test is as follows:

**Table 5-15 Hypothesis 5: T-1**

Z-Score	Ssq	Dof	Var	F-Ratio	P-Value
M	2309.022	1	2309.022	25.854	0.000
Err	5894.353	66	89.308		
St	8203.376	67	122.438		
Sm	932.552	1		5.085	0.000
ST	9135.928	68			

The p-value obtained is 0.000. Therefore, Ho is rejected in favor of Ha, and it can be said that the mean Z-Score of T-1 for NPN17 > PN17 at alpha = 0.05.

### 5.5.6 Hypothesis 6: Z-Score T-0

Ho: The mean Z-Score of T-0 for NPN17 <= PN17

Ha: The mean Z-Score of T-0 for NPN17 > PN17

The mean NPN17 = 2.215 and the mean PN17 = -16.519. Using analysis of variance, the results for this test is as follows:

**Table 5-16 Hypothesis 6: T-0**

Z-Score	Ssq	Dof	Var	F-Ratio	P-Value
M	5567	1	5566.511	26.805	0.000
Err	12875	62	207.668		
St	18442	63	292.729		
Sm	2519	1		5.177	0.000
ST	20961	64			

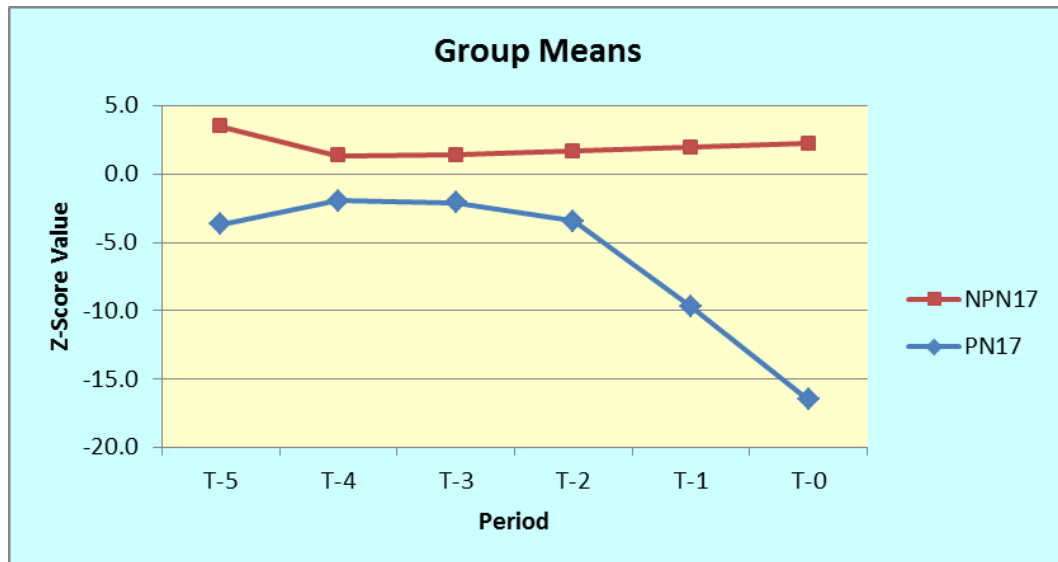
The p-value obtained is 0.000. Therefore, Ho is rejected in favor of Ha, and it can be said that the mean Z-Score of T-0 for NPN17 > PN17 at alpha = 0.05.

This concept could be tested together using the analysis of variance (ANOVA). The overall summary is given Table 5-17.

**Table 5-17 Collation of Hypotheses for Periods T-5 through T-0**

Z-Score	T-5	T-4	T-3	T-2	T-1	T-0
PN17	-3.677	-1.968	-2.085	-3.426	-9.704	-16.519
NPN17	3.489	1.347	1.418	1.662	1.955	2.215
No.	70	70	70	70	68	64
p-value	0.002	0.007	0.000	0.000	0.000	0.000

Note that the sample sizes in T-1 and T-0 are less than 70 observations. This is because of removing 2 and 6 observations respectively as outliers with Z-Scores values above 100 standard deviations. The mean values for PN17 and NPN17 are shown diagrammatically Figure 5-8.



**Figure 5-9 Collation of Hypotheses for Periods T-5 through T-0**

In all cases,  $H_0$  is rejected and data is consistently in favor of  $H_a$ . The detail breakdowns are shown in Table 5-17. This implies that the Z-Score mean of NPN17 is greater than the mean of PN17 and therefore permits subsequent analysis of the MDA and LRA.

## 5.6 Comparison of Model Characteristics

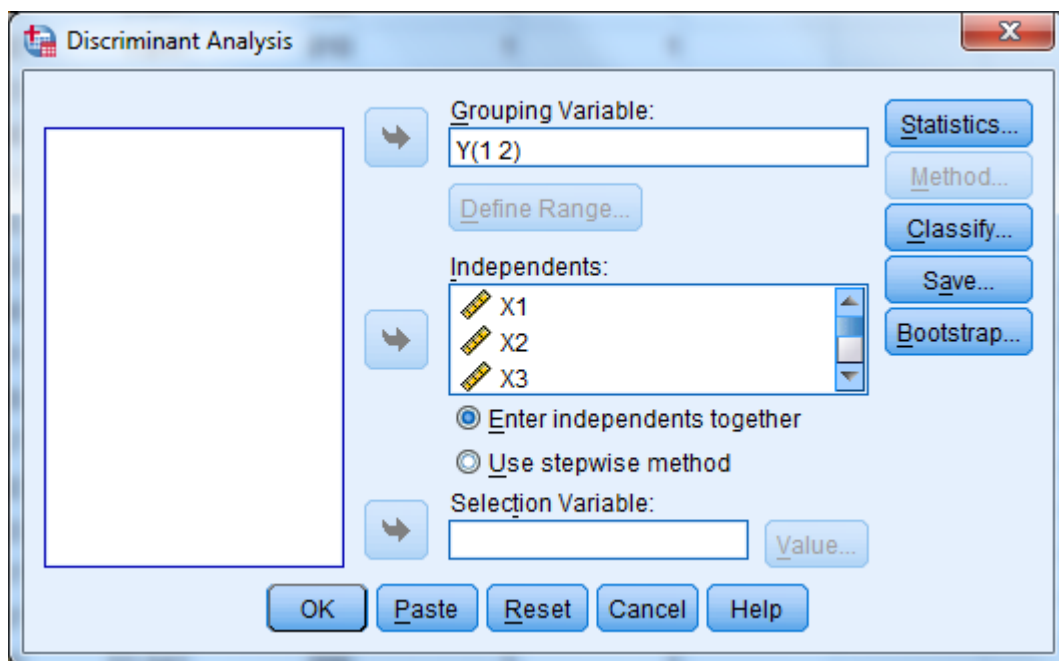
### 5.6.1 Multiple Discriminant Analysis Model

The aim of the present study was to investigate the performance of MDA to the differential diagnosis of PN17 and NPN17 companies based on the secondary data. The objective was to establish if MDA could be used to predict company financial distress ahead of time.

MDA begins with items that are at least in two groups. MDA used the covariance matrix to identify eigenvectors that best discriminate the original item data classification. The eigenvectors are essentially a linear combination of quantitative predictor variables that best characterize the differences among the groups. The linear combination represents the coefficients for each variable which when multiplied by the predictor variables results in the discriminant function.

MDA can then be used to classify item data into the two groups. A comparison of the original classification against the MDA classification will enable a researcher to compare how well different models fit a given set of data. In this study, the researcher compares an existing 5-Variable model against a proposed 6-Variable model. The better model would be the one that gives better accuracy of prediction together with the smaller alpha error and beta error.

In this study, the researcher studied 6-Variables (X1 through X6). All the variables have been defined and were intended to be in the model. Therefore, the “Enter independents together” function was used. If it had been necessary to reduce the number of variables (e.g. if there had been 10 or more variables in the original model) then “Use stepwise method” would have been more appropriate. Thus, for the purpose of this study, the “Enter independents together” function was used consistently (see Figure 5-10).



**Figure 5-10** Choice of Variable Selection into Model

MDA was conducted in order to distinguish differences among groups of companies. The ultimate purpose of MDA would be to classify a new company observation into one of the established groups. This could be achieved by using the discriminant function together with the observed variables. In this study, the Enter variables method was used in the MDA analysis in SPSS.

In MDA, Wilk's Lambda statistic was used to test whether the discriminant model was significant. The significance was tested for each variable where p value of less than 0.05 meant significance. Significant variables were retained in the model.

In this study, there are only 2 groups, namely PN17 and NPN17. Hence, there will be only one discriminant function.

The structure matrix for each discriminant function was obtained. The structure matrix is a linear combination indicating how well the variable was correlated to the discriminant function. The structure matrix is usually shown sorted in absolute magnitude.

The Canonical Discriminant Function Coefficients represents the parameters for the variables. Using this function, the Z-Score values were calculated. The group centroids were then used to allocate the company to either group. Correct classification was defined as the concordant cases where PN17 is predicted as PN17 and NPN17 is predicted as NPN17. This classification was done for all 420 data points in the data set. The results of this classification were then used to establish Type I error, Type II error and Accuracy. A p-value <0.05 was deemed to be statistically significant.

### 5.6.2 Logistic Regression Analysis Model

In a linear regression model with a variable dependent data, the dependent variable is regressed on the independent variable(s) such that  $\mathbf{Y} = \boldsymbol{\beta}\mathbf{X} + \boldsymbol{\varepsilon}$  where  $\mathbf{X}$  represents the independent variable(s). In this case, the coefficient of correlation is defined as  $r$

where  $r = \frac{\sum z_X z_Y}{N}$  and  $z_X$  and  $z_Y$  are the normalized values of  $X$  and  $Y$



respectively. By this definition,  $r$  the coefficient of determination is the  $r^2$  value. This value of  $r^2$  summarizes the proportion of variance in the dependent variable associated with the independent variables.  $r^2$  can take values between 0 (no correlation) and 1 (perfect correlation). Hence, larger  $r^2$  values indicate that more of the variation is explained by the model.

For a regression model with a categorical dependent variable, it is not possible to compute a single  $r^2$  statistic that has all of the characteristics of  $r^2$  in the case of the linear regression model. Since there are several ways of calculating the  $r^2$  value, the  $r^2$  value for categorical dependent data is often called pseudo coefficient of determination.

The more common method of calculating the  $r^2$  value is by

- Cox and Snell
- Nagelkerke
- McFadden

Cox and Snell's  $r^2$  is based on the log likelihood for the model compared to the log likelihood for a baseline model. However, with categorical outcomes, it has a theoretical maximum value of less than 1, even for a "perfect" model.

Nagelkerke's  $r^2$  is an adjusted version of the Cox & Snell  $r^2$  that adjusts the scale of the statistic to cover the full range from 0 to 1.

McFadden's  $r^2$  is based on the log-likelihood kernels for the intercept-only model and the full estimated model.

What constitutes a "good"  $r^2$  value depends on the interpretation of what is regarded as best. In this study, the researcher uses Nagelkerker's  $r^2$  as this is the closest interpretation of the explained variables.

## 5.7 MDA and LRA for 5-Variable Malaysian Data

### 5.7.1 Altman's Z-Score Model

The original Altman's Z-Score Model took the following form:

$$Z = 0.012 X_1 + 0.014 X_2 + 0.033 X_3 + 0.006 X_4 + 0.999 X_5$$

Where:

$X_1$  = Working capital / Total assets;

$X_2$  = Retained earnings / Total assets;

$X_3$  = Earnings before interest and taxes / Total assets;

$X_4$  = Market value of equity / Book value of Debt (Total Liabilities);

$X_5$  = Sales / Total assets.

Z = Overall index

The cut-off points for this model are shown in Table 5-18 below.

**Table 5-18 Cut-off Points for Altman's Z-Score Model**

$Z < 1.81$	$1.81 \leq Z \leq 2.99$	$Z > 2.99$
Distress Zone:	Grey Zone:	Safe Zone:
Risk that company will go bankrupt within two years	Could go either way	Considered financially healthy

Source: Altman, E.I. (1968), p. 604, section IV, paragraph 6.

Using the Altman's Z-Score Model, the current data was analyzed under the same conditions. Note that, although Altman (1968; p. 606, section 5) used the Z boundaries for classifying the financial health, the classification for the data analysis is based on the weighted average of the lower and upper cut-off points. This is evident from the citation of Altman (1968; p. 12) as follows:

*“Note that the model does not contain a constant (y-intercept) term. This is due to the particular software utilized and, as a result, the relevant cut-off score between the two groups is not zero. Other software programs, like SAS and SPSS, have a constant term, which standardizes the cut-off score at zero if the samples sizes of the two groups are equal.”*

Hence, if the sample sizes are equal, then the cut-off is the midpoint of the lower and upper boundaries. If the discriminant score of the function is less than or equal to the cut-off, the case is classed as 1 or, if above it is classed as 2. When group sizes are equal, the cut-off is the mean of the two centroids for two-group Multiple Discriminant Analysis. If the groups are unequal, the cut-off is the weighted mean.

Using the Altman Coefficients, the function corresponding to the Z-Score for each record is calculated as:

$$Z = 0.012 X_1 + 0.014 X_2 + 0.033 X_3 + 0.006 X_4 + 0.999 X_5$$

Then, the value of the Z-Score is compared to the cut-off points. If the Z-Score value is:

- a) less than the lower cut-off point it is assigned to the Financial Distress group
- b) greater than the lower cut-off point but less than the upper cut-off point it is assigned to the Uncertain group
- c) greater than the upper cut-off point it is assigned to the Non-Financial Distress group

**Table 5-19 Arrangement of Data**

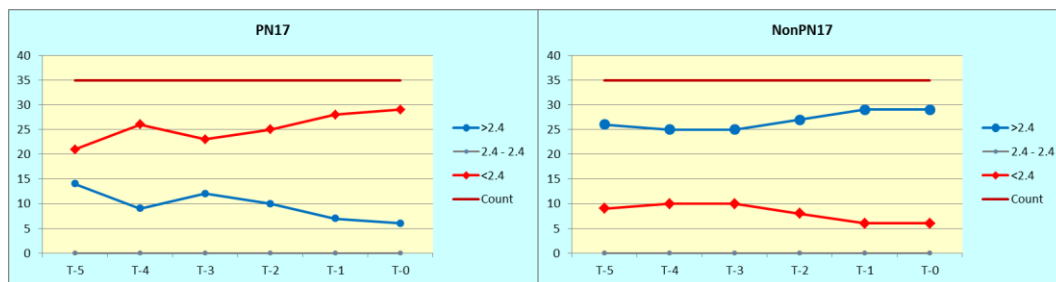
Original		X0	X1	X2	X3	X4	X5	X6	Z-Score	Class
PN17	No.	0.000	1.200	1.400	3.300	0.600	0.999	0.000		
T-5: 1	1	1.000	0.547	0.365	-0.004	397.903	0.002	1.000	239.898	1
T-5: 1	2	1.000	0.097	0.051	0.007	3.971	0.004	1.000	2.596	1
T-5: 1	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
T-5: 1	35	1.000	0.075	-0.675	-0.168	1.306	0.000	1.000	-0.625	0
NPN17										
T-5: 2	1	1.000	0.439	0.013	0.007	403.121	0.047	1.000	242.488	1
T-5: 2	2	1.000	0.590	0.066	0.173	32.249	0.175	1.000	20.895	1
T-5: 2	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
T-5: 2	35	1.000	0.451	0.024	0.080	1.731	0.000	1.000	1.878	0

From this data, the count of companies classified according to Safe Zone, Grey Zone and Distress Zone.

**Table 5-20 Arrangement of Data for PN17 and NPN17**

PN17	<2.4	2.4 - 2.4	>2.4	Count	Auditor
T-5	21	0	14	35	35
T-4	26	0	9	35	35
T-3	23	0	12	35	34
T-2	25	0	10	35	35
T-1	28	0	7	35	26
T-0	29	0	6	35	19
Total	152	0	58		
Gtotal	210				

NonPN17	<2.4	2.4 - 2.4	>2.4	Count	Auditor
T-5	9	0	26	35	35
T-4	10	0	25	35	35
T-3	10	0	25	35	35
T-2	8	0	27	35	35
T-1	6	0	29	35	35
T-0	6	0	29	35	35
Total	49	0	161		
Gtotal	210				



**Figure 5-11 Comparison of PN17 and NPN17 Counts**

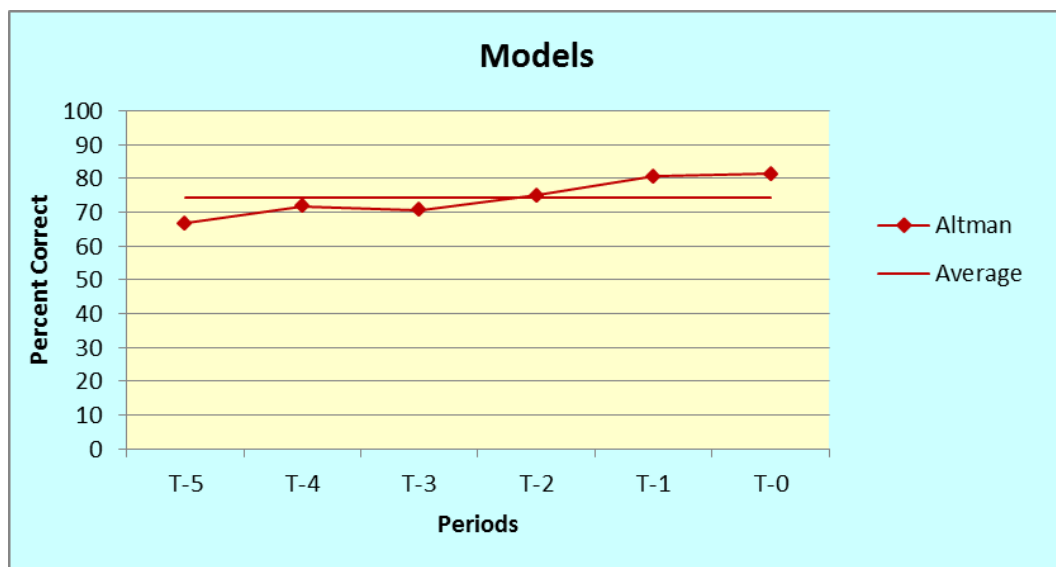
Based on this classification, (PN17, PredFail) and (NPN17, PredPass) add up to correct classification. This evaluation is done for all six periods (T-5 to T-0). The result for the current case is shown below. Then the frequencies of companies falling

in the financial distress, uncertain and non-financial distress group are computed and shown below as both counts and percentage. The overall quantities are also shown. Note that the top table shows Counts and the bottom table shows Percentage for convenience.

**Table 5-21 Count of Prediction Values**

Count	T-5	T-4	T-3	T-2	T-1	T-0	Overall
Pred Fin Dist	30	36	33	33	34	35	201
Uncertain	0	0	0	0	0	0	0
Pred NonFin Dist	40	34	37	37	36	35	219
Total	70	70	70	70	70	70	420
Correct Prediction	47	51	48	52	57	58	313
Percentage	T-5	T-4	T-3	T-2	T-1	T-0	Overall
Pred Fin Dist	42.86	51.43	47.14	47.14	48.57	50.00	47.86
Uncertain	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pred NonFin Dist	57.14	48.57	52.86	52.86	51.43	50.00	52.14
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Correct Prediction	67.14	72.86	68.57	74.29	81.43	82.86	74.52

The Correct Prediction is shown graphically in percentage in Figure 5-12 below.



**Figure 5-12 Percent Correct Count for Altman's Z-Score Model**

The correct predictions for Predicted Fail and Predicted Pass are then tabulated as Table 5.22 below.

**Table 5-22 Contingency Data for Altman's Z-Score Model**

Altman	Pred Fail	Uncertain	Pred Pass	GrdTotal
PN17	152		58	210
NPN17	49		161	210
Total	201		219	420
Correct	313			
Incorrect	107			

The following table shows an analysis of error rates.

**Table 5-23 Error Rates and Accuracy for Altman's Z-Score Model**

Altman		Condition		
		NPN17	PN17	
Test	Test Positive	161	58	219
	Test Negative	49	152	201
		210	210	420

False Positive Rate, alpha	27.6
TNR = Specificity	72.4
False Negative Rate, beta	23.3
TPR = Power = Sensitivity = Recall	76.7
Inaccuracy	25.5
Accuracy	74.5

The False Positive Rate is the error of classifying a PN17 company as a NPN17. This would cause an investor to invest in a financial distress company thinking it would be a non-financial distress company. This would very likely result in the investor to incur a loss due to incorrect investment decision.

The False Negative Rate is the error of classifying a NPN17 company as a PN17. This would cause an investor to not invest in a non-financial distress company thinking it would be a financial distress company. This would very likely discourage the investor and hence the loss would be a lost opportunity.

The accuracy is the ratio of the total number of correct predictions to the actual classification. Hence,

$$\begin{aligned}
 \text{Accuracy} &= \frac{\text{Total number of correct predictions}}{\text{Number of PN17 and NPN17 companies}} \\
 &= \frac{\text{True Positive} + \text{True Negative}}{\text{Number in PN17} + \text{Numer in NPN17}} \\
 &= \frac{\text{True Positive} + \text{True Negative}}{35 + 35} \\
 &= \frac{\text{True Positive} + \text{True Negative}}{70}
 \end{aligned}$$

Of the two types of errors, False Positive Rate and False Negative Rate, the former would be more unacceptable to the investor since it involves a definite loss of money. From the table, it can be seen that Type I error is 27.6% and the Type II error is 23.3%, with an overall accuracy of 74.5%.

### 5.7.2 MDA 5V Model

The MDA 5-Variable Malaysian data was studied with the reduced data. This data set was used to develop the model based on MDA. This data set had 404 records with 16 records removed for outliers. The MDA function was used with X1, X2, X3, X4 and X5 with Y response.

The group means suggest that X4 has a high mean and large standard deviation. Although it could be normalized, this process was not considered as the model was intended to be based on raw data. Note also that there are 194 observations in PN17 and 194 observations in NPN17. Consequently, the prior probabilities were computed from “All groups equal”.

**Table 5-24 Group Statistics**

Group Statistics					
Y	Mean	Std. Deviation	Valid N (listwise)		
			Unweighted	Weighted	
1	X1	.01614	1.948796	194	194.000
	X2	-.91252	3.645705	194	194.000
	X3	-.41061	2.927628	194	194.000
	X4	50.89996	207.247371	194	194.000
	X5	.11534	.213542	194	194.000
2	X1	.39627	.236208	194	194.000
	X2	.11912	.120414	194	194.000
	X3	.07698	.082288	194	194.000
	X4	200.64748	528.106256	194	194.000
	X5	.19097	.284430	194	194.000
Total	X1	.20621	1.399299	388	388.000
	X2	-.39670	2.627241	388	388.000
	X3	-.16682	2.082641	388	388.000
	X4	125.77372	407.588748	388	388.000
	X5	.15316	.254009	388	388.000

The tests of Equality of Group Means showed that the Wilk's Lambda was greater than 0.950 in all 5 variables. Wilks' lambda is a test statistic used in multivariate analysis of variance (MANOVA) to test whether there are differences between the



means of identified groups of subjects on a combination of dependent variables. Wilk's Lambda can range from 0 to 1, where 0 is total discrimination and 1 is no discrimination. The change in Lambda is tested by the F-test. For  $\alpha = 0.05$ ,  $df_1 = 1$  and  $df_2 = 386$ , the significant F-test value is 3.866. Alternatively, the significance value corresponding to the F-test is given in the last column, where all the values are lesser than  $p = 0.05$ . Therefore, all the variables must be retained in the model.

**Table 5-25 Test of Equality of Group Means**

Tests of Equality of Group Means					
	Wilks' Lambda	F	df1	df2	Sig.
X1	.982	7.275	1	386	.007
X2	.961	15.517	1	386	.000
X3	.986	5.377	1	386	.021
X4	.966	13.517	1	386	.000
X5	.978	8.773	1	386	.003

The Pooled Within-Groups Matrices displays a pooled within-groups covariance matrix, which may differ from the total covariance matrix. The matrix is obtained by averaging the separate covariance matrices for all groups. Since the covariance is an extrinsic quantity, it is preferable to consider the correlation.

**Table 5-26 Pooled within Groups Matrices**

Pooled Within-Groups Matrices						
		X1	X2	X3	X4	X5
Covariance	X1	1.927	3.238	2.803	14.151	-.016
	X2	3.238	6.653	4.966	-24.995	-.003
	X3	2.803	4.966	4.289	3.261	-.011
	X4	14.151	-24.995	3.261	160923.845	-11.617
	X5	-.016	-.003	-.011	-11.617	.063
Correlation	X1	1.000	.904	.975	.025	-.046
	X2	.904	1.000	.930	-.024	-.004
	X3	.975	.930	1.000	.004	-.020
	X4	.025	-.024	.004	1.000	-.115
	X5	-.046	-.004	-.020	-.115	1.000

a. The covariance matrix has 386 degrees of freedom.

The within-groups correlation matrix shows the correlations between the predictors. From the table, it is noted that X3 is highly correlated with X1. This could result in multicollinearity. If one of the independent variables is very highly correlated with another independent variable, then the tolerance value for that variable will approach 0 and the matrix will not have a unique discriminant solution. There must also be low multicollinearity of the independents. To the extent that independents are correlated, the standardized discriminant function coefficients will not reliably assess the relative importance of the predictor variables. Logistic regression may offer an alternative to MDA, considered in the next section, as it usually involves fewer violations of assumptions.

The Rank indicates the number of independent variables in this case. Since discriminant analysis assumes homogeneity of covariance matrices between groups, the rank should be equal. The Log Determinant is the logarithm of the determinant for the covariance matrix between groups. The larger the log determinant the more that group's covariance matrix differs.

**Table 5-27 Test Results**

Test Results		
Box's M		2069.312
	Approx.	136.045
	df1	15
F	df2	599904.947
	Sig.	.000

Tests null hypothesis of equal population covariance matrices.

Box's M tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups, i.e., assumption of homoscedasticity, using the F-test. If the p-value is  $<0.05$ , then the variances are significantly different and there is inequality of variances of the independent variables. For the present case, the significance value is less than 0.05, indicating that the equal variances assumption is violated for this variable.

**Table 5-28 Test Results**

Box's M	2069.312
Approx.	136.045
F	
df1	15
df2	599904.947
Sig.	.000

Tests null hypothesis of equal population covariance matrices

Wilks' Lambda tests the significance of each discriminant function in MDA by testing the Eigenvalue. The % of variance explained in this case is 100%. Since there are only two groups (PN17 and NPN17) there is only 1 discriminant function. The eigenvalue is the proportion of the variance in the dependent variable that is explained by that function. The Canonical Correlation is the percentage of variance explained in the dependent variable and is equivalent to the Pearson's correlation between the discriminant scores and the groups.

**Table 5-29 Eigenvalues**

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.156 <sup>a</sup>	100.0	100.0	.368

a. First 1 canonical discriminant functions were used in the analysis.

Wilks' lambda is a measure of how well each function separates cases into groups. The associated chi-square statistic tests the hypothesis that the means of the functions listed are equal across groups. The small significance value indicates that the discriminant function does better than chance at separating the groups. The Test of Function(s) shows that Wilks' Lambda is 0.865 with a Chi-square value of 55.694, with 5 degrees of freedom corresponding to a significance of less than 0.05.

**Table 5-30 Wilks' Lambda**

Wilks' Lambda				
Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.865	55.694	5	.000

The Structure Matrix coefficients are the Pearson correlations between an independent variable and the discriminant score with a particular discriminant function. The correlations serve like factor loadings in factor analysis, i.e. by identifying the largest absolute correlations associated with each discriminant function. If there were more than one discriminant function, this would help the researcher gain insight into how to name each function. Loading less than 0.30 may be removed from the model.

**Table 5-31 Structure Matrix**

Structure Matrix	
	Function
	1
X2	.507
X4	.473
X5	.381
X1	.347
X3	.299

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions. Variables ordered by absolute size of correlation within function.

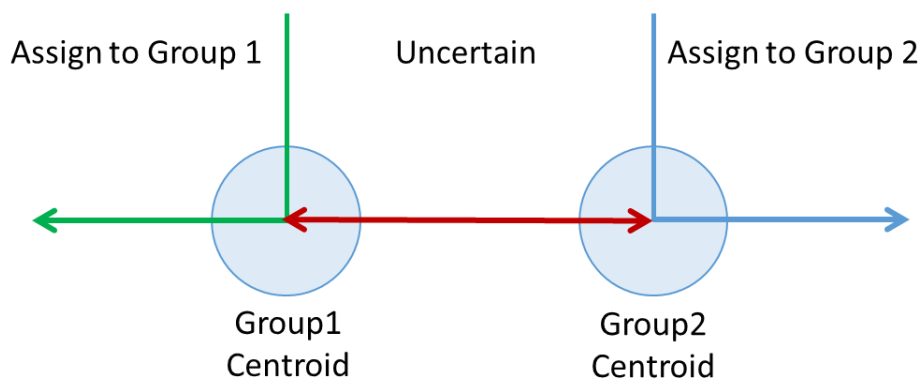
The Functions at Group Centroids show the position of the group centroid calculated from the mean of all the X variables for Group 1 and Group 2. For two groups, the Groups Centroids will be equal in magnitude if the numbers of samples are the same.

**Table 5-32 Functions at Group Centroids**

Functions at Group Centroids	
Y	Function
	1
1	-.394
2	.394

Unstandardized canonical discriminant functions evaluated at group means

In MDA, the centroids of Group 1 and Group 2 are used for counting the number of points falling in Group 1 and Group 2.

**Figure 5-13 Cut-off Points for Group 1 and Group 2 Centroids in MDA**

The Canonical Discriminant Function Coefficients reflect the contribution of each variable to the discriminant function. These would be used like unstandardized regression coefficients in multiple regression, i.e. they are used to construct the actual prediction equation which can be used to classify new cases. However, although the coefficient may be small, e.g. X4 below, the value of X4 may be large so that the contribution may still be important.

**Table 5-33 Canonical Discriminant Function Coefficients**

**Canonical Discriminant  
Function Coefficients**

	Function
	1
X1	.873
X2	.688
X3	-1.219
X4	.001
X5	1.816
(Constant)	-.560

Unstandardized coefficients

Using the Canonical Discriminant Function Coefficients, discriminant function corresponding to the Z-Score for each record is calculated as:

$$Z = -0.560 + 0.873X1 + 0.688X2 - 1.219X3 + 0.001X4 + 1.816X5$$

The cut-off points for this model are shown in Table 5-34.

**Table 5-34 Cut-off Points for 5-Variable MDA Model**

$Z < -0.394$	$-0.394 \leq Z \leq 0.394$	$Z > 0.394$
Distress Zone	Grey Zone	Safe Zone

Then, the value of the Z-Score is compared to the cut-off points. If the Z-Score value is

- a) less than the lower cut-off point it is assigned to the Financial Distress group
- b) greater than the lower cut-off point but less than the upper cut-off point it is assigned to the Uncertain group
- c) greater than the upper cut-off point it is assigned to the Non-Financial Distress group.

**Table 5-35 Arrangement of Data**

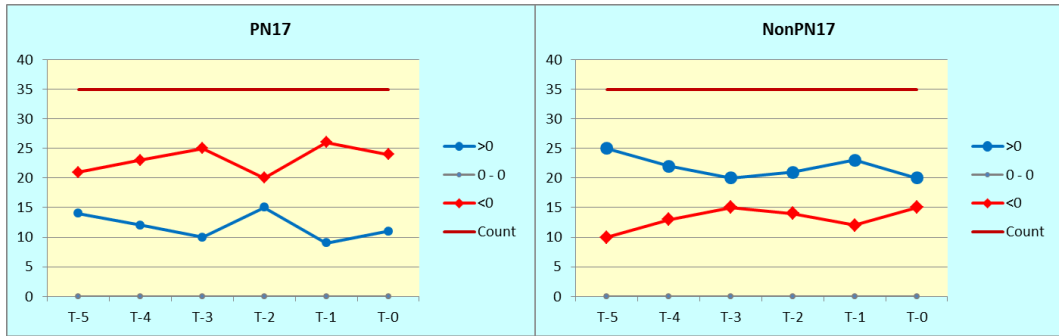
MDA-5V		X0	X1	X2	X3	X4	X5	X6	Z-Score	Class
PN17	No.	-0.560	0.873	0.688	-1.219	0.001	1.816	0.000		
T-5: 1	1	1.000	0.547	0.365	-0.004	397.903	0.002	1.000	0.576	1
T-5: 1	2	1.000	0.097	0.051	0.007	3.971	0.004	1.000	-0.438	0
T-5: 1	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
T-5: 1	35	1.000	0.075	-0.675	-0.168	1.306	0.000	1.000	-0.753	0
NPN17										
T-5: 2	1	1.000	0.439	0.013	0.007	403.121	0.047	1.000	0.312	1
T-5: 2	2	1.000	0.590	0.066	0.173	32.249	0.175	1.000	0.141	1
T-5: 2	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
T-5: 2	35	1.000	0.451	0.024	0.080	1.731	0.000	1.000	-0.246	0

From this data, the count of companies classified according to Safe Zone, Grey Zone and Distress Zone (Financial Distress, Uncertain and Non-Financial Distress) are computed.

**Table 5-36 Arrangement of Data for PN17 and NPN17**

MDA-5V	PN17					MDA-5V NonPN17					
	<0	0 - 0	>0	Count	Auditor	<0	0 - 0	>0	Count	Auditor	
T-5	21	0	14	35	35	T-5	10	0	25	35	35
T-4	23	0	12	35	35	T-4	13	0	22	35	35
T-3	25	0	10	35	34	T-3	15	0	20	35	35
T-2	20	0	15	35	35	T-2	14	0	21	35	35
T-1	26	0	9	35	26	T-1	12	0	23	35	35
T-0	24	0	11	35	19	T-0	15	0	20	35	35
Total	139	0	71			Total	79	0	131		
Gtotal	210					Gtotal	210				

The data is shown clearly in the following graphs. The total of companies always remains the same at 35 for the PN17 and NPN17. It can be restated here that although the data points for establishing the coefficients are based on the reduced data set with outliers removed, the model is applied on all 35 companies for both the PN17 and NPN17 companies.



**Figure 5-14 Comparison of PN17 and NPN17 Counts**

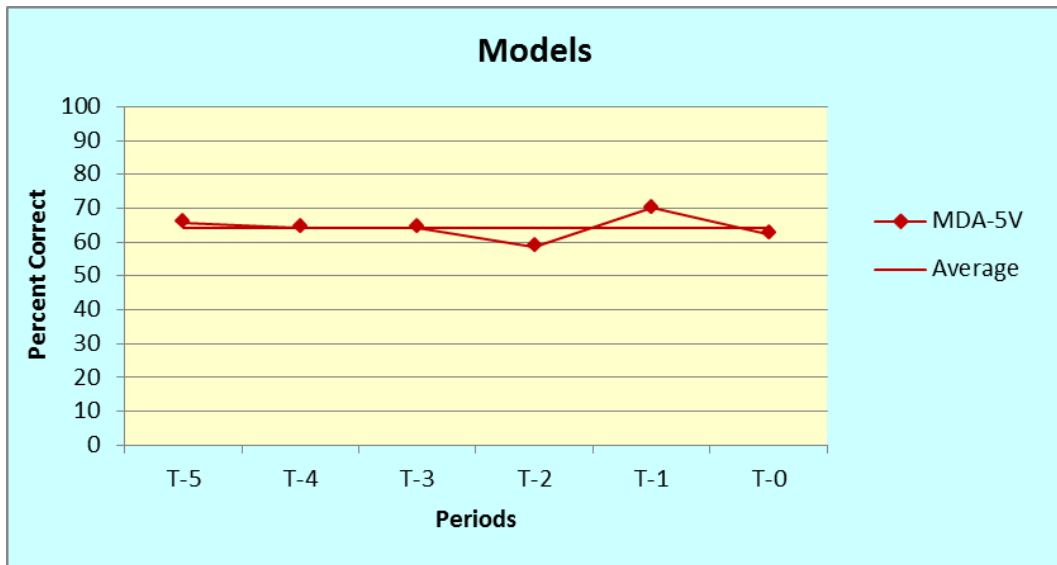
Based on this classification, (PN17, PredFail) and (NPN17, PredPass) add up to correct classification. This evaluation is done for all six periods (T-5 to T-0). The result for the current case is shown below. Note that the top table shows Counts and the bottom table shows Percentage for convenience.

**Table 5-37 Count of Prediction Values**

Count	T-5	T-4	T-3	T-2	T-1	T-0	Overall
Pred Fin Dist	31	36	40	34	38	39	218
Uncertain	0	0	0	0	0	0	0
Pred NonFin Dist	39	34	30	36	32	31	202
Total	70	70	70	70	70	70	420
Correct Prediction	46	45	45	41	49	44	270
Percentage	T-5	T-4	T-3	T-2	T-1	T-0	Overall
Pred Fin Dist	44.29	51.43	57.14	48.57	54.29	55.71	51.90
Uncertain	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pred NonFin Dist	55.71	48.57	42.86	51.43	45.71	44.29	48.10
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Correct Prediction	65.71	64.29	64.29	58.57	70.00	62.86	64.29



This percentage data is also shown in the graph below.



**Figure 5-15 Percent Correct Count for MDA Model**

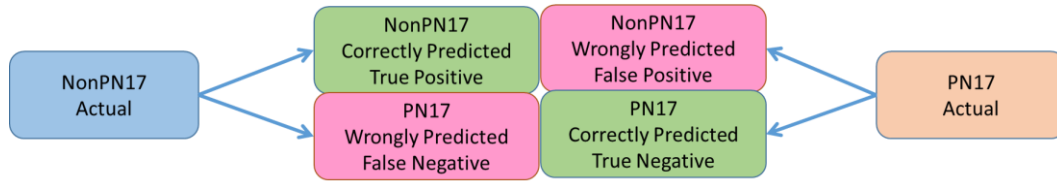
The correct predictions for Predicted Fail and Predicted Pass are then tabulated as in Table 5-38.

**Table 5-38 Contingency Data for MDA Model**

MDA-5V	Pred Fail	Uncertain	Pred Pass	GrdTotal
PN17	139		71	210
NPN17	79		131	210
Total	218		202	420
Correct	270			
Incorrect	150			

The data is rearranged into a standard contingency table as shown below.

**Table 5-39 Standard Contingency Table**



The contingency table then allows for an easy analysis of contingency statistics.

		Condition		
		Condition Positive	Condition Negative	
Test	Test Positive	True Positive	False Positive Type I Error	PPV $= \frac{\sum TruePositive}{\sum TestPositive}$
	Test Negative	False Negative Type II Error	True Negative	NPV $= \frac{\sum TrueNegative}{\sum TestNegative}$
		Sensitivity $= \frac{\sum TruePositive}{\sum ConditionPositive}$	Specificity $= \frac{\sum TrueNegative}{\sum ConditionNegative}$	Accuracy $= \frac{\sum True(+) + \sum True(-)}{\sum Total}$

**Figure 5-16 Contingency Statistics Analysis**

Based on the contingency table, the data above is analyzed as follows.

**Table 5-40 Contingency Data for MDA Model**

MDA-5V		Condition		
		NPN17	PN17	
Test	Test Positive	131	71	202
	Test Negative	79	139	218
		210	210	420

False Positive Rate, alpha	33.8
TNR = Specificity	66.2
False Negative Rate, beta	37.6
TPR = Power = Sensitivity = Recall	62.4
Inaccuracy	35.7
Accuracy	64.3

The False Positive Rate is the error of classifying a PN17 company as a NPN17. This would cause an investor to invest in a financial distress company thinking it would be non-financial distress company. This would very likely result in the investor to incur a loss due to incorrect investment decision.

The False Negative Rate is the error of classifying a NPN17 company as a PN17. This would cause an investor to not invest in a non-financial distress company thinking it would be a financial distress company. This would very likely discourage the investor and hence the loss would be a lost opportunity.

Of the two types of errors, the former is more unacceptable to the investor as there is definite loss. From the table it can be seen that Type I error is 33.8% and the Type II error is 37.6%, with an overall accuracy of 64.3%.

### 5.7.3 LRA 5V Model

The data structure for the LRA model is exactly the same as that for MDA. Initially, the 5-Variable model is developed by using exactly the same data set. Since the method of calculation is by minimizing the Log Likelihood, it is important to see the convergence of the Logistic Regression method.

**Table 5-41 Iteration History**

Iteration History <sup>a,b,c,d</sup>							
Iteration	-2 Log likelihood	Coefficients					
		Constant	X1	X2	X3	X4	X5
1	475.316	-.384	.598	.471	-.836	.001	1.245
2	443.278	-.345	.523	1.222	-1.375	.002	1.321
3	400.712	-.413	.861	2.171	-1.242	.002	1.323
4	362.959	-.560	1.147	2.532	1.361	.002	1.140
5	335.239	-.587	.933	3.229	5.777	.002	.583
6	324.355	-.684	.856	3.963	10.399	.003	-.089
7	322.679	-.766	.851	4.382	13.056	.003	-.335
8	322.643	-.781	.852	4.469	13.492	.003	-.366
9	322.643	-.782	.852	4.472	13.502	.003	-.367
10	322.643	-.782	.852	4.472	13.502	.003	-.367

a. Method: Enter

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 537.882

d. Estimation terminated at iteration number 10 because parameter estimates changed by less than .001.

From the LRA, the Model Summary shows that Cox & Snell R Square is 0.430. Since this R Square never reaches 1.0 even for perfect data, the Nagelkerke R Square is used since its formulation adjusts for the lack of reaching 1.0.

**Table 5-42 Model Summary**

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	322.643 <sup>a</sup>	.426	.568

a. Estimation terminated at iteration number 10 because parameter estimates changed by less than .001.

This model fit is then tested with Hosmer and Lemeshow Test resulting in Chi-square value of 46.554, with 8 degrees of freedom and a significance of less than 0.001. This indicates that there is very good fit in the data.

**Table 5-43 Hosmer and Lemeshow Test**

Step	Chi-square	df	Sig.
1	46.554	8	.000

The correlation matrix is shown below.

**Table 5-44 Correlation Matrix**

	Constant	X1	X2	X3	X4	X5
Constant	1.000	-.725	-.018	-.191	-.170	-.258
X1	-.725	1.000	-.180	-.060	-.080	.055
X2	-.018	-.180	1.000	.141	.157	-.261
X3	-.191	-.060	.141	1.000	-.040	-.308
X4	-.170	-.080	.157	-.040	1.000	.101
X5	-.258	.055	-.261	-.308	.101	1.000

The Variables in the Equation shows coefficients of each variable. The Parameter Estimates shows the coefficients for the LRA model:

**Table 5-45 The Parameter Estimates for the LRA Model**

	B	S.E.	Wald	df	Sig.	Exp(B)	
Step 1 <sup>a</sup>	X1	.852	.622	1.877	1	.171	2.345
	X2	4.472	.854	27.432	1	.000	87.501
	X3	13.502	2.703	24.948	1	.000	730790.693
	X4	.003	.001	6.872	1	.009	1.003
	X5	-.367	.687	.285	1	.594	.693
	Constant	-.782	.268	8.482	1	.004	.458

The Parameter Estimates shows the coefficients for the LRA model. Using the Logistic Regression Coefficients, the predicted values corresponding to the Z-Score for each record is calculated as:

$$Z = -0.782 + 0.852X1 + 4.472X2 + 13.502X3 + 0.003X4 - 0.367X5$$

The cut-off points for this model are shown in Table 5-46.

**Table 5-46 Cut-off Points for 6-Variable LRA Model**

Z < 0.500		Z > 0.500
Distress Zone	No Grey Zone	Safe Zone

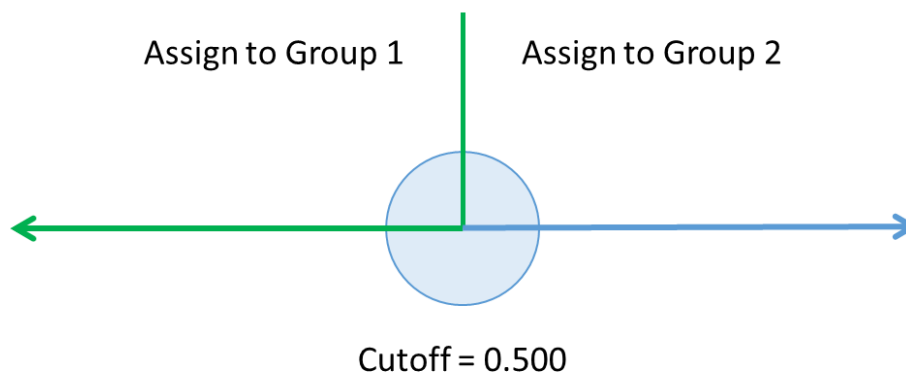
Then, the value of the Z-Score is compared to the cut-off points. If the Z-Score value is:

- a) less than the lower cut-off point it is assigned to the Financial Distress group,
- b) greater than the lower cut-off point but less than the upper cut-off point it is assigned to the Uncertain group,
- c) greater than the upper cut-off point it is assigned to the Non-Financial Distress group.

**Table 5-47 Arrangement of Data**

LRA-5V		X0	X1	X2	X3	X4	X5	X6	Z-Score	Class
PN17	No.	-0.782	0.852	4.472	13.502	0.003	-0.367	0.000		
T-5: 1	1	1.000	0.547	0.365	-0.004	397.903	0.002	1.000	2.452	1
T-5: 1	2	1.000	0.097	0.051	0.007	3.971	0.004	1.000	-0.368	0
T-5: 1	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
T-5: 1	35	1.000	0.075	-0.675	-0.168	1.306	0.000	1.000	-5.998	0
NPN17										
T-5: 2	1	1.000	0.439	0.013	0.007	403.121	0.047	1.000	0.940	1
T-5: 2	2	1.000	0.590	0.066	0.173	32.249	0.175	1.000	2.383	1
T-5: 2	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
T-5: 2	35	1.000	0.451	0.024	0.080	1.731	0.000	1.000	0.798	1

From this data, the count of companies classified according to Safe Zone, Grey Zone and Distress Zone. In LRA, the cut-off point is always 0.500. Consequently, all Z-Score values less than 0.500 are assigned to Group 1 and all Z-Score values greater than 0.500 are assigned to Group 2.

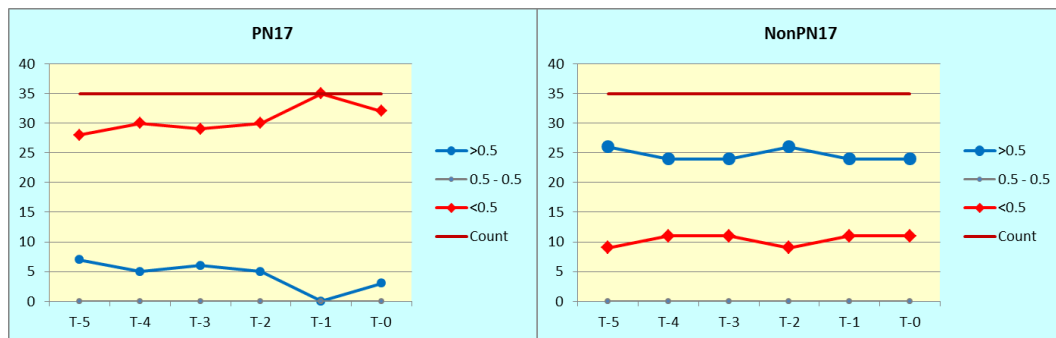
**Figure 5-17 Midpoint for Group 1 and Group 2 Cut-off in LRA**

Then, the value of the Z-Score is compared to the cut-off point. If the Z-Score value is less than the cut-off point it is assigned to the Financial Distress group, if it is greater than the cut-off point it is assigned to the Non-Financial Distress group. Note that there is no Uncertain group as in the MDA. This is evident from the central column being all zeroes.

**Table 5-48 Arrangement of Data for PN17 and NPN17**

LRA-5V						LRA-5V					
PN17	<0.5	0.5 - 0.5	>0.5	Count	Auditor	NonPN17	<0.5	0.5 - 0.5	>0.5	Count	Auditor
T-5	28	0	7	35	35	T-5	9	0	26	35	35
T-4	30	0	5	35	35	T-4	11	0	24	35	35
T-3	29	0	6	35	34	T-3	11	0	24	35	35
T-2	30	0	5	35	35	T-2	9	0	26	35	35
T-1	35	0	0	35	26	T-1	11	0	24	35	35
T-0	32	0	3	35	19	T-0	11	0	24	35	35
Total	184	0	26			Total	62	0	148		
Gtotal	210					Gtotal	210				

The data is shown clearly in the following graphs. The total of companies always remains the same at 35 for the PN17 and NPN17. It can be restated here that although the data points for establishing the coefficients are based on the reduced data set with outliers removed, the model is applied on all 35 companies for both the PN17 and NPN17 companies.



**Figure 5-18 Comparison of PN17 and NPN17 Counts**

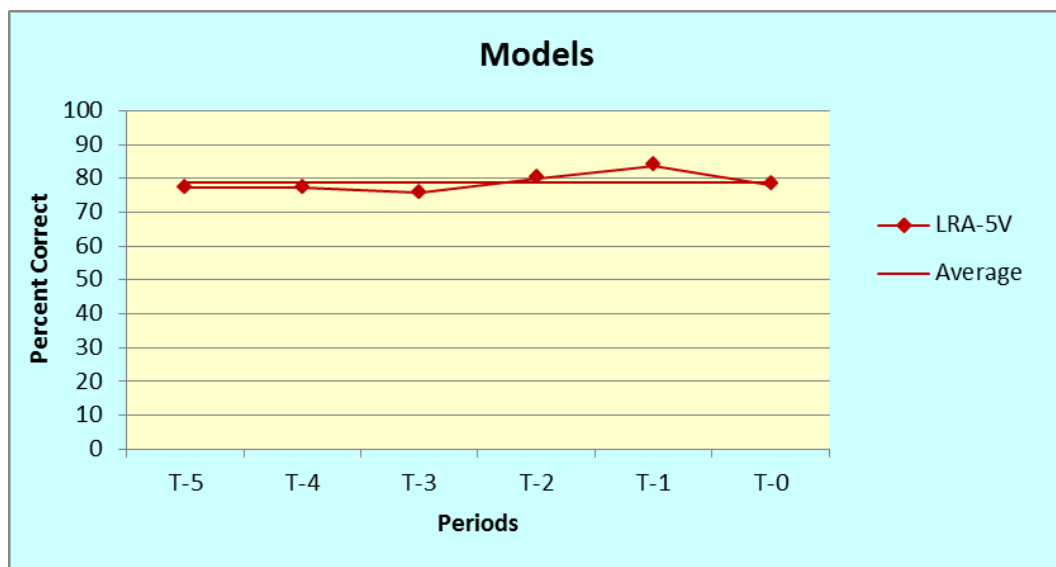
Based on this classification, (PN17, PredFail) and (NPN17, PredPass) add up to correct classification. This evaluation is done for all six periods (T-5 to T-0). The result for the current case is shown below. Then the frequencies of companies falling in the financial distress, uncertain and non-financial distress are computed and shown below as both counts and percentage. The overall quantities are also shown. Note that the top table shows Counts and the bottom table shows Percentage for convenience.



**Table 5-49 Count of Prediction Values**

Count	T-5	T-4	T-3	T-2	T-1	T-0	Overall
Pred Fin Dist	37	41	40	39	46	43	246
Uncertain	0	0	0	0	0	0	0
Pred NonFin Dist	33	29	30	31	24	27	174
Total	70	70	70	70	70	70	420
Correct Prediction	54	54	53	56	59	56	332
Percentage	T-5	T-4	T-3	T-2	T-1	T-0	Overall
Pred Fin Dist	52.86	58.57	57.14	55.71	65.71	61.43	58.57
Uncertain	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pred NonFin Dist	47.14	41.43	42.86	44.29	34.29	38.57	41.43
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Correct Prediction	77.14	77.14	75.71	80.00	84.29	80.00	79.05

This percentage data (prediction accuracy) is also shown in the graph below.



**Figure 5-19 Percent Correct Count for LRA Model**

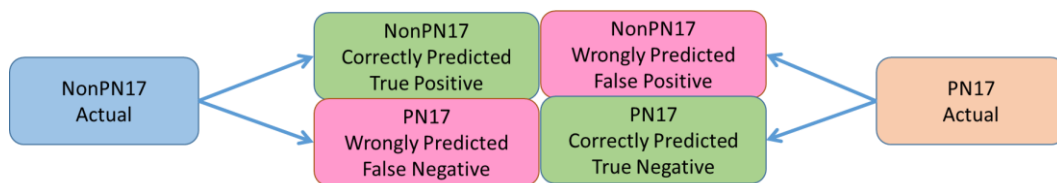
The Classification Table shows the frequencies of the Observed and Predicted counts. Note that the cut-off value is 0.50. The correct predictions for Predicted Fail and Predicted Pass are then tabulated as in Table 5-50 below.

**Table 5-50 Contingency Data for LRA Model**

LRA-5V	Pred Fail	Uncertain	Pred Pass	GrdTotal
PN17	184		26	210
NPN17	62		148	210
Total	246		174	420
Correct	332			
Incorrect	88			

The data is rearranged into a standard contingency table as shown below.

**Table 5-51 Standard Contingency Table**



The contingency table then allows for an easy analysis of contingency statistics.

		Condition		
		Condition Positive	Condition Negative	
Test	Test Positive	True Positive	False Positive Type I Error	PPV $= \frac{\sum True\ Positive}{\sum Test\ Positive}$
	Test Negative	False Negative Type II Error	True Negative	NPV $= \frac{\sum True\ Negative}{\sum Test\ Negative}$
		Sensitivity $= \frac{\sum True\ Positive}{\sum Condition\ Positive}$	Specificity $= \frac{\sum True\ Negative}{\sum Condition\ Negative}$	Accuracy $= \frac{\sum True(+)+\sum True(-)}{\sum Total}$

**Figure 5-20 Contingency Statistics Analysis**

Based on the contingency table, the data above is analyzed as follows.

**Table 5-52 Error Rates and Accuracy for LRA Model**

LRA-5V		Condition		
		NPN17	PN17	
Test	Test Positive	148	26	174
	Test Negative	62	184	246
		210	210	420

False Positive Rate, alpha	12.4
TNR = Specificity	87.6
False Negative Rate, beta	29.5
TPR = Power = Sensitivity = Recall	70.5
Inaccuracy	21.0
Accuracy	79.0

The False Positive Rate is the error of classifying a PN17 company as a NPN17. This would cause an investor to invest in a financial distress company thinking it would be non-financial distress company. This would very likely result in the investor to incur a loss due to incorrect investment decision.

The False Negative Rate is the error of classifying a NPN17 company as a PN17. This would cause an investor to not invest in a non-financial distress company thinking it would be financial distress company. This would very likely discourage the investor and hence the loss would be a lost opportunity.

Of the two types of errors, the former would be more unacceptable to the investor. From the table it can be seen that Type I error is 12.4% and the Type II error is 29.5%, with an overall accuracy of 79.0%.

## 5.8 MDA and LRA for 6-Variable Malaysian Data

### 5.8.1 MDA 6V Model

The MDA 6-Variable Malaysia data was first studied with the reduced data. This data set was used to develop the model based on the MDA. This data set had 404 records with 16 records removed for outliers. The MDA function was used with X1, X2, X3, X4, X5 and very importantly, X6 with Y response.

The X6 variable is introduced by the researcher and reflects:

- Auditors' Opinion agrees with the non-financial distress condition of a company it is labeled as unqualified (clean report) and coded as = 1.
- Auditors' Opinion disagrees the non-financial distress condition of a company it is labeled as qualified (modified Auditors' Opinion) and coded as = 0.

The group means (Table 5-53 below) suggest that X4 has a high mean and large standard deviation. Although it could be normalized this process was not considered as the model was intended to be based on raw data. Note also that there are 194 observations in PN17 and 194 observations in NPN17. Consequently, the prior probabilities were computed from "All groups equal".

**Table 5-53 Group Statistics**

Group Statistics					
Y	Mean	Std. Deviation	Valid N (listwise)		
			Unweighted	Weighted	
1	X1	.01614	1.948796	194	194.000
	X2	-.91252	3.645705	194	194.000
	X3	-.41061	2.927628	194	194.000
	X4	50.89996	207.247371	194	194.000
	X5	.11534	.213542	194	194.000
	X6	.89175	.311497	194	194.000
2	X1	.39627	.236208	194	194.000
	X2	.11912	.120414	194	194.000
	X3	.07698	.082288	194	194.000
	X4	200.64748	528.106256	194	194.000
	X5	.19097	.284430	194	194.000
	X6	1.00000	.000000	194	194.000
Total	X1	.20621	1.399299	388	388.000
	X2	-.39670	2.627241	388	388.000
	X3	-.16682	2.082641	388	388.000
	X4	125.77372	407.588748	388	388.000
	X5	.15316	.254009	388	388.000
	X6	.94588	.226554	388	388.000

The tests of Equality of Group Means showed that the Wilk's Lambda was greater than 0.950 in all 5 variables. Wilks' lambda is a test statistic used in multivariate analysis of variance (MANOVA) to test whether there are differences between the means of identified groups of subjects on a combination of dependent variables. Wilk's Lambda can range from 0 to 1, where 0 is total discrimination and 1 is no discrimination. The change in Lambda is tested by the F-test. For alpha =0.05, dof1=1 and dof2=402, the significant F-test value is 3.865. Therefore, all the variables must be retained in the model. Alternatively, the significance value corresponding to the F-test is given in the last column, where all the values are lesser than  $p = 0.05$ .

**Table 5-54 Test of Equality of Group Means**

	Wilks' Lambda	F	df1	df2	Sig.
X1	.982	7.275	1	386	.007
X2	.961	15.517	1	386	.000
X3	.986	5.377	1	386	.021
X4	.966	13.517	1	386	.000
X5	.978	8.773	1	386	.003
X6	.943	23.428	1	386	.000

The Pooled Within-Groups Matrices displays a pooled within-groups covariance matrix, which may differ from the total covariance matrix. The matrix is obtained by averaging the separate covariance matrices for all groups. Since the covariance is an extrinsic quantity, it is preferable to consider the correlation.

**Table 5-55 Pooled Within Groups Matrices**

	X1	X2	X3	X4	X5	X6	
Covariance	X1	1.927	3.238	2.803	14.151	-.016	.100
	X2	3.238	6.653	4.966	-24.995	-.003	.225
	X3	2.803	4.966	4.289	3.261	-.011	.148
	X4	14.151	-24.995	3.261	160923.845	-11.617	-3.181
	X5	-.016	-.003	-.011	-11.617	.063	.000
	X6	.100	.225	.148	-3.181	.000	.049
Correlation	X1	1.000	.904	.975	.025	-.046	.328
	X2	.904	1.000	.930	-.024	-.004	.397
	X3	.975	.930	1.000	.004	-.020	.324
	X4	.025	-.024	.004	1.000	-.115	-.036
	X5	-.046	-.004	-.020	-.115	1.000	-.007
	X6	.328	.397	.324	-.036	-.007	1.000

a. The covariance matrix has 386 degrees of freedom.

From the table, it is noted that X3 is highly correlated with X1. This could result in multicollinearity. If one of the independent variables is very highly correlated with another independent variable, then the tolerance value for that variable will approach 0 and the matrix will not have a unique discriminant solution. There must also be low

multicollinearity of the independents. To the extent that independents are correlated, the standardized discriminant function coefficients will not reliably assess the relative importance of the predictor variables. Logistic regression may offer an alternative to MDA as it usually involves fewer violations of assumptions.

**Table 5-56 Log Determinants**

Log Determinants		
Y	Rank	Log Determinant
1	6	5.662
2	5	0.000
Pooled within-groups	6	4.968

The ranks and natural logarithms of determinants printed are those of the group covariance matrices.

Box's M tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups, i.e. assumption of homoscedasticity, using the F-test. If the p-value is  $<0.05$ , then the variances are significantly different and there is inequality of variances of the independent variables. For the present case, the significance value is less than 0.05, indicating that the equal variances assumption is somewhat violated for this variable.

Wilks' Lambda tests the significance of each discriminant function in MDA by testing the Eigenvalue. The % of variance explained in this case is 100%.

**Table 5-57 Eigenvalues**

Eigenvalues				
Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.181 <sup>a</sup>	100.0	100.0	.392

a. First 1 canonical discriminant functions were used in the analysis.

The Test of Function(s) shows that Wilks' Lambda is 0.859 with a Chi-square value of 60.776, with 5 degrees of freedom and significant at 0.05.

**Table 5-58 Wilks' Lambda**

Wilks' Lambda				
Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.846	63.857	6	.000

The Structure Matrix coefficients are the Pearson correlations between an independent variable and the discriminant score with a particular discriminant function. The correlations serve like factor loadings in factor analysis, i.e. by identifying the largest absolute correlations associated with each discriminant function. If there were more than one discriminant function, this would provide an insight into how to name each function. Loading less than 0.30 may be deemphasized in the model.

**Table 5-59 Structure Matrix**

Structure Matrix	
	Function
	1
X6	.578
X2	.471
X4	.439
X5	.354
X1	.322
X3	.277

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions. Variables ordered by absolute size of correlation within function.

The Functions at Group Centroids show the position of the group centroid calculated from the mean of all the X variables for Group 1 and Group 2. For two groups, the Groups Centroids would be equal in magnitude, having the same number of samples.

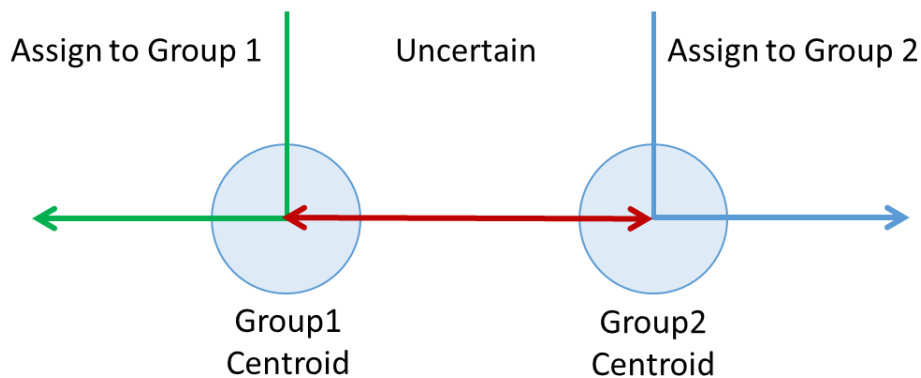


**Table 5-60 Functions at Group Centroids**

Functions at Group Centroids	
Y	Function
	1
1	-.425
2	.425

Unstandardized canonical discriminant functions evaluated at group means

In MDA, the centroids of Group 1 and Group 2 are used for counting the number of points falling in Group 1 and Group 2.

**Figure 5-21 Cut-off Points for Group 1 and Group 2 Centroids in MDA**

The Canonical Discriminant Function Coefficients reflect the contribution of each variable to the discriminant function. These would be used like unstandardized regression coefficients in multiple regression, i.e. they are used to construct the actual prediction equation which can be used to classify new cases. However, although the coefficient may be small, e.g. X4 below, the value of X4 may be large so that the contribution may still be important.

**Table 5-61 Canonical Discriminant Function Coefficients**

Canonical Discriminant Function Coefficients	
	Function
	1
X1	.730
X2	.527
X3	-1.014
X4	.001
X5	1.697
X6	1.862
(Constant)	-2.294

Unstandardized coefficients

Using the Canonical Discriminant Function Coefficients, the discriminant function corresponding to the Z-Score for each record is calculated as:

$$Z = -2.294 + 0.730X1 + 0.527X2 - 1.014X3 + 0.001X4 + 1.697X5 + 1.862X6$$

The cut-off points for this model are shown in Table 5-62 below.

**Table 5-62 The Cut-off Points for 6-Variable MDA Model**

$Z < -0.425$	$-0.425 \leq Z \leq 0.425$	$Z > 0.425$
Distress Zone	Grey Zone	Safe Zone

Then, the value of the Z-Score is compared to the cut-off points. If the Z-Score value is:

- less than the lower cut-off point, it is assigned to the Financial Distress group;
- greater than the lower cut-off point but less than the upper cut-off point, it is assigned to the Uncertain group; and
- greater than the upper cut-off point, it is assigned to the Non-Financial Distress group.

**Table 5-63 Arrangement of Data**

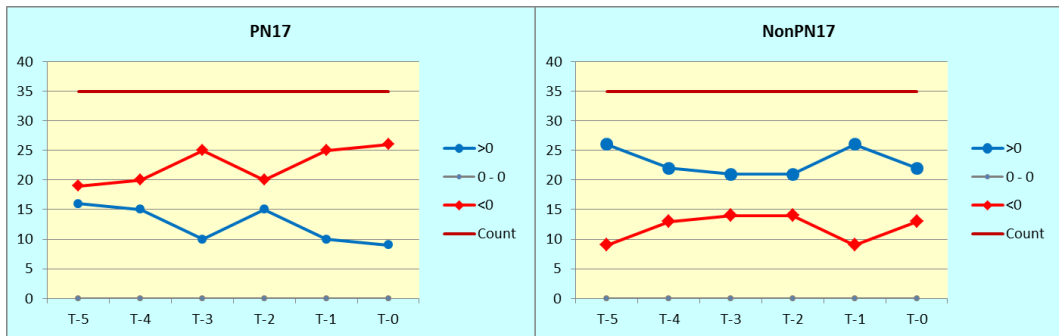
MDA-6V		X0	X1	X2	X3	X4	X5	X6	Z-Score	Class
PN17	No.	-2.294	0.730	0.527	-1.014	0.001	1.697	1.862		
T-5: 1	1	1.000	0.547	0.365	-0.004	397.903	0.002	1.000	0.566	1
T-5: 1	2	1.000	0.097	0.051	0.007	3.971	0.004	1.000	-0.331	0
T-5: 1	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
T-5: 1	35	1.000	0.075	-0.675	-0.168	1.306	0.000	1.000	-0.561	0
NPN17										
T-5: 2	1	1.000	0.439	0.013	0.007	403.121	0.047	1.000	0.371	1
T-5: 2	2	1.000	0.590	0.066	0.173	32.249	0.175	1.000	0.188	1
T-5: 2	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
T-5: 2	35	1.000	0.451	0.024	0.080	1.731	0.000	1.000	-0.169	0

From this data, the count of companies classified according to Safe Zone, Grey Zone and Distress Zone (Financial Distress, Uncertain and Non-Financial Distress) are computed.

**Table 5-64 Arrangement of Data for PN17 and NPN17**

MDA-6V	PN17					MDA-6V					NonPN17						
	<0	0 - 0	>0	Count	Auditor	<0	0 - 0	>0	Count	Auditor	<0	0 - 0	>0	Count	Auditor		
T-5	19	0	16	35	35	T-5	9	0	26	35	35	T-5	9	0	26	35	35
T-4	20	0	15	35	35	T-4	13	0	22	35	35	T-4	13	0	22	35	35
T-3	25	0	10	35	34	T-3	14	0	21	35	35	T-3	14	0	21	35	35
T-2	20	0	15	35	35	T-2	14	0	21	35	35	T-2	14	0	21	35	35
T-1	25	0	10	35	26	T-1	9	0	26	35	35	T-1	9	0	26	35	35
T-0	26	0	9	35	19	T-0	13	0	22	35	35	T-0	13	0	22	35	35
Total	135	0	75			Total	72	0	138			Total	72	0	138		
Gtotal	210					Gtotal	210					Gtotal	210				

The data is shown clearly in the following graphs. The total of companies always remains the same at 35 for the PN17 and NPN17. It can be restated here that although the data points for establishing the coefficients are based on the reduced data set with outliers removed, the model is applied on all 35 companies for both the PN17 and NPN17 companies.



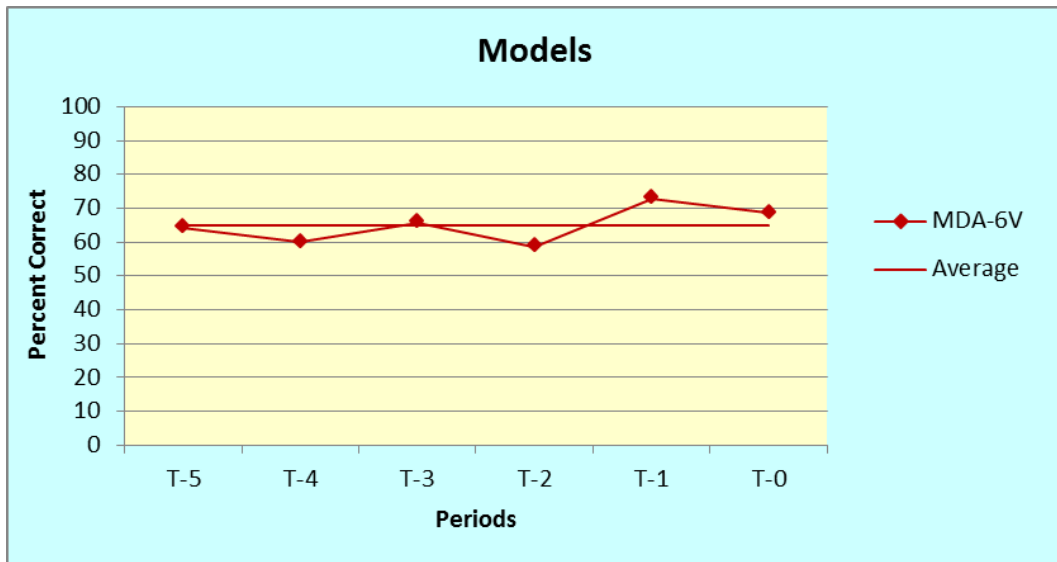
**Figure 5-22 Comparison of PN17 and NPN17 Counts**

Based on this classification, (PN17, PredFail) and (NPN17, PredPass) add up to correct classification. This evaluation is done for all six periods (T-5 to T-0). The result for the current case is shown below. Note that the top table shows Counts and the bottom table shows Percentage for convenience.

**Table 5-65 Count of Prediction Values**

Count	T-5	T-4	T-3	T-2	T-1	T-0	Overall
Pred Fin Dist	28	33	39	34	34	39	207
Uncertain	0	0	0	0	0	0	0
Pred NonFin Dist	42	37	31	36	36	31	213
Total	70	70	70	70	70	70	420
Correct Prediction	45	42	46	41	51	48	273
Percentage	T-5	T-4	T-3	T-2	T-1	T-0	Overall
Pred Fin Dist	40.00	47.14	55.71	48.57	48.57	55.71	49.29
Uncertain	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pred NonFin Dist	60.00	52.86	44.29	51.43	51.43	44.29	50.71
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Correct Prediction	64.29	60.00	65.71	58.57	72.86	68.57	65.00

The Correct Prediction is shown graphically in percentage below.



**Figure 5-23 Percent Correct Count for MDA Model**

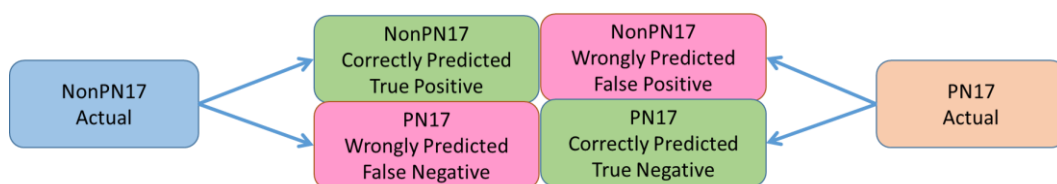
The correct predictions for Predicted Fail and Predicted Pass are then tabulated as in Table 5-66 below.

**Table 5-66 Contingency Data for MDA Model**

MDA-6V	Pred Fail	Uncertain	Pred Pass	GrdTotal
PN17	135		75	210
NPN17	72		138	210
Total	207		213	420
Correct	273			
Incorrect	147			

The data is rearranged into a standard contingency table as shown below.

**Table 5-67 Standard Contingency**



The contingency table then allows for an easy analysis of contingency statistics.

		Condition		
		Condition Positive	Condition Negative	
Test	Test Positive	True Positive	False Positive Type I Error	PPV $= \frac{\sum True Positive}{\sum Test Positive}$
	Test Negative	False Negative Type II Error	True Negative	NPV $= \frac{\sum True Negative}{\sum Test Negative}$
		Sensitivity $= \frac{\sum True Positive}{\sum Condition Positive}$	Specificity $= \frac{\sum True Negative}{\sum Condition Negative}$	Accuracy $= \frac{\sum True(+) + \sum True(-)}{\sum Total}$

**Figure 5-24 Contingency Statistics**

Based on the contingency table, the data above is analyzed as follows:

**Table 5-68 Error Rates and Accuracy for MDA Model**

MDA-6V		Condition		
		NPN17	PN17	
Test	Test Positive	138	75	213
	Test Negative	72	135	207
		210	210	420

False Positive Rate, alpha	35.7
TNR = Specificity	64.3
False Negative Rate, beta	34.3
TPR = Power = Sensitivity = Recall	65.7
Inaccuracy	35.0
Accuracy	65.0

The False Positive Rate is the error of classifying a PN17 company as a NPN17. This would cause an investor to invest in a financial distress company thinking it would be a non-financial distress company. This would very likely result in the investor incurring a loss due to incorrect investment decision.

The False Negative Rate is the error of classifying a NPN17 company as a PN17. This would cause an investor not to invest in a non-financial distress company, thinking it would be a financial distress company. This would very likely discourage the investor and hence the loss would be a lost opportunity.

Of the two types of errors, the former is more unacceptable to the investor as there is definite loss. From the table it, can be seen that Type I error is 35.7% and the Type II error is 34.3%, with an overall accuracy of 65.0%.

### 5.8.2 LRA 6V Model

The data structure for the LRA Model is exactly the same as that for MDA. Initially, the 6-Variable model is developed. When running the LRA, the Iteration History is analyzed to ensure that there is a smooth convergence as shown in the table below:

**Table 5-69 Iteration History**

Iteration	-2 Log likelihood	Coefficients						
		Constant	X1	X2	X3	X4	X5	X6
1	467.315	-1.659	.528	.381	-.733	.001	1.227	1.346
2	437.236	-2.270	.401	1.101	-1.308	.002	1.352	2.003
3	390.198	-1.560	.855	2.093	-.787	.002	1.229	1.176
4	352.567	-2.400	1.025	2.482	2.228	.003	1.065	1.882
5	329.241	-3.153	.831	3.200	6.622	.003	.487	2.586
6	321.416	-3.809	.768	3.899	10.754	.003	-.091	3.146
7	320.378	-4.574	.763	4.263	12.764	.003	-.285	3.853
8	320.323	-5.554	.763	4.324	13.022	.003	-.307	4.826
9	320.308	-6.557	.763	4.325	13.026	.003	-.308	5.828
10	320.303	-7.558	.763	4.325	13.026	.003	-.308	6.829

a. Method: Enter

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 537.882

d. Estimation terminated at iteration number 10 because maximum iterations has been reached.

The Model Summary shows that Cox & Snell R Square is 0.430. Since this R Square never reaches 1.0 even for perfect data, the Nagelkerke R Square is used since its formulation adjusts for the lack of reaching 1.0.

**Table 5-70 Model Summary**

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	320.303 <sup>a</sup>	.429	.572

a. Estimation terminated at iteration number 10 because maximum iterations has been reached. Final solution cannot be found.

This model fit is then tested with Hosmer and Lemeshow Test, resulting in the Chi-square value of 27.812, with 8 degrees of freedom and a significance of 0.001. This shows that there is good fit in the data.

**Table 5-71 Hosmer and Lemeshow Test**

Step	Chi-square	df	Sig.
1	46.226	8	.000

The correlation matrix is shown in Table 5.72 below.

**Table 5-72 Correlation Matrix**

	Constant	X1	X2	X3	X4	X5	X6
Constant	1.000	-.003	.008	.005	-.014	-.007	-1.000
X1	-.003	1.000	-.179	-.055	-.059	.059	-.005
X2	.008	-.179	1.000	.158	.012	-.283	-.008
Step 1 X3	.005	-.055	.158	1.000	-.073	-.318	-.007
X4	-.014	-.059	.012	-.073	1.000	.147	.012
X5	-.007	.059	-.283	-.318	.147	1.000	.004
X6	-1.000	-.005	-.008	-.007	.012	.004	1.000



**Table 5-73 Variables in the Equation**

Variables in the Equation						
	B	S.E.	Wald	df	Sig.	Exp(B)
X1	.763	.630	1.466	1	.226	2.144
X2	4.325	.868	24.809	1	.000	75.560
X3	13.026	2.691	23.427	1	.000	453950.012
Step 1 <sup>a</sup> X4	.003	.001	5.911	1	.015	1.003
X5	-.308	.691	.198	1	.656	.735
X6	6.829	24.959	.075	1	.784	924.335
Constant	-7.558	24.959	.092	1	.762	.001

a. Variable(s) entered on step 1: X1, X2, X3, X4, X5, X6.

The Parameter Estimates shows the coefficients for the LRA model. Using the Logistic Regression Coefficients, the predicted values corresponding to the Z-Score for each record is calculated as:

$$Z = -7.558 + 0.763X1 + 4.325X2 + 13.026X3 + 0.003X4 - 0.308X5 + 6.829X6$$

The cut-off points for this model are shown in Table 5-74 below.

**Table 5-74 Cut-off Points for 6-Variable LRA Model**

Z < 0.500		Z > 0.500
Distress Zone	No Grey Zone	Safe Zone

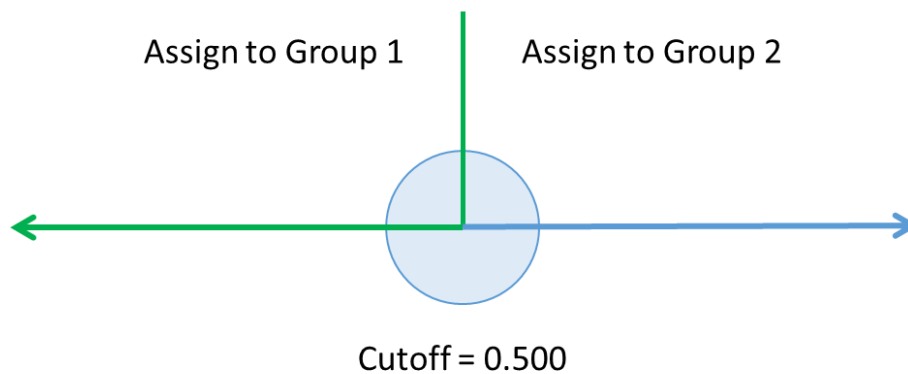
Then, the value of the Z-Score is compared to the cut-off points. If the Z-Score value is:

- less than the lower cut-off point, it is assigned to the Financial Distress group;
- greater than the lower cut-off point but less than the upper cut-off point, it is assigned to the Uncertain group: and
- greater than the upper cut-off point, it is assigned to the Non-Financial Distress group.

**Table 5-75 Arrangement of Data**

LRA-6V		X0	X1	X2	X3	X4	X5	X6	Z-Score	Class
PN17	No.	-7.558	0.763	4.325	13.026	0.003	-0.308	6.829		
T-5: 1	1	1.000	0.547	0.365	-0.004	397.903	0.002	1.000	2.404	1
T-5: 1	2	1.000	0.097	0.051	0.007	3.971	0.004	1.000	-0.334	0
T-5: 1	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
T-5: 1	35	1.000	0.075	-0.675	-0.168	1.306	0.000	1.000	-5.772	0
NPN17										
T-5: 2	1	1.000	0.439	0.013	0.007	403.121	0.047	1.000	0.951	1
T-5: 2	2	1.000	0.590	0.066	0.173	32.249	0.175	1.000	2.301	1
T-5: 2	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
T-5: 2	35	1.000	0.451	0.024	0.080	1.731	0.000	1.000	0.769	1

From this data, the count of companies classified according to Safe Zone, Grey Zone and Distress Zone. In LRA, the cut-off point is always 0.500. Consequently, all Z-Score values less than 0.500 are assigned to Group 1 and all Z-Score values greater than 0.500 are assigned to Group 2.

**Figure 5-25 Midpoint for Group 1 and Group 2 Cut-off in LRA**

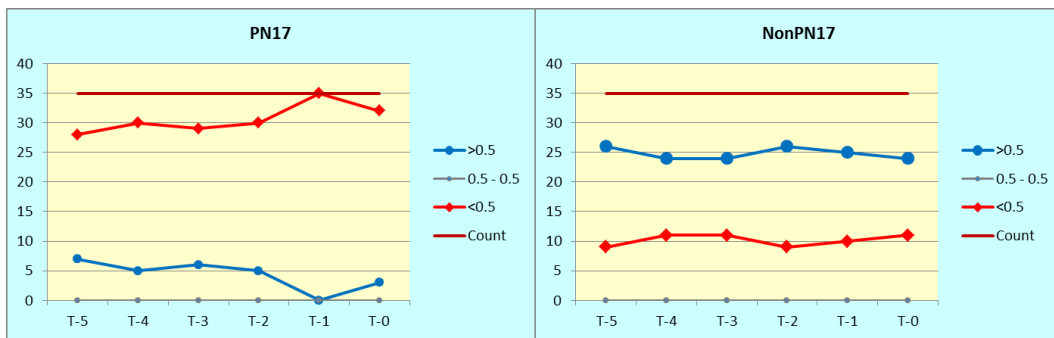
Then, the value of the Z-Score is compared to the cut-off point. If the Z-Score value is less than the cut-off point, it is assigned to the financial distress group; if it is greater than the cut-off point, it is assigned to the non-financial distress group. Note that there is no uncertain group as in the MDA. This is evident from the central column being all zeroes.

**Table 5-76 Arrangement of Data for PN17 and NPN17**

LRA-6V	LRA-6V					LRA-6V	LRA-6V				
PN17	<0.5	0.5 -	>0.5	Count	Auditor	NonPN17	<0.5	0.5 -	>0.5	Count	Auditor
T-5	28	0	7	35	35	T-5	9	0	26	35	35

T-4	30	0	5	35	35	T-4	11	0	24	35	35
T-3	29	0	6	35	34	T-3	11	0	24	35	35
T-2	30	0	5	35	35	T-2	9	0	26	35	35
T-1	35	0	0	35	26	T-1	10	0	25	35	35
T-0	32	0	3	35	19	T-0	11	0	24	35	35
Total	184	0	26			Total	61	0	149		
Gtotal	210					Gtotal	210				

The data is shown clearly in the following graphs. The total number of companies always remains the same at 35 for both the PN17 and NPN17. It can be restated here that although the data points for establishing the coefficients are based on the reduced data set with outliers removed, the model is applied on all 35 companies for both the PN17 and NPN17 companies.



**Figure 5-26 Comparison of PN17 and NPN17 Counts**

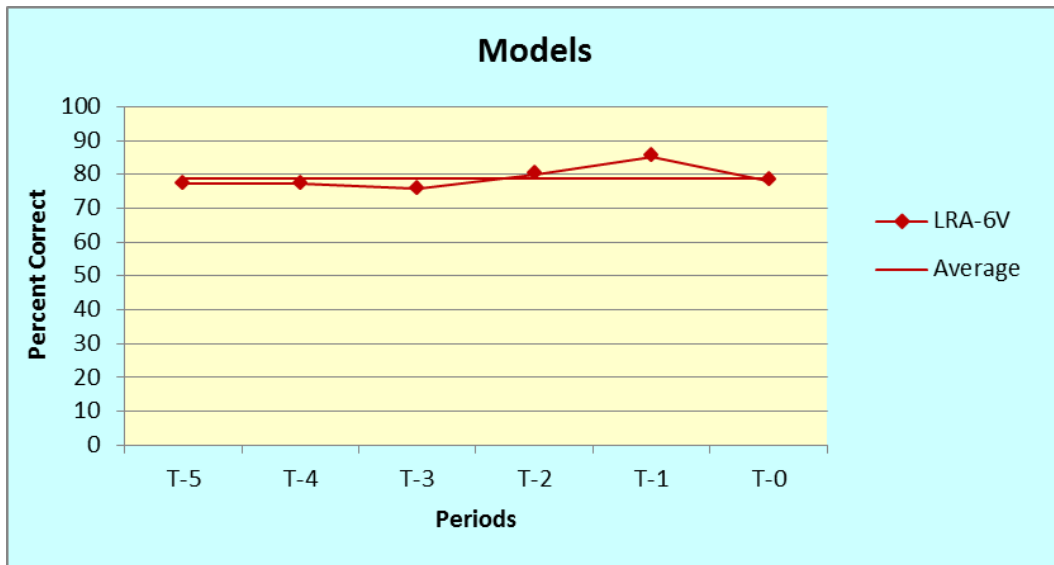
Based on this classification, (PN17, PredFail) and (NPN17, PredPass) add up to correct classification. This evaluation is done for all six periods (T-5 to T-0). The result for the current case is shown in Table 5.77 below. Then the frequencies of companies falling in the financial distress, both uncertain and non-financial distress are computed and shown below as both counts and percentage. The overall quantities are also shown. Note that the top table shows Counts and the bottom table shows Percentage for convenience.

**Table 5-77 Count of Prediction Values**

Count	T-5	T-4	T-3	T-2	T-1	T-0	Overall
Pred Fin Dist	37	41	40	39	45	43	245
Uncertain	0	0	0	0	0	0	0
Pred NonFin Dist	33	29	30	31	25	27	175
Total	70	70	70	70	70	70	420

Correct Prediction	54	54	53	56	60	56	333
Percentage	T-5	T-4	T-3	T-2	T-1	T-0	Overall
Pred Fin Dist	52.86	58.57	57.14	55.71	64.29	61.43	58.33
Uncertain	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pred NonFin Dist	47.14	41.43	42.86	44.29	35.71	38.57	41.67
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Correct Prediction	77.14	77.14	75.71	80.00	85.71	80.00	79.29

The prediction accuracy is shown graphically in Figure 5-27 below:



**Figure 5-27 Percent Correct Count for LRA Model**

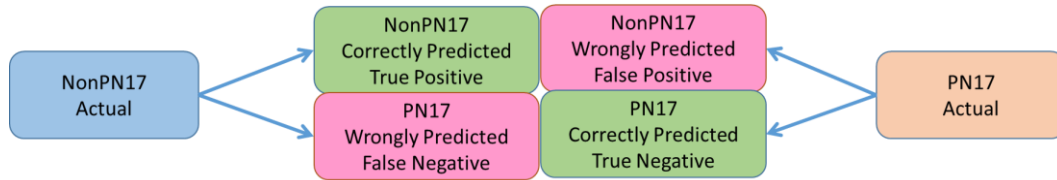
The Classification Table shows the frequencies of the Observed and Predicted counts. Note that the cut-off value is 0.50. The correct predictions for Predicted Fail and Predicted Pass are then tabulated as in **Error! Reference source not found.** elow.

**Table 5-78 Contingency Data for Logistic Regression Model**

LRA-6V	Pred Fail	Uncertain	Pred Pass	GrdTotal
PN17	184		26	210
NPN17	61		149	210
Total	245		175	420
Correct	333			
Incorrect	87			

The data is rearranged into a standard contingency table as shown in below.

**Table 5-79 Standard Contingency Table**



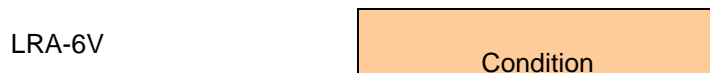
The contingency table then allows for an easy analysis of contingency statistics.

		Condition		
		Condition Positive	Condition Negative	
Test	Test Positive	True Positive	False Positive Type I Error	PPV $= \frac{\sum True Positive}{\sum Test Positive}$
	Test Negative	False Negative Type II Error	True Negative	NPV $= \frac{\sum True Negative}{\sum Test Negative}$
		Sensitivity $= \frac{\sum True Positive}{\sum Condition Positive}$	Specificity $= \frac{\sum True Negative}{\sum Condition Negative}$	Accuracy $= \frac{\sum True (+) + \sum True (-)}{\sum Total}$

**Figure 5-28 Contingency Statistics Analysis**

Based on the contingency table, the data above is analyzed as follows.

**Table 5-80 Error Rates and Accuracy for Altman’s Z-Score Model**



		NPN17	PN17	
Test	Test Positive	149	26	175
	Test Negative	61	184	245
		210	210	420

False Positive Rate, alpha	12.4
TNR = Specificity	87.6
False Negative Rate, beta	29.0
TPR = Power = Sensitivity = Recall	71.0
Inaccuracy	20.7
Accuracy	79.3

The False Positive Rate is the error of classifying a PN17 company as a NPN17. This would cause an investor to invest in a financial distress company, thinking it would be a non-financial distress company. This would very likely result in the investor incurring a loss due to incorrect investment decision.

The False Negative Rate is the error of classifying a NPN17 company as a PN17. This would cause an investor not to invest in a non-financial distress company, thinking it would be a financial distress company. This would very likely discourage the investor and hence the loss would be a lost opportunity.

Of the two types of errors, the former would be more unacceptable to the investor. From the table, it can be seen that Type I error is 12.4% and the Type II error is 29.0%, with an overall accuracy of 79.3%.

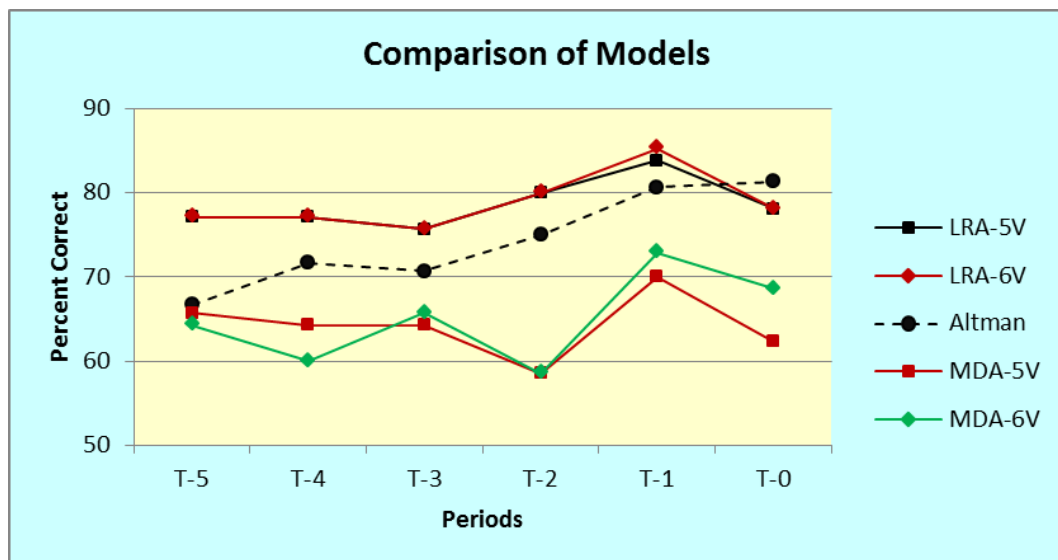
## 5.9 Selection of the Best Model

In this study, the researcher has compared 5 models:

- 1) 5-Variable Altman's Z-Score Model (MDA)
- 2) 5-Variable MDA
- 3) 5-Variable LRA
- 4) 6-Variable MDA
- 5) 6-Variable LRA

### 5.9.1 Select on Best Trend

From the 5 models above, the researcher compared the accuracy performance of the models from T-5 to T-0 as shown in Figure 5-29 below:



**Figure 5-29 Comparison of Trends in All Models**

The models with 5-Variables are implied to have variables (X1, X2, X3, X4 and X5) while the models with 6-Variables are implied to have variables (X1, X2, X3, X4, X5 and X6). Each data set was run once for MDA and once for LRA, so that there were 4 models. The Altman's Z-Score Model was always used as a baseline for comparison. Hence, for the purpose of this study, there are a total of 5 models.

From the graph above, it is clear that the MDA models (MDA-5V, MDA-6V) had performed rather poorly. The Altman's Z-Score Model had performed better than the MDA Models in this study, namely, the 5-Variable and 6-Variable models.

However, the researcher's LRA models, namely, the 5-Variable and 6-Variable models had outperformed the Altman's Z-Score Model. Specifically, the 6-Variable is consistently better by an average of about 4.8% points as calculated by the average of the corresponding differences, based on a year-by-year accuracy data. The average difference is defined as

$$AvgDiff = \frac{\sum_{t=0}^5 (A_{6-V LRModel} - A_{AltmanModel})}{6}$$

Graphically, it can be seen that the Altman's Z-Score Model has a relatively poor accuracy performance for longer periods of forward prediction. In other words, the prediction at T-5 is 67.14%. In direct comparison, the researcher's 5-Variable and 6-Variable models each have better accuracy even at T-5 period, with an accuracy prediction at 77.14%. At the current year, the Altman's Z-Score Model had predicted 82.86% while the researcher's models for both 5 and 6-Variables had predicted 80%. However, the Altman's Z-Score Model had compromised the overall accuracy at 74.52% compared to 79.05% and 79.29% overall percentages for the LRA 5 and 6-Variable models respectively. Clearly, the LRA Models are better than the Altman's model.

**Table 5-81 Accuracy Performance of All Models**

		T-5	T-4	T-3	T-2	T-1	T-0	
Altman	1	67.14	72.86	68.57	74.29	81.43	82.86	74.52
LRA-5V	28	77.14	77.14	75.71	80.00	84.29	80.00	79.05
LRA-6V	29	77.14	77.14	75.71	80.00	85.71	80.00	79.29
MDA-5V	30	65.71	64.29	64.29	58.57	70.00	62.86	64.29
MDA-6V	31	64.29	60.00	65.71	58.57	72.86	68.57	65.00



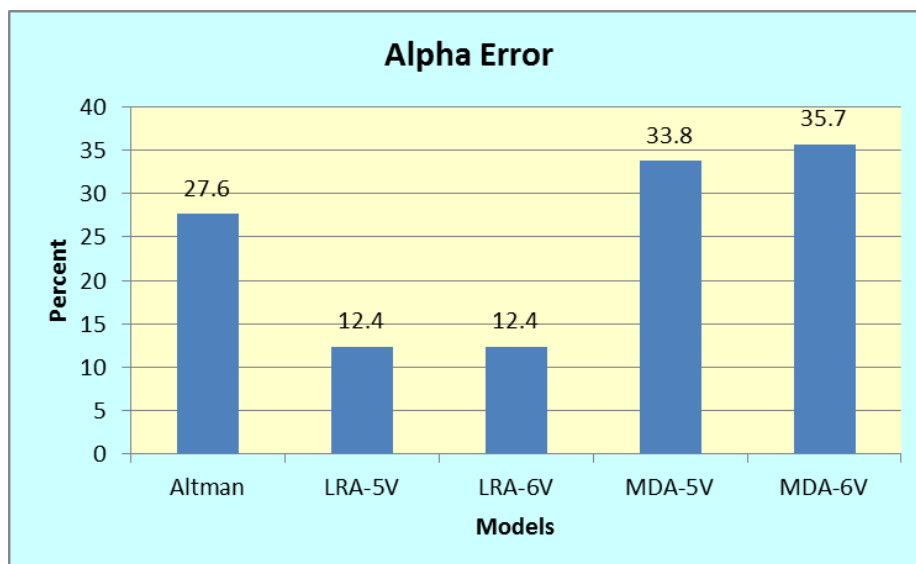
### 5.9.2 Comparison of Contingency Performance – Alpha Error

The following section compares the overall model contingency performance.

**Table 5-82 Contingency Performance of All Models**

	1 Altman	28 LRA-5V	29 LRA-6V	30 MDA-5V	31 MDA-6V
False Positive Rate, alpha TNR = Specificity	27.6	12.4	12.4	33.8	35.7
False Negative Rate, beta TPR = Power = Sensitivity = Recall	23.3	29.5	29.0	37.6	34.3
Inaccuracy	25.5	21.0	20.7	35.7	35.0
Accuracy	74.5	79.0	79.3	64.3	65.0

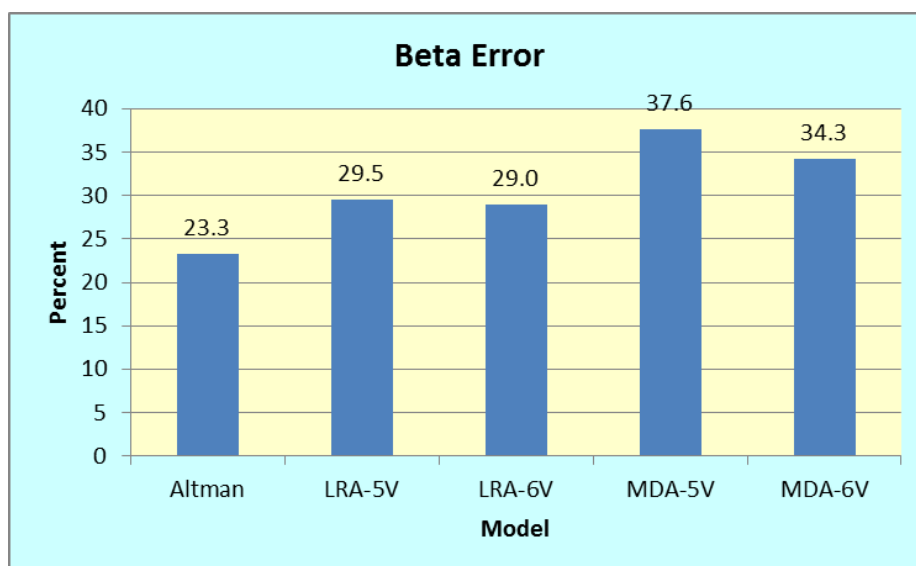
In particular, the researcher compared the alpha error in the 5 models. The data labels are shown in the graph in Figure 5-30 and it is obvious that the researcher's model based on the LRA gives the lowest alpha error. In this research, the alpha error is the error of wrongly classifying a PN17 company as a NPN17 company. This would tempt an investor to invest in the company when in fact it would fail in the near future.



**Figure 5-30 Comparison of Alpha Error in Models**

### 5.9.3 Comparison of Contingency Performance – Beta Error

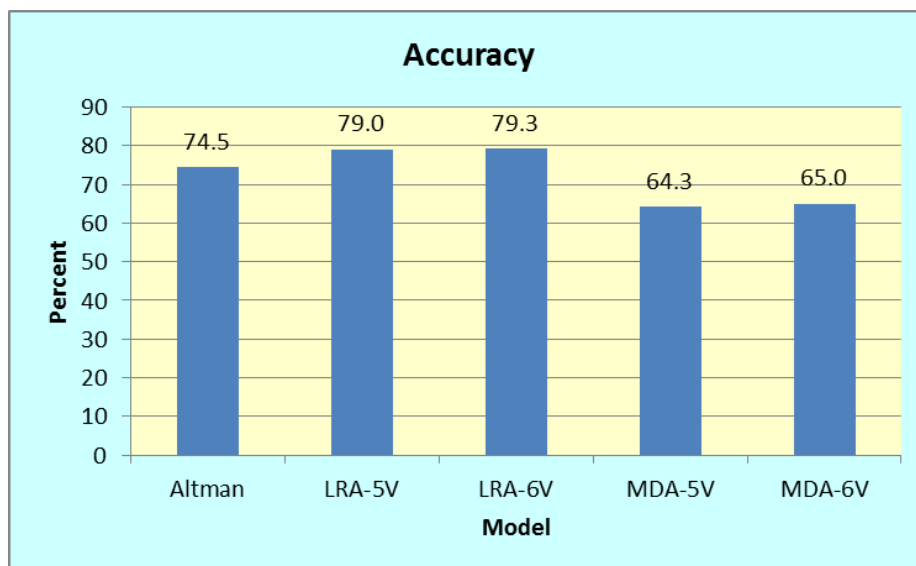
Concurrently, it is important to estimate the beta error in the 5 models. The data labels are shown in the graph Figure 5-31 and it is obvious that the researcher's model based on the LRA gives the lowest beta error except for the Altman's Z-Score Model. In this research, the beta error is the error of wrongly classifying a NPN17 company as a PN17 company. This error is not as grave as the alpha error because this would caution an investor to not invest in the company when in fact it would pass in the near future. Although the Altman's Z-Score Model seems to have a lower beta error, this advantage is only in the beta error.



**Figure 5-31 Comparison of Beta Error in Models**

### 5.9.4 Comparison of Contingency Performance – Accuracy

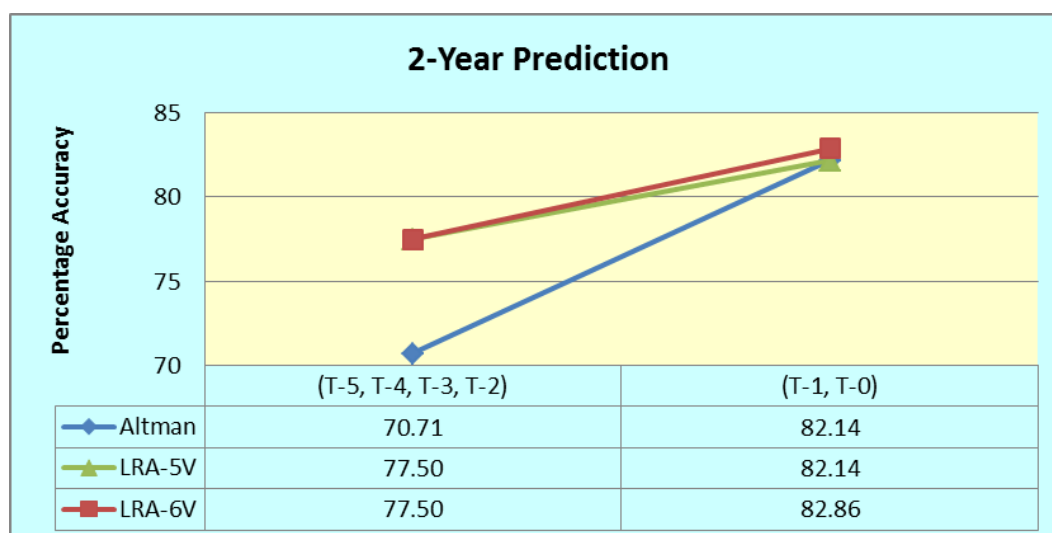
Next, the researcher considered the overall accuracy in the 5 models. This is done by comparing the accuracy data for each model. The data labels are shown in the graph Figure 5-32 below and it is obvious that the researcher's model based on the 6-Variable LRA gives the highest accuracy. In this research, the accuracy is the percentage of correctly classifying a NPN17 company as a NPN17 company, and classifying a PN17 company as a PN17 company. The error of not classifying a company correctly is called misclassification and it is the complement of accuracy.



**Figure 5-32 Comparison of Accuracy in Models**

### 5.9.5 Comparison of Predictability – Next Two Years

The researcher's model is also superior in another way. The ability to forecast a company's financial status within the next two years has a particular interest for investors and similar to the intention of the Altman's Z-Score Model. In this regard, the researcher had regrouped the period data for 4Yr (T-5, T-4, T-3, T-2) and compared them against 2Yr (T-1, T-0). The averages for the 4Yr period and 2Yr period are shown in Figure 5-33 and Table 5-83 below respectively. At this stage only the three best models need to be compared as shown below.



**Figure 5-33 Comparison of Predictability – Next Two Years**

Here, once again, it can be seen graphically that both the researcher's model are superior to the Altman's Z-Score Model. This can also be shown statistically using a 2-way analysis of variance with the original non-averaged data shown in Table 5-83 below.

**Table 5-83 Comparison of Altman's Z-Score Model and 6-Variable Model**

	T-5	T-4	T-3	T-2	T-1	T-0
Altman	67.14	72.86	68.57	74.29	81.43	82.86
LRA-6V	77.14	77.14	75.71	80.00	85.71	80.00

The 2-way classification of data is shown in Table 5-84 below.

**Table 5-84 ANOVA of Altman's Z-Score Model vs. 6-Variable Model**

Exp	T(4) vs T(2)	Alt vs YHL	Obs1	Obs2	Obs3	Obs4
1	1	1	67.14	72.86	68.57	74.29
2	1	2	77.14	77.14	75.71	80.00
3	2	1	81.43	82.86		
4	2	2	85.71	80.00		

And the analysis of variance is shown in Table 5-84.

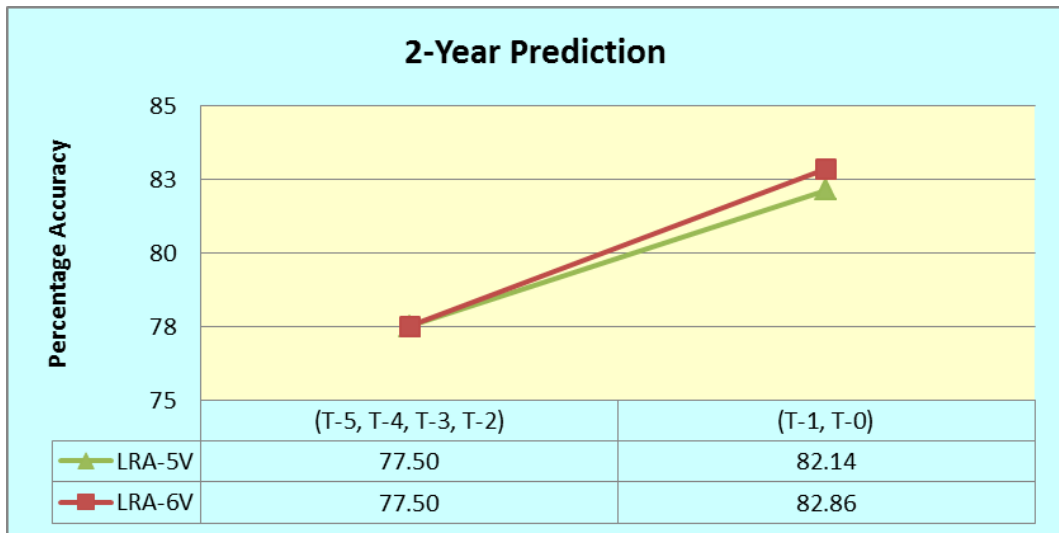
**Table 5-85 Comparison of 2-Year Prediction by Altman's Z-Score Model vs. 6-Variable**

Source	SSQ	DoF	Variance	F-Ratio	p-value
T(4) vs T(2)	187.840	1	187.84	19.59	0.002
Alt vs LRA	68.027	1	68.03	7.09	0.026
Error	86.310	9	9.59		
St	342.177	11			
Sm	70972.109	1			
ST	71314.286	12			

From the ANOVA, it can be shown conclusively that the mean accuracy (82.50%) of the 2-year forecast 2YF (T-1, T-0) is significantly higher than the mean accuracy (74.11%) of the 5-year forecast 5YF (T-5, T-4, T-3, T-2) at  $\alpha = 0.05$  since the corresponding p value is 0.002. Hence, it is important to note that the preference of the 2-Year prediction of the researcher's model against the Altman's Z-Score Model has been shown through a statistical significance and not merely a graphically representation.

### 5.9.6 Comparison of Predictability – 5-Variable and 6-Variable

Finally, it can also be shown that the researcher's model (LRA-6V, mean = 79.29%) is better than the Altman's Z-Score Model (Altman, mean = 74.52%) at  $\alpha = 0.05$  since the corresponding p value is 0.026.



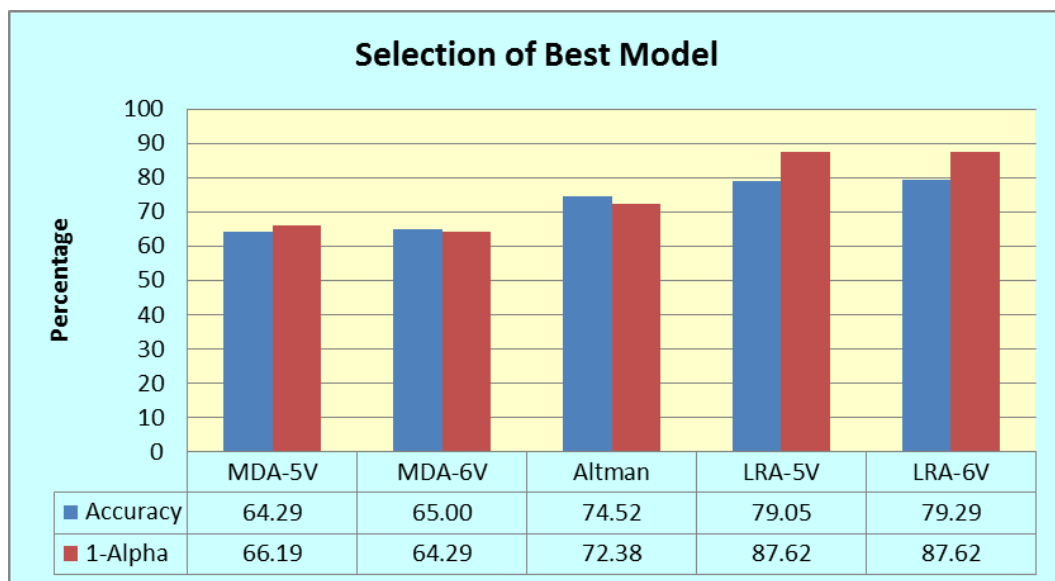
**Figure 5-34 Comparison of the Predictability – 5 and 6-Variable Models**

These findings are summarized as follows:

**Table 5-86 Summary Comparison of Performances by Different Models**

	Trend	Alpha	Beta	Accuracy	T(5 yr) - T(2 yr)	Alt - LRA
Altman			✓			
LRA-5V						
LRA-6V	✓	✓	✓	✓	✓	✓
MDA-5V						
MDA-6V						

A detailed comparison of the two most important characteristics, i.e., accuracy and (1-alpha) error is shown in the following graph:



**Figure 5-35 Comparison of Accuracy and (1-Apha) for All Models**

Based on all the foregoing arguments the researcher has demonstrated beyond reasonable doubt that the LRA-6V is the best model for the prediction of a company's financial status, namely, both financial distress and non-financial distress. The final model is stated as follows:

$$Z = -7.558 + 0.763X1 + 4.325X2 + 13.026X3 + 0.003X4 - 0.308X5 + 6.829X6$$

Where:

X1 = Working capital / Total assets

X2 = Retained earnings / Total assets

X3 = Earnings before interest and taxes / Total assets

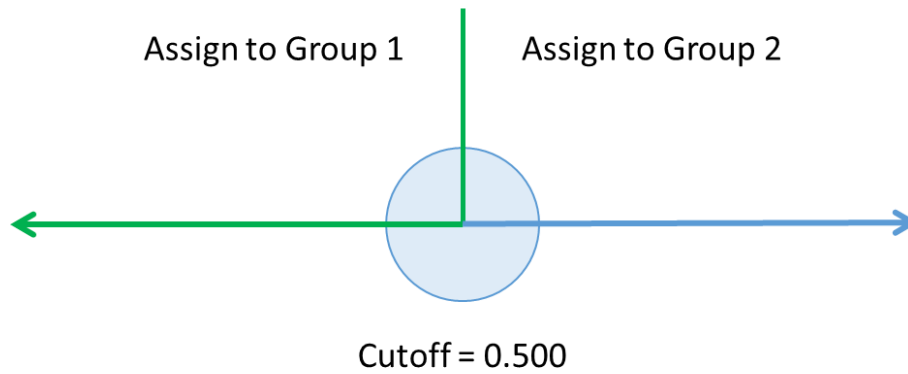
X4 = Market value of equity / Book value of Debt

X5 = Sales / Total assets

X6 = Auditors' Opinion as introduced by the researcher

The model is based on the cut-off point at 0.50, and to be interpreted as shown in

below:



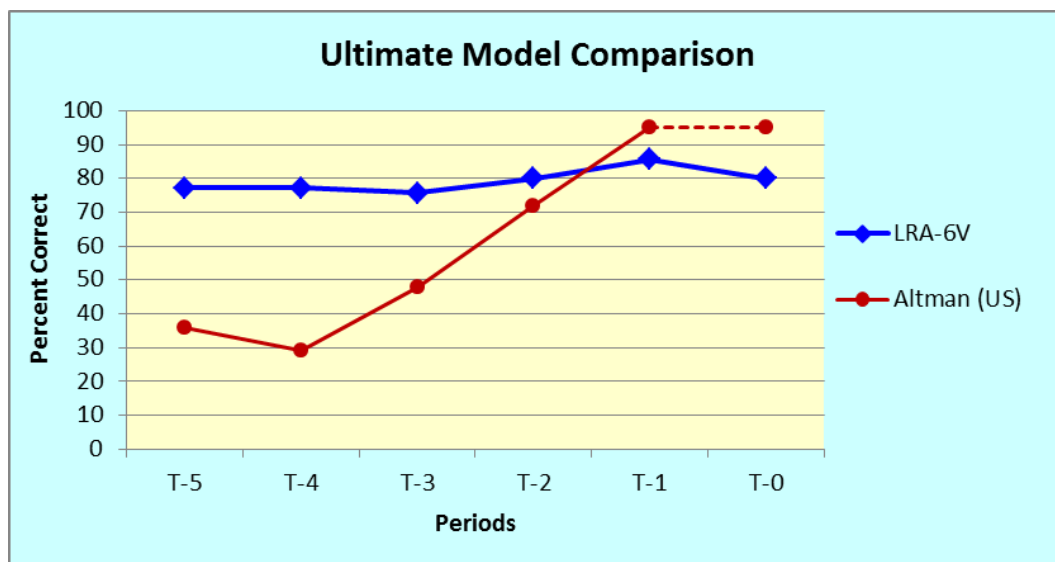
**Figure 5-36 Midpoint for Group 1 and Group 2 Cut-off in LRA**

Thus, the best model is determined to be the 6-Variable LRA model where the variable X6 is uniquely introduced by the researcher. The ultimate verification of this is shown in Figure 5-37 below using the accuracy data shown in the following Table 5-87, provided in Altman's paper (Altman E. I., 1968), page 604 although he did not provide the T-0 data.

**Table 5-87 Ultimate accuracy model comparison**

	T-5	T-4	T-3	T-2	T-1	T-0
LRA-6V	77.14	77.14	75.71	80.00	85.71	80.00
Altman (US)	36.00	29.00	48.00	72.00	95.00	95.00





**Figure 5-37 Altman vs. Researcher's Prediction Model Comparison**

The overall performance of the researcher's prediction model against the Altman's Z-Score Model is shown in Figure 5-37 above which shows the data for T-5 through T-1, as the T-0 data is not provided by Altman. It also shows that Altman's prediction model deteriorates rapidly after the T-2 period, as acknowledged by Altman himself in Altman, E.L. (1969; p. 604, section IV, para 6).

### 5.10 Justification for Selection of Researcher's 6-Variable Model

In conclusion, it can be shown categorically that the researcher's suggested model (LRA-6V) in this research is far superior to that of the Altman's Z-Score Model especially over a 5-year period. This is achieved by establishing a systematic approach of reasoning as follows:

- The data cleaning for outliers (see section 5.3).
- Testing variables (X1 through X6) to ensure there is a significant difference between PN17 and NPN17 at alpha equal to 0.05 (see section 5.4).
- Testing Z-Score values for T-5 through T-0 to ensure there is a significant difference between PN17 and NPN17 at alpha equal to 0.05 (see section 5.5).
- Characterizing the Altman's Z-Score Model using the Multiple Discriminant Analysis (see section 5.7.1).

- Characterizing the 5-Variable model using the Multiple Discriminant Analysis (see section 5.7.2).
- Characterizing the 5-Variable model using the Logistic Regression Analysis (see section 5.7.3).
- Characterizing the 6-Variable model using the Multiple Discriminant Analysis (see section 5.8.1).
- Characterizing the 6-Variable model is characterized using the Logistic Regression Analysis (see section 5.8.2).

At this stage, the following models have been considered:

1. Altman's Z-Score Model (see section 5.7.1)
2. MDA 5-Variable (see section 5.7.2)
3. LRA 5-Variable (see section 5.7.3)
4. MDA 6-Variable (see section 5.8.1)
5. LRA 6-Variable (see section 5.8.2)

Using all five of the above models, the selection of the better models was based on:

- Comparison of the Trend (see Figure 5-29)
- Comparison of Alpha error (see Figure 5-30)
- Comparison of Beta error (see Figure 5-31)
- Comparison of Accuracy (see Figure 5-32)

At this stage, the MDA 5-Variable and MDA 6-Variable were dropped from further consideration and the remaining models were:

1. Altman's Z-Score Model (see section 5.7.1)
2. LRA 5-Variable (see section 5.7.3)
3. LRA 6-Variable (see section 5.8.2).

Following this, the 5-Variable and 6-Variable models were evaluated on:

- Comparison of Predictability for next two year (see Figure 5-33)

At this stage, the Altman's Z-Score Model had failed badly (see section 5.9.5) so the remaining models were:

1. LRA 5-Variable (see section 5.7.3)
2. LRA 6-Variable (see section 5.8.2).

Note that the 5-Variable model is the standard model for prediction and the 6-Variable model is the model proposed by the researcher, as argued in section 5.9. The final choice between the 5-Variable and the 6-Variable model was decided on:

- Comparison of Predictability based on the 5-Variable and 6-Variable models (see section 5.9.6 and Figure 5-34).

At this point, it was clear that the 6-Variable model was better than the 5-Variable so the remaining model was:

The LRA 6-Variable (see section 5.8.2).

A tabulation of all the comparative evaluations is shown in Table 5-47. Note that all the comparisons have been conducted using a statistical significance of alpha equal to 0.05 and not merely graphical interpretations. The successful model is thus

$$Z = -7.558 + 0.763X1 + 4.325X2 + 13.026X3 + 0.003X4 - 0.308X5 + 6.829X6$$

Where:

X1 = Working capital/Total assets

X2 = Retained earnings/ Total assets

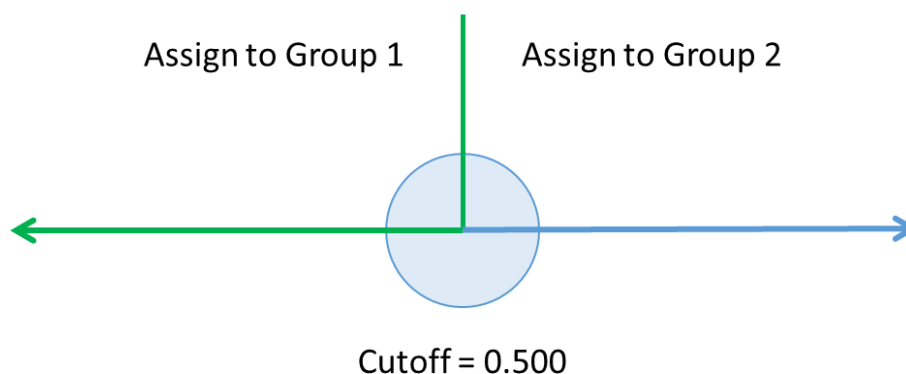
X3 = Earnings before interest and taxes/Total assets

X4 = Market value of equity/Book value of Debt

X5 = Sales/Total assets

X6 = Auditors' Opinion as introduced by the researcher

The model is based on the cut-off point at 0.500, and to be interpreted as shown in Figure 5-38 below.



**Figure 5-38 Midpoint for Group 1 and Group 2 Cut-off in LRA**

Hence, the researcher's proposed 6-Variable model known as the YHL Z-Score Auditors' Opinion Model is vigorously shown to be the best model with the highest accuracy for prediction of financial distress amongst the PLCs in Malaysia.

## 5.11 Chapter Summary

In this chapter, the researcher had conducted an extensive range of data analyses which, in turn, were presented as findings of this study. The step-by-step approach employed by the researcher had provided a systematic and structured presentation of data analyses as a whole.

The models tested and data collection were discussed in the earlier parts of the chapter, followed by the hypotheses testing of X-Variables and the presentation of the Z-Score. Subsequently, a comparison of model characteristics between the Multiple Discriminant Analysis model and the Logistic Regression Analysis model was discussed and presented extensively.

Towards the end of this chapter, the researcher systematically presented the selection of the best model with detailed discussion and explanation for the benefit of all readers. Next, the researcher provided the justification for the selection of the 6-Variables model, known as the YHL Z-Score Auditors' Opinion Model, as the best model to predict financial distress amongst the PLCs in Malaysia.

## CHAPTER SIX

### 6 DISCUSSION, RECOMMENDATIONS AND CONCLUSION

#### 6.1 Introduction

This final chapter summarizes the findings of the study, presents its discussion, limitations, makes recommendations for future research, and draws conclusions from the empirical analyses presented in Chapter 5.

#### 6.2 Discussion

This study was successful in that it was able to thoroughly answer all the original research hypotheses to meet the aims and objectives of this study.

##### 6.2.1 Discussion of Hypotheses on X Variables

In this study, the independent variables were represented by six derived measurements related to the financial status of a company as follows:.

- X1 = Working Capital / Total Assets
- X2 = Retained Earnings / Total Assets
- X3 = Earnings before Interest and Taxes / Total Assets
- X4 = Market Value of Equity / Book Value of Debt
- X5 = Sales / Total Assets
- X6 = Auditors' Opinion proposed by the researcher

Data cleaning was then conducted using the Mahalanobis Distances method on the derived data to ensure that outliers were eliminated from the data. Subsequently, the X-Variables were assigned values corresponding to the NPN17 and PN17. In all cases of the Hypotheses testing of X-Variables, the analyses of variance clearly showed that  $NPN17 > PN17$  at  $\alpha = 0.05$  (see Hypothesis Testing of X-Variables, page 142). This is a necessary tenet to show that the financial status of the two

groups of companies (NPN17 and PN17) were indeed statistically different. Had these not been statistically different, the assumption that there was anything materially different between the two group means would be invalid. In other words, the classification of NPN17 and PN17 would be degenerate.

### **6.2.2 Discussion of Hypotheses on Z-Score**

The Z-Score was calculated using X coefficients established by either the Multiple Discriminant Analyses (MDA) or the Logistic Regression Analyses (LRA). The Z-Score was computed for NPN17 and PN17 for the periods T-5 to T-0. In all cases of the Hypotheses testing of Z-Score, the analyses of variance clearly showed that  $NPN17 > PN17$  at  $\alpha = 0.05$  (see Hypotheses Testing of Z-Score of Periods, page 148). This is a necessary tenet to show that the financial status of the two groups of companies (NPN17 and PN17) were indeed statistically different. Had these not been statistically different, the assumption that there was anything materially different between the two group Z-Scores would be invalid. In other words, the classification of NPN17 and PN17 would be degenerate.

### **6.2.3 Discussion on Multiple Discriminant Analyses**

The purpose of MDA is to obtain a model to predict a single qualitative variable from one or more independent variables (X-Variables). In this study, Wilk's Lambda statistic was used to test whether the discriminant model was significant. The significance was tested for each variable where p value of less than 0.05 meant significance. Significant variables were retained in the model. The MDA derived an equation as linear combination of the independent variables that would discriminate best between the groups (NPN17 and PN17) in the dependent variable (Z-Score). This linear combination or discriminant function was then used to weight the independent variables, i.e., the discriminant coefficients. The calculated Z-Scores are then used to establish the prediction accuracy of the proposed model.

#### 6.2.4 Discussion on Logistic Regression Analyses

LRA is a statistical method for analyzing a dataset in which there is one or more independent variables (X-Variables) that determine an outcome. The outcome is measured with a dichotomous variable ((NPN17 or PN17). The goal of LRA is to find the best fitting model to describe the relationship between the independent variables and the dependent variable. LRA generates the coefficients that best predicts the dependent variable. Several features, Cox and Snell, Nagelkerke and McFadden methods were studied but the final version used was the Nagelkerke's  $r^2$  that adjusts the scale of the statistic to cover the full range from 0 to 1, as this is the closest interpretation of the explained variables. The logistic regression coefficients were then used to weight the independent variables. The calculated Z-Scores are then used to establish the prediction accuracy of the proposed model.

#### 6.2.5 Discussion on Research Gaps

An important gap in this research is that there is no explicit study which focuses on financial distress in Malaysia. By focusing on the PLCs in Malaysia, this study attempts to fill this gap.

Secondly, while there are studies that focus on financial distress in Malaysia, these are based on the Altman's Z-Score Model. A revised model that is specific to Malaysia has remained a gap. This gap has now been studied in this research.

Thirdly, the literature searches do not show instances where the Altman's Z-Score incorporated the Auditors' Opinion on going concern for the prediction of financial distress of a company.

These three gaps are summarized as follows:

a) Gap 1

No explicit study of financial distress prediction model for PLCs in Malaysia.

b) Gap 2

No revised financial distress prediction model that is specific to PLCs in Malaysia.

c) Gap 3

No study that incorporated the Auditors' Opinion on going concern in the financial distress prediction model for PLCs in Malaysia.

### **6.2.6 Discussion on Research Strategy**

Initially, the Malaysian data is acquired for 35 NPN17 and PN17 companies in Malaysia and then represented in terms of the X-Variables.

- a) The data was then fed to the Altman's Z-Score Model as a baseline.
- b) An appropriate data analysis was conducted to formulate the MDA Models based on X1 to X5 variables, with the addition of X6 variable.
- c) An appropriate data analysis was conducted to formulate the LRA Models based on X1 to X5 variables, with the addition of X6 variable.
- d) Both the MDA Model and the LRA Model were compared with the Altman's Z-Score Model for both the X1-X5 models and then the X1-X6 models.
- e) Based on the findings, it was established that the LRA Model was preferable and that the X1-X6 variable model had higher prediction accuracy.

### **6.2.7 Discussion on Research Objectives**

To achieve the aims of this study, the research objectives are as follows:

- a) To determine the prediction accuracy of the 5-Variable Altman's Z-Score Model to predict financial distress amongst the PLCs in Malaysia.

The results show that the overall prediction accuracy of the Altman's Z-Score Model was determined to be 74.5%, based on the direct application of the Altman's Z-Score Model.

- b) To develop a revised 5-Variable Altman's Z-Score Model using Malaysian data to predict financial distress amongst the PLCs in Malaysia.



The results show that the two models developed to achieve this objective, namely, the MDA Model and the LRA Model as follows: The MDA Model resulted in a drop (from 74.5% to 64.3%) in the overall prediction accuracy but the LRA Model resulted in a rise (from 74.5% to 79.0%) in the overall prediction accuracy. Thus, the revised LRA Model resulted in a better model for prediction accuracy.

- c) To develop a 6-Variable model based on the 5-Variable Altman's Z-Score Model and incorporating the Auditors' Opinion on going concern, as the sixth (6th) variable, using Malaysian data to predict financial distress amongst the PLCs in Malaysia.

The results show that both the MDA Model and LRA Model were studied with the 6-Variable model incorporating the Auditors' Opinion of Going concern. Although both resulted in improved overall prediction accuracy, the MDA gave 65.0% accuracy while the LRA gave 79.3% accuracy.

- d) To compare and analyze the 5-Variable and 6-Variable prediction models to establish the best model with the highest accuracy to predict financial distress amongst the PLCs in Malaysia.

The results show that the 5-Variable MDA Model gave an overall prediction accuracy of 64.3% while the 6-Variable MDA Model gave an overall prediction accuracy of 65.0%. The 5-Variable LRA Model gave an overall prediction accuracy of 79.0% while the 6-Variable LRA Model gave an overall prediction accuracy of 79.3%.

Although both resulted in improved prediction accuracy, the MDA gave 65.0% overall prediction accuracy while the LRA gave 79.3% overall prediction accuracy. Clearly, the LRA Model gave the best prediction accuracy in the entire study.

### **6.2.8 Research Questions**

- a) What is the prediction accuracy of the 5-Variable Altman's Z-Score Model in predicting financial distress amongst the PLCs in Malaysia?

The answers suggest that from the data analysis in section 5.7.1 the Altman Z-Score Model and Table 5-23 - the overall accuracy of the Altman's Z-Score Model is only 74.5%. This is based on the direct application of the Altman's Z-Score Model. The prediction accuracy is 82.14% on average for the current and 1 year prior to financial distress and 70.71% for 2 to 5 years prior to financial distress.

- b) Can the prediction accuracy of the 5-Variable Altman's Z-Score Model be improved by using data of the PLCs in Malaysia?

The answers suggest that from the data analysis in section 5.7.2 MDA 5V Model and Table 5-40, the overall accuracy dropped to 64.3%.; that is, the MDA model had failed to improve the Altman's Z-Score Model (from 74.5% to 64.3%) by using data of the PLCs in Malaysia. The prediction accuracy dropped to 66.43% (Altman: 82.14%) on average for the current and 1 year prior to financial distress and 63.22% (Altman: 70.71%) for 2 to 5 years prior to financial distress.

However, from the data analysis in section 5.7.3 LRA 5V Model and Table 5-52, the overall accuracy increased to 79.0%; that is, the LRA Model succeeded to improve the Altman's Z-Score Model (from 74.5% to 79.0%) by using data of the PLCs in Malaysia. The prediction accuracy is 82.14% (Altman: 82.14%) on average for the current and 1 year prior to financial distress and 77.50% (Altman: 70.71%) for 2 to 5 years prior to financial distress.

- c) Can the prediction accuracy of the 5-Variable Altman's Z-Score Model be improved by incorporating another variable, the Auditors' Opinion on going concern, as a 6-Variable model using data of the PLCs in Malaysia?

The answers suggest that from the data analysis in section 5.8.1 MDA 6V Model and Table 5-68, the overall accuracy increased from 64.3% to 65.0% when the 5-Variable Altman's Z-Score Model was replaced by the 6-Variable MDA Model. This represents a 0.7% improvement with the 6-Variable model.

The prediction accuracy dropped to 70.72% (Altman: 82.14%) on average for the current and 1 year prior to financial distress and 62.14% (Altman: 70.71%) for 2 to 5 years prior to financial distress.

Also, from the data analysis in section 5.8.2 LRA 6V Model and Table 5-80, the overall accuracy increased from 79.0% to 79.3% when the 5-Variable Altman's Z-Score Model was replaced by the 6-Variable LRA Model. This represents a 0.3% improvement with the 6-Variable model. The prediction accuracy increased to 82.86% (Altman: 82.14%) on average for the current and 1 year prior to financial distress and 77.50% (Altman: 70.71%) for 2 to 5 years prior to financial distress.

- d) What is the best revised model that can be used with the highest prediction accuracy for financial distress amongst the PLCs in Malaysia?

The answers suggest that in both cases (MDA and LRA), the 6-Variable MDA Model had shown an improvement in the overall prediction accuracy over the corresponding 5-Variable model when compared to the Altman's Z-Score Model.

However, only the LRA 6-Variable model had shown an improvement in prediction for both the current and 1 year prior to financial distress and for 2 to 5 years prior to financial distress as compared to the Altman's Z-Score Model. Clearly the 6-Variable LRA Model gave the best prediction accuracy in the entire study. Thus, the 6-Variable LRA Model can be adopted as the best model to predict financial distress amongst the PLCs in Malaysia.

The LRA 6-Variable model, known as the YHL Z-Score Auditors' Opinion Model, has been statistically proven to be the best, with the highest prediction accuracy of 82.86% on average for the current and 1 year prior to financial distress and 77.5% for 2 to 5 years prior to financial distress. On the other hand, the original Altman's Z-Score Model has a lower prediction accuracy of 82.14% on average for the current and 1 years prior to financial distress and 70.71% on average for 2 to 5 years prior to financial distress.

The YHL Z-Score Auditors' Opinion Model is shown below:

$$Z = -7.558 + 0.763X1 + 4.325X2 + 13.026X3 + 0.003X4 - 0.308X5 + 6.829X6$$

Where:

X1 = Working Capital / Total Assets

X2 = Retained Earnings / Total Assets

X3 = Earnings before Interest and Taxes / Total Assets

X4 = Market Value of Equity / Book Value of Debt

X5 = Sales / Total Assets

X6 = Auditors' Opinion

Z = Overall index or Z-Score

From this formula, it can be derived that if  $Z < 0.50$ , the company is in financial distress (unhealthy) and if  $Z > 0.50$ , the company is in non-financial distress (healthy) position.

### **6.2.9 Discussion on Contribution to Knowledge**

This study has demonstrated that:

a) Gap 1 Closed

There is now an explicit study of financial distress prediction model for the PLCs in Malaysia.

b) Gap 2 Closed

There is now a revised financial distress prediction model that is specific to the PLCs in Malaysia. This model is based on LRA and it has been determined with new parametric constants for the X1-X6 variables.

### c) Gap 3 Closed

This study has incorporated the Auditors' Opinion on going concern in the financial distress prediction model for the PLCs in Malaysia. It has been shown in section 5.10 Justification for Selection of Researcher's 6-Variable Model page 212 that the X6 variable, i.e. the incorporation of Auditors' Opinion on going concern has actually increased the prediction accuracy.

Other than improving the prediction accuracy of financial distress, the YHL Z-Score Auditors' Opinion Model has also widened the scope of application of financial distress prediction model in Malaysia. The statutory auditors of the PLCs, who are required by law to determine a company's ability to continue its existence as a going concern, could be equipped with such prediction knowledge and skills by applying the revised prediction model to create the needed transparency and accountability for effective corporate governance.

## **6.3 Recommendations**

Upon completing this study, the researcher is of the opinion that there is still plenty of room for improvement and expansion of scope for future research. The recommendations in this study are twofold: for future studies and for the PLCs which are PN17 and NPN17.

### **6.3.1 Recommendation for Future Studies**

Future research should include multiple bourses or stock exchanges with larger samples of companies on both categories. The threat of attrition in such study setting comes from the fact that a company might be tracked from a period of say 5 years prior to financial distress. While such companies would provide immense information that can help in further financial distress prediction modelling, the imminent danger that accompanies their inclusion is evident.

Further research needs to be carried out to understand the basis of Auditors' Opinion on going concern based on both the financial and non-financial factors that contribute to financial distress. As it is now, the non-financial factors used are not

very obvious. This is probably where the non-financial factors would be helpful. Future research studies should explore methodologies and approaches through which the non-financial factors can be included into the modelling and quantified for model standardization purposes.

This study should provide stepping stones for future research studies that focus on comparing various financial distress prediction models with the aim of coming up with the best combination of models that do the best work in predicting financial distress among PLCs. From this study, LRA appears to have a superior accuracy to the MDA Model. Further research studies should be conducted to test this finding or complement it as an additional point of reference.

Areas for future research should incorporate other variables in predicting financial distress including a model for specific industry such trading, manufacturing, service sector and others. It should also include a larger sample size and cover a longer period, for example, covering up to and over a 10-year period of financial performance.

Other studies could be conducted on the bankruptcy costs as a result of financial distress which have significant impact on the stakeholders, government and the economy of the country. And it could also extend the financial distress model to include small and medium sized companies which form the backbone of the economy of Malaysia and other countries.

### **6.3.2 Recommendation to PN17 Companies**

The researcher proposes to use and implement the YHL Z-Score Auditors' Opinion Model with the highest prediction accuracy up to 2 years before financial distress among the Malaysian companies.

The final findings of this study establish the formula as shown below:

$$Z = -7.558 + 0.763X1 + 4.325X2 + 13.026X3 + 0.003X4 - 0.308X5 + 6.829X6$$

From this formula, it can be derived that if  $Z < 0.5$ , the company is in financial distress (unhealthy) and if  $Z > 0.5$ , the company is in non-financial distress (healthy) position.

This formula, fulfilling an objective of the study, has established that the result or findings should be of a higher positive score, being classified as “the higher score, the better”. The negative indication in the formula above suggests that it is a constant and not affected by Independent Variables as reflected by X1, X2, X3, X4, X5 and X6.

Based on the findings shown in the following tabulated summary, the researcher is able to formulate some practicable recommendations to be taken by the PN17 companies to overcome and manage the immediate financial distress status, enabling them to steer away from the impending predicted financial distress. The detailed recommendations are listed in Table 6-1 below.

**Table 6-1 Reflection of Desired NPN17 Objectives and Actions to be Taken**

<b>Variable</b>	<b>Description</b>	<b>Preferred Value</b>	<b>Desired Objective/Actions to be Taken</b>
X1	Working Capital / Total Assets	Higher	Higher working capital <ul style="list-style-type: none"> <li>• Increase credit sales</li> <li>• Tighten credit control</li> <li>• Reduce current liabilities</li> </ul>
X2	Retained Earnings / Total Assets	Higher	Higher retained earnings <ul style="list-style-type: none"> <li>• Declare lower dividends</li> <li>• Increase current and future earnings</li> <li>• Review accounting policies and treatments</li> </ul>
X3	Earnings before Interest and Taxes / Total Assets	Higher	Higher earnings before interest and taxes <ul style="list-style-type: none"> <li>• Reduce interest expense</li> <li>• Reduce taxes with tax planning</li> <li>• Reduce cost of sales and other expenses</li> </ul>
X4	Market Value of Equity / Book Value of Debt	Higher / Lower	Higher market value of equity <ul style="list-style-type: none"> <li>• Enhance branding and market position</li> </ul>

Variable	Description	Preferred Value	Desired Objective/Actions to be Taken
			<ul style="list-style-type: none"> <li>• Enhance investor relations</li> <li>• Consistent dividend policy</li> <li>• Lower book value of debt</li> <li>• Reduce short term and long term debts</li> <li>• Review of debts and equity structure.</li> <li>• Rationalization of debts</li> </ul>
X5	Sales / Total Assets	Lower	Higher total assets <ul style="list-style-type: none"> <li>• Increase investment and assets.</li> <li>• Purchase own assets</li> <li>• Enhance value of assets</li> </ul>
X6	Auditors' Opinion proposed by the researcher	Higher	Unqualified report <ul style="list-style-type: none"> <li>• Increase financial results</li> <li>• Enhance the financial position</li> <li>• Ensure compliance of accounting standards and relevant legislations.</li> </ul>

Source: Researcher's own work

### 6.3.2.1 Recommendations to Achieve Higher Working Capital

- a) The companies should find ways and means to increase credit sales and possibly extend longer credit term in number of days to the customers resulting in higher trade receivables. By doing this, the companies may be able to achieve higher working capital which is best for managing the possibility of financial distress.
- b) The companies could look into the credit control measures for faster collection of trade receivables. Some prompt payment discount and incentives could be offered to encourage earlier payment. This allows earlier collection to increase the cash and cash equivalents of the companies.
- c) Reducing the overall current liabilities will increase the working capital of the companies. Therefore, senior management should work towards reducing the current liabilities with cash flow management of receipts and payments. The



aim should be to minimize the short-term borrowings, resulting in an increase of the working capital. This could also be achieved by reducing the short-term borrowings and/or sourcing cheaper alternative financing.

#### **6.3.2.2 Recommendations to Achieve Higher Retained Earnings**

- a) The companies could possibly declare lower dividends to the shareholders as part of the initiative to maintain higher retained earnings.
- b) The companies could review and formulate strategic business plan to increase earnings for current and future financial years. This will be ideal for achieving higher retained earnings over total assets that will support better management of the financial risks of the companies.
- c) The companies have to review the accounting policies and treatments to reflect higher retained earnings. Such review could include depreciation policy, impairment of assets, revenue recognition, and other accounting adjustments to enable the companies to achieve higher retained earnings necessary to reflect better financial position.

#### **6.3.2.3 Recommendations to Achieve Higher Earnings Before Interest and Taxes**

- a) The companies need to increase sales in order to achieve higher earnings before interest and taxes. In addition, interest expenses should be minimized by reducing borrowings particularly short-term borrowings such as bank overdraft and hire purchase financing. The company would need corporate tax planning to minimize taxes within the tax legislations. These measures are in line with the objectives of the companies to increase profit before interest and taxes. This could be done conscientiously in all the business activities and steps of the management of the companies to maximize profit at all times.
- b) While the companies are on a profit-maximization drive, the companies also need to be mindful of reduction in cost of sales. The company's profit could be increased, with a reduction in the costs of sales by reviewing the supply chain and supplier selection processes.

- c) The companies must also be careful in containing the operating expenses. There are many possible ways to manage the operating costs on an acceptable level. This will be necessary to reduce the overall operating costs that will be favor achieving higher earnings before interest and taxes of the companies.

#### **6.3.2.4 Recommendations to Achieve Higher Market Value of Equity**

- a) The companies can greatly benefit from taking part in corporate initiatives to enhance branding. There are many sector-specific government initiatives to support branding of companies, both locally and also in the foreign market. Companies should put in more effort and expenditure on sales and marketing aimed at enhancing the company's branding and market position.
- b) Higher market value of company equity can be achieved by improving and enhancing investor relations. This could include better communication with well-supported corporate social responsibility, investor relations and customer service activities. This will also improve the corporate image and profile of the companies in the eyes of the customers, investors and public.
- c) The companies can and should develop a dividend policy to declare to their shareholders on regular intervals. This will increase the confidence level of the investors by giving consistent dividend income and return that will result in a higher market value of equity.

#### **6.3.2.5 Recommendations to Reduce Book Value of Debt**

- a) The researcher strongly recommends that companies to reduce their short-term and long-term debts as part of their financing policy of the companies. This will be a strong and useful catalyst for the companies to manage the level of book value of debt and gearing ratio to a desired and acceptable level.
- b) It is always beneficial to the companies to have a regular review of their debts and equity structure. All possible actions must be taken to maintain an optimal level of debts and equity at all times. This will ensure sustainability of the company in the long run.
- c) The companies must consider restructuring all the existing debts with the view of reducing the debts from time to time. Rationalization of debts in line

with the strategic business plan of the company will allow a better cash flow for working capital and reduce the book value of debt.

#### **6.3.2.6 Recommendations to Achieve Higher Total Assets**

- a) In order to improve and maintain a healthy and non-financial distress status, companies must work towards increasing investment and/or acquisition of assets. The senior management must find ways to invest in assets that will appreciate over time and are able to generate reasonable return on investment.
- b) The company must devise a plan to purchase its own assets instead of renting and leasing. Renting and leasing should be phased out in stages by the companies in the short-term to enable purchase and operation from its own assets. This will result in increase of the total assets of the companies and reduce its expenses at the same time.
- c) Upon acquiring assets, the companies must attempt to keep the assets in good condition without deterioration so as to maintain the assets value and to avoid impairment of assets. Any lack of maintenance will soon erode the value of the assets. Good repair and maintenance will not only maintain the value but could also enhance the value of assets particularly land and buildings in the future.

#### **6.3.2.7 Recommendations to Achieve Unqualified Report (Clean Report)**

- a) Senior management must strategize to increase the financial results of the company with viable and profitable current and future businesses. This must be reviewed and monitored by the management and board of directors with utmost priority at all times.
- b) Every effort and initiative must be put in place to enhance the financial position of the company. All actions must be aimed at improving and maintaining a strong financial position (balance sheet) of the company with quality assets while reducing and managing liabilities.
- c) Senior management must have high regard for, and aspire to ensure, compliance of accounting standards, tax and relevant legislations. Good corporate governance and internal control systems should be put in place by the board of directors of the company as high level control.

## 6.4 Significance and Implications

### 6.4.1 Theoretical Contribution

On the one hand, the LRA 6-Variable model (with X6 as additional independent variable), known as the YHL Z-Score Auditors' Opinion Model, has been statistically proven to be the best model, with the highest prediction accuracy of 82.86% on average for the current and 1 year prior to financial distress and 77.5% for 2 to 5 years prior to financial distress. On the other hand, the original 5-Variable Altman Z-Score Model has a lower prediction accuracy of 82.14% on average for the current and 1 years prior to financial distress and 70.71% on average for 2 to 5 years prior to financial distress.

The YHL Z-Score Auditors' Opinion Model is shown below:

$$Z = -7.558 + 0.763X1 + 4.325X2 + 13.026X3 + 0.003X4 - 0.308X5 + 6.829X6$$

Where:

X1 = Working Capital / Total Assets

X2 = Retained Earnings / Total Assets

X3 = Earnings before Interest and Taxes / Total Assets

X4 = Market Value of Equity / Book Value of Debt

X5 = Sales / Total Assets

X6 = Auditors' Opinion

Z = Overall index or Z-Score

From this model, it can be derived that if  $Z < 0.50$ , the company is in financial distress (unhealthy) and if  $Z > 0.50$ , the company is in non-financial distress (healthy) position.

Thus, the YHL Z-Score Auditors' Opinion Model has been statistically proven to be the best with the highest prediction accuracy in Malaysia.

#### **6.4.2 Implication for Managerial Practice**

Based on the findings as shown in the summary in Table 6.1, the researcher is able to formulate some practicable recommendations to be taken by the PN17 companies to overcome and manage its immediate financial distress status in order to steer away from the impending predicted financial distress. The detailed recommendations are set out in section 6.3.2 Recommendations to the PN17 companies.

#### **6.4.3 Implication for Regulatory Authority**

The YHL Z-Score Auditors' Opinion Model could be used by the regulatory authorities in Malaysia as part of their early warning system to monitor, regulate and formulate preventive measures for short, medium and long-term.

#### **6.4.4 Implication for Society and Investors.**

The YHL Z-Score Auditors' Opinion Model could be used by the investors as a tool or technique to make a well-informed investment decision on taking calculated risk and assisting in identifying the opportunity for profitable investment, thus minimizing incorrect investment that will incur a loss which will not benefit the society as a whole.

### **6.5 Limitations**

An obvious limitation in this study is the small sample size which only involved 35 selected PN17 companies. This is due to the data availability of only 6 years for the 36 PN17 companies as at 1st September 2010. The limited and small sample size of PN17 companies for data analyses had to be matched with NPN17 companies as at 1st September 2010. This is due to the threat of attrition that limited the size of the companies of 35 for the financial distress and 35 for non-financial distress as paired samples, making it difficult to estimate what kind of results the study might have generated had more companies been incorporated or even if it was possible to carry a cross-bourse analysis. Moreover, it also made it less helpful to generalize the results.

Another major limitation of this study concerns the self-funding situation of the researcher, being an integral part of his total self-financed PhD program for his career development. Such financial constraint does take its toll on the division of time for professional and academic work, the extent and depth of research-survey engagements which could have been more comprehensive.

Time was also a crucial limitation of this study which witnessed the researcher doing the research on part-time basis while working full-time. In addition, the researcher has to complete the study within the stipulated period by the university as a requirement of his PhD program.

## **6.6 Delimitations**

The delimitations of this study is a limited sample size used for data analyses. The limited and small sample size of PN17 companies has to be matched with NPN17 companies as at 1<sup>st</sup> September 2010. This is due to the threat of attrition that limited the size of the companies of 35 for the financial distress and 35 for non-financial distress ones as paired samples; which makes it difficult to estimate what kind of results the study might have generated had more companies been incorporated or even if it was possible to carry a cross-bourse analysis. It also made it less helpful to generalize the results.

## **6.7 Conclusion**

The prediction of financial distress amongst the PLCs Malaysian employed the five variables of the Altman's Z-Score Model, using the MDA alongside the Auditors' Opinion on going concern as the sixth variable. In addition to carrying out the MDA, the analysis was also carried out using the LRA (also referred to as Logit Analysis). The sample size comprised of 35 financial distress (unhealthy) companies and 35 non-financial distress (healthy) companies. In other words, 35 of the companies in the selected sample were classified as PN17 while the other 35 are NPN17.

The objective of the study is to use a modified model that combines the Altman's Z-Score Model and the Auditors' Opinion on going concern in predicting financial

distress amongst the PLCs in Malaysia. The LRA, alongside with the MDA, provided the predictive power of the two financial distress prediction models for the Malaysian case.

This study has demonstrated that the research objectives are achieved whereby the original Altman Z-Score Model has been improved after the Auditors' Opinion on going concern was incorporated to develop the YHL Z-Score Auditors' Opinion Model. The latter is deemed the best statistical model which is the most feasible and with the highest prediction accuracy has been recommended to predict financial distress amongst PLCs in Malaysia.

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