CORPORATE FAILURE PREDICTION: ASSESSING THE ACCURACY OF DIFFERENT BANKRUPTCY PREDICTION MODELS ON MALTESE SMES

BY

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A dissertation submitted in partial fulfilment of the requirements
for the award of the Master in Accountancy degree in the
Department of Accountancy at the
Faculty of Economics, Management and Accountancy
at the University of Malta

May 2020

20MACC012

Abstract

Title: Corporate Failure Prediction: Assessing the Accuracy of Different Bankruptcy Prediction Models on Maltese SMEs

Purpose: The study aims at examining which Maltese economic characteristics best forecast the potential for bankruptcy. The dissertation also tested different bankruptcy models developed through different statistical techniques and assessed their performance when applied to the Maltese context.

Design: To tackle the objectives of this study, a quantitative approach was adopted. A paired-sample design was employed comprising of twenty-eight pairs of failed and non-failed local Small and Medium-sized Entities (SMEs). The necessary financial data was extracted from the financial statements of the last three years prior to the submission of the declaration of voluntary dissolution and winding up. Based upon the availability of financial data, the Altman Z”-score Model (2000) and the Zmijewski’s X-score Model (1984) were selected for the scope of this study. Statistical testing was carried out using discriminant analysis and probit regression analysis respectively. This enabled the development of models using a data set which better reflected the local economic environment.

Findings: Findings suggest that both models are unstable and sensitive to changes in time periods. Moreover, profitability ratios are identified as the sole contributors in predicting financial distress within the local context. Between the two statistical techniques employed, evidence obtained favours the probit analysis technique for having the better predictive ability amongst local entities.

Conclusions: The research concludes that the development of a bankruptcy prediction model using probit regression analysis as a statistical technique is the most suited for Maltese SMEs. Furthermore, the incorporation of profitability ratios in bankruptcy prediction models should yield higher predictive accuracy.

Value: The study provides a better understanding of the statistical technique that best incorporates local traits into an effective bankruptcy prediction model specifically developed for Maltese SMEs.

Keywords: Probability of default, Predictive accuracy, Discriminant analysis, Probit regression analysis

Dedication

To Nanna Carmena

(1939 - 2017)

For her guidance, her warmth, and her love,

Because she always understood.

Acknowledgements

I would like to express my sincere gratitude and appreciation to all those individuals who have assisted and guided me in conducting and successfully completing this dissertation.

My deepest gratitude goes first to my dissertation supervisor, Dr. Justin Chircop, B.Accty. (Hons) (Melit.), M.Sc. (Econ.) (Accty.&Fin.) (Aberd.), Ph.D. (Lancs.), P.G.C.A.P. (Lancs.), M.C.S.E., M.C.A.D., F.C.C.A., F.H.E.A., C.P.A., for his sustained interest, invaluable guidance, constructive advice, and continuous dedication and support which proved to be of immense value for this dissertation.

Acknowledgements are also reserved to Dr. David Paul Suda, for his suggestions and assistance with statistical testing. I am also grateful to the Malta Business Registry which granted me authorisation and access to the database from which the sample data set was selected and provided me with the information required.

A special word of thanks also goes to all lecturers and staff of the Faculty of Economics, Management and Accountancy for their professional contribution and guidance which made it possible for me to complete the past five academic years at the University of Malta.

My appreciation is extended to Ms. Charmaine Dalli, BPsy (Hons), PGCE, MSc (Dev. Psychopathology), MPsy (Clin.), for her constant support, professional guidance, and enlightenment in strenuous times of psychological well-being.

Lastly, I am highly indebted to my parents Michael and Lucienne, my boyfriend Luke, and all my family and friends for their continuous patience and encouragement during all my years of study, for their valuable advice, and for showing me that perseverance is the ultimate key to success.

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List of Abbreviations

Abbreviation	Term
ANNs	Artificial Neural Networks
AUC	Area Under the Curve
BV	Book Value
EBIT	Earnings Before Interest and Tax
EU	European Union
IAS	International Accounting Standard
IASB	International Accounting Standards Board
IFAC	International Federation of Accountants
IFRSs	International Financial Reporting Standards
ISA	International Standard on Auditing
LM	Maltese Lira
MBR	Malta Business Registry
MDA	Multiple Discriminant Analysis
MV	Market Value
ROC	Receiver Operating Characteristic
ROTA	Return on Total Assets
S&P	Standard and Poor
SME/s	Small and Medium-sized Entity/Entities
SPSS	Statistical Package for the Social Sciences

Chapter 1
Introduction

1.1 Chapter Overview

This chapter introduces the subject matter of this study. Section 1.2 describes the main concepts underpinning the study. Section 1.3 presents the rationale for the study, while Section 1.4 sets out the research objectives of this study. Finally, Section 1.5 presents the structure of the dissertation.

Figure 1.1 hereunder, illustrates the structure of this chapter.

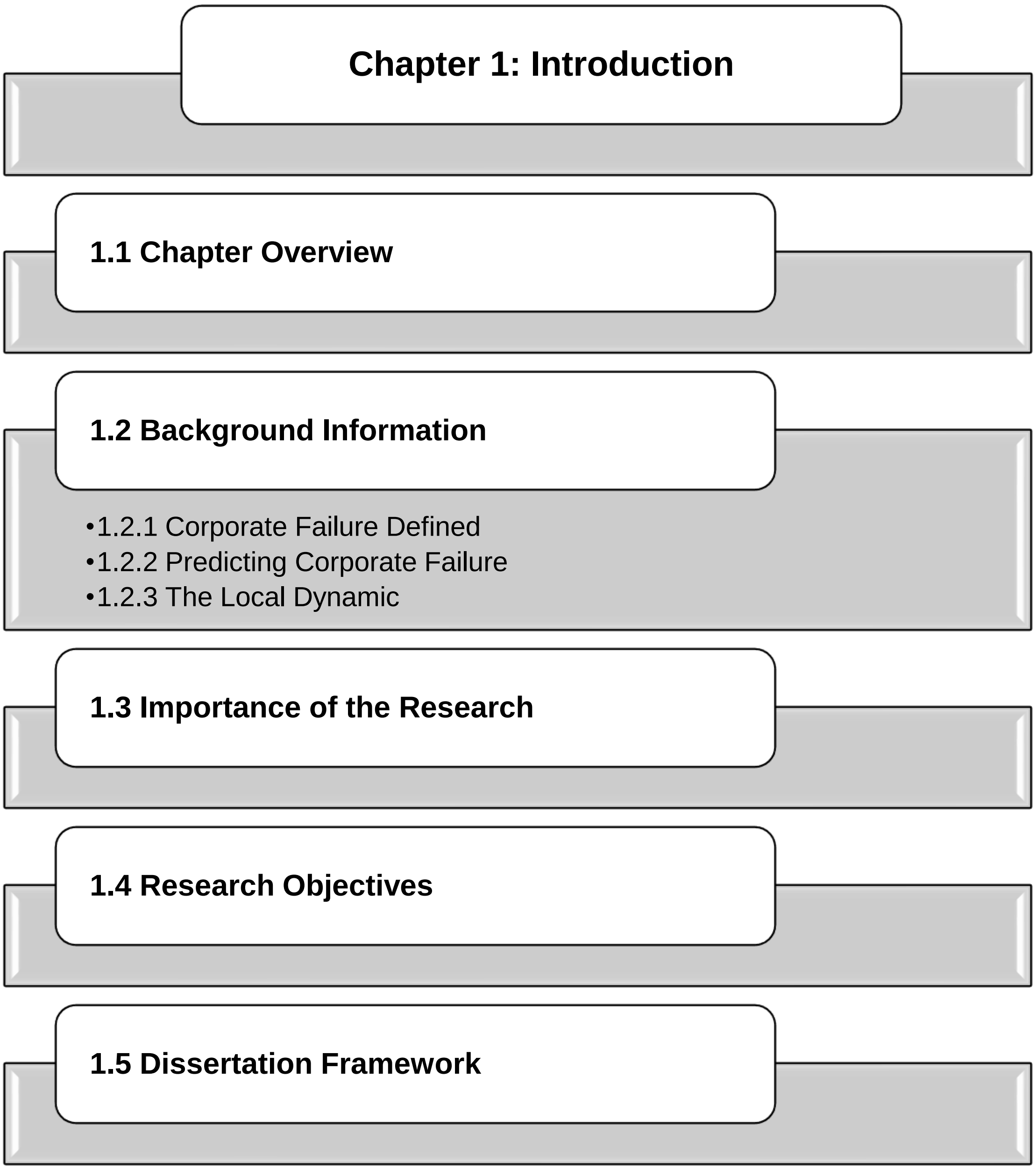

Figure 1.1 - Overview of Chapter 1

1.2 Background Information

Companies are often regarded as the engine of the country. The reason is that companies are significant contributors to the country's economic growth, mass creators of employment as well as the main source for the provision of income to both employees and business holders. However, in the present day, companies operate within dynamic settings and are repeatedly faced with unfavourable circumstances which may put into doubt the going concern of the company. In fact, the most significant threat for a company in the present economy, despite its operational nature and size, is bankruptcy.

1.2.1 Corporate Failure Defined

The term 'corporate failure' is ambiguous in interpretation:

> "Real insolvency, technical insolvency, bankruptcy, liquidation and dissolution, economic losses and accounting losses have all been used in different contexts to signify the event at the end of the business failing process." (Francalanza, Borg 2000, p. 30)

This is further supported by Bruno and Leidecker (1988) who emphasise how no two individuals are capable of defining business failure in the same way. One universally recognised definition is proposed by William H. Beaver who defines failure as "the inability of a firm to pay its financial obligations as they mature" (Beaver 1966, p. 80). This corresponds with the definition of solvency as stipulated by the Insolvency Act (1986), that is, a firm will go bankrupt when it fails to pay its promised financial obligations or else the company's liabilities exceed its assets.

From here on, a 'failed firm' refers to a company which was wound up by the Court due to its inability to settle its liabilities in accordance with Article 214(2)(a)(ii) of the local Companies Act of 1995.

1.2.2 Predicting Corporate Failure

The assessment of possible warning signals associated with bankruptcy is crucial in the hope of lessening the consequences of corporate failure. According to Platt and Platt (2002), an early warning system model will provide management with a powerful tool to help pinpoint, and more importantly, rectify complications before they reach disastrous levels.

The prediction of corporate failure has proved to be a heated topic of debate for multiple decades. Over the years, numerous academics have pursued different approaches in researching significant contributors that are capable in accurately predicting the probability of default. However, with their publication, Altman, Sabato, and Wilson (2008) acknowledged that the introduction of the Basel II Accord in 2007, as well as the financial crisis of 2008, provided a further impetus to find a suitable method to predict financial distress.

The use of bankruptcy prediction models is the most prominent practice in the prediction of financial distress, and these may be categorised as quantitative or qualitative models. According to Mossman et al. (1998), any model of either type, may be further categorised upon the basis of its inputs. These inputs are often categorised into four groupings, particularly financial statement ratios, return standard deviations, cash flows, and stock returns. With particular reference to those models which are formulated through the use of financial statement ratios, these are again subdivided in accordance with the statistical technique applied in the calculation of their parameters, namely Multiple Discriminate Analysis (MDA), logit and probit analysis, Gambler's Ruin Mathematical/Statistical models, and Artificial Neural Networks (ANNs) models (Kidane 2004).

1.2.3 The Local Dynamic

Bankruptcy is pervasive even in the domestic market. Over the recent decade, numerous bankruptcies shook the local business setting, with their adverse repercussions causing a ripple effect over the whole national economy. Such events ignited the interest of numerous local researchers in analysing the effectiveness of corporate failure models and whether they are capable of promptly signalling distress.

The relation between the Springate's S-score Model and non-financial measures in predicting bankruptcy was put to test by Vella (2004). Non-failed private manufacturing firms were put under the microscope and findings revealed that both techniques show favourable conclusions in identifying failed firms from their non-failed counterparts. Conversely, Zammit (2005) took a different approach by researching the explanatory power of conventional accounting ratios. The results collected indicate that the current ratio and the working capital to total assets ratio were the ratios most impacted by company failure. Zammit (2005) highlighted that Maltese companies holding insufficient working capital were more at risk of experiencing financial distress, indicating that inadequate working capital may be one trait associated with the possibility of future local bankruptcy.

Other studies examined the applicability of bankruptcy prediction models to the local setting. Azzopardi (2007) shows that although these models prove to be fruitful in predicting failure, local awareness of corporate failure prediction models is significantly low. In fact, it was highlighted that only 43% of local professionals interviewed, namely stockbrokers, were knowledgeable of bankruptcy prediction models. Further, none of the interviewees had ever applied these models in practice. Similarly, Falzon (2011) tested the applicability of two models on Maltese Small and Medium-Sized Entities (SMEs). The study identified two logistic Z-score regression models that could be utilised by SMEs in predicting failure.

A more specialised procedure was used by Vassallo (2016), who studied local behaviours and tendencies that jeopardised the going concern of Maltese companies. The study indicated that lack of knowledge is considerable amongst Maltese professionals when it comes to decreasing bankruptcy potential. Moreover, numerous professionals still rely on outdated practices in the hope of overcoming financial distress. A significant proportion of the data obtained by Vassallo (2016) highlighted the need for amendments in present local policies and legal provisions aimed at safeguarding creditors. As a result, the study calls for increased education amongst local stakeholders with particular reference to financial and succession planning, credit management, and also with regard to the proper use of financial statements for the correct analysis of the company’s financial health.

1.3 Importance of the Research

Statistical techniques are fundamental to the development of corporate prediction models, and numerous academics have tested different approaches in the hope of discovering the model that provides the highest accuracy. The use of MDA for the development of corporate bankruptcy prediction models has proven to be highly effective in achieving accurate results (Allen, Chung 1998). For this reason, models such as that of Altman (1968) have been exhaustedly tested in different geographical settings. However, regardless of the popularity of this statistical technique in formulating bankruptcy prediction models, its application in distinct time horizons and financial environments provides uncertainty to its predictive accuracy when subjected to these variables.

The nature of this study is value-adding given that it provides insight into which Maltese financial traits best forecast the potential for bankruptcy. Identifying these traits will provide stakeholders with better understanding of which factors signify red flags with respect to the financial standing of local companies. This is beneficial to the users of financial statements with particular reference to lending institutions as they would be in a better position to assess the future prospects of the company.

Further, the study provides an understanding of the statistical technique that best incorporate the identified local traits, if any, into an effective bankruptcy prediction model suited for Maltese SMEs. Over the years, numerous academics have identified score models that can be utilised by local companies in predicting failure. However, many failed to identify the specific statistical techniques which perform best in the local context. This study contributes to this debate by testing different bankruptcy models developed through distinct statistical techniques and assessing their performance when applied to the Maltese context. As a result, this procedure will identify the statistical model which is best at predicting bankruptcy for Maltese companies.

This may also prove to be beneficial for the management of local companies, namely the shareholders and directors. The reason is that a corporate failure prediction model specifically developed for Maltese companies can be used as an early indicator of distress, enabling the management to take precautionary measures in adequate timeframes.

1.4 Research Objectives

The central objective of the study is to determine the accuracy of different bankruptcy models when it comes to corporate failure prediction within the Maltese context. The objectives of the study are:

To determine the accuracy of different bankruptcy models developed through different statistical techniques,

To evaluate the explanatory power of the financial ratios making up the chosen bankruptcy models, and

To identify the bankruptcy prediction model most suited for Maltese SMEs.

1.5 Dissertation Framework

This dissertation is divided into six chapters. These are:

Chapter 1: Introduction - provides an outline of the main concepts surrounding corporate failure as well as an overview of numerous local studies conducted relating to this matter. It presents the importance of this research, followed by the focal objectives of the study. In addition, it also describes the framework of the dissertation.

Chapter 2: Literature Review - contains an overview of the literature pertinent to the subject area. Corporate failure is presented together with a description of relevant accounting and auditing provisions which are intended to lessen its adverse impacts. The chapter also provides an in-depth explanation of the major corporate failure prediction models developed throughout the years and identifies existing empirical studies through which these models have been tested, and also criticised.

Chapter 3: Research Methodology - outlines how the sample data is collected. It also presents an overview of the research procedure and strategy applied alongside the methods used in the collection and analysis of the secondary data obtained. An explanation of how any limitations encountered are managed is also disclosed.

Chapter 4: Research Findings - highlights and describes the findings obtained from the data collected and the statistical testing applied relating to the suitability of statistical techniques in predicting corporate failure within the local dynamic.

Chapter 5: Discussion of Findings - provides an in-depth discussion of the findings obtained from the data collected and the statistical testing applied. The main aspects are highlighted and linked to the scope and the objectives of the research question.

Chapter 6: Conclusions - summarises the principal concepts highlighted by the means of this research alongside the limitations encountered whilst conducting the study. The sphere of statistical technique which best suits the local dynamic in predicting corporate is highlighted. Finally, proposals for future research in the subject area are also disclosed.

Figure 1.2 hereunder, illustrates the organisation of the dissertation, highlighting the relevant six chapters making up this study.

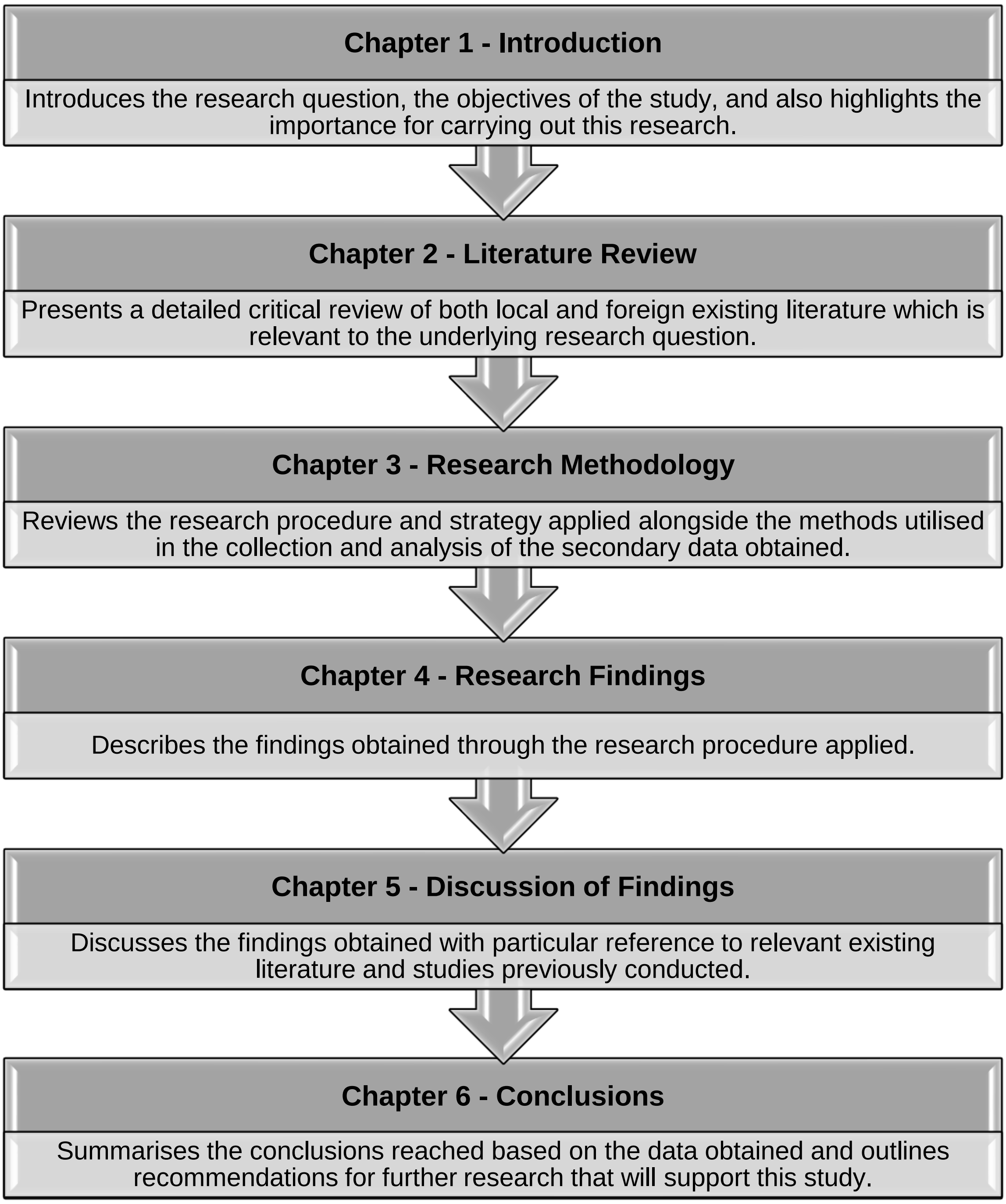

Figure 1.2 - Overview of dissertation structure

Chapter 2
Literature Review

2.1 Introduction

This chapter gives an overview of the literature pertinent to the subject area. Firstly, the term ‘corporate failure’ is defined in Section 2.2 with reference made to the presumed roots of failure as well as the path leading up to it. This is followed by references made to relevant accounting and auditing provisions, intended to lessen the adverse impacts of corporate failure in Section 2.3. The chapter proceeds with an in-depth explanation of the major corporate failure prediction models developed throughout the years in Section 2.4, while Section 2.5 identifies existing empirical studies through which these models have been tested. Lastly, Section 2.6 will illustrate limitations associated with the default prediction models mentioned, and Section 2.7 concludes the chapter.

Figure 2.1 hereunder, illustrates the structure of this chapter.

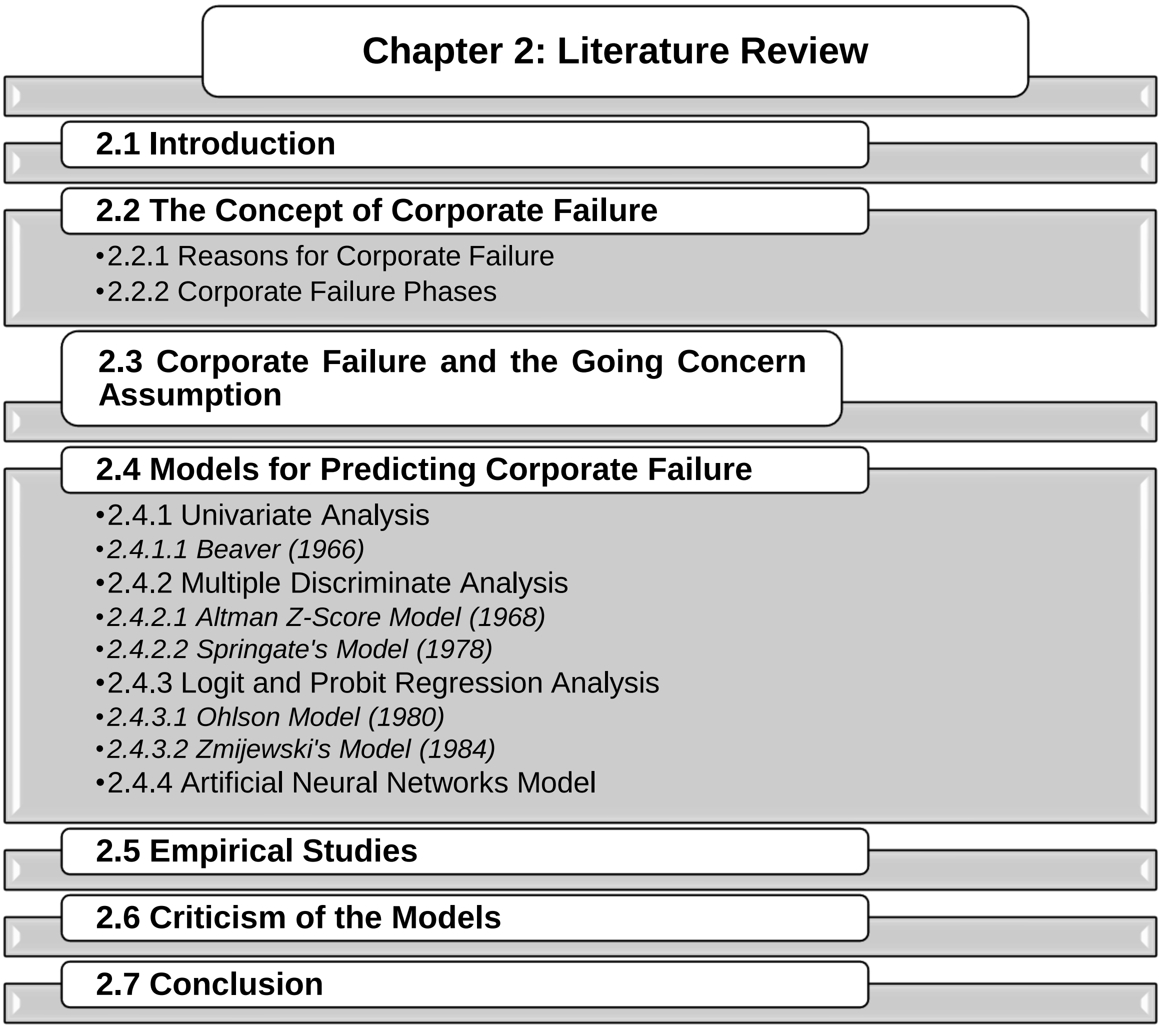

Figure 2.1 - Overview of Chapter 2

2.2 The Concept of Corporate Failure

The term 'corporate failure' is the cause of numerous heated debates amongst academics due to its opaque nature. Even so, Argenti (1976) proposed a two-fold interpretation, namely economic and financial failure. Economic failure relates to the instance when a company fails to attain the return on capital invested, whereas financial failure implies a position of financial deterioration.

2.2.1 Reasons for Corporate Failure

Considerable research has been undertaken to gain insight into the leading causes of corporate failure. Levratto (2013) argued both internal and external factors may have a significant contribution to a company's default position. Factors mentioned in the study circulated around aspects of deterioration in the customer base, the company's geographical location, and rising competition amongst others. Financial factors also rank high on the list as contributors of corporate failure, with high proportion of debt and loss of capital being the main reasons of corporate failure identified in literature (Bradley, Rubach 2002).

Ooghe and Waeyaert (2004) have gathered the leading possible causes into one conceptual model, comprising five fundamental categories. 'The conceptual failure model of possible causes of bankruptcy' (Figure 2.2), delineates the possible roots of failure, as well as the mutual relation between exogenous and endogenous causes. Categories include:

1. **General environment**: refers to aspects which are introduced by the external environment in which a company operates within. The government's attitude and its efforts to assist ventures as well as alterations in macroeconomic factors prove to be concrete examples of such external causes. These factors can be detrimental to a company's wellbeing if they remain unidentified and unmanaged, with severe consequences impacting the future prosperity of the company.
2. **Immediate environment**: this category lists down all stakeholders with which a company constantly interacts, namely customers, suppliers, competitors, financial institutions, and stockholders. The direct influence

exercised by these parties upon the company render this category of utmost importance since a company's interaction with its stakeholders will ascertain its advancement into either a favourable or unfavourable direction.

3. **Management**: refers to the motivation, qualities, and skills of top management. Both personal traits and management attitude have significant effects on a company's prosperity. Qualities of over-optimistic behaviour and a risk-seeking attitude employed by management has been proved to be one of the qualities associated with endangering a company's continuity. In addition, ignorance and reluctance to take on new business opportunities or promptly exercise safeguarding action in instances of evident threats have also proven to be a hazardous management feature.
4. **Corporate policy**: involves aspects such as corporate strategy, financial management, and the commercial aspect related to the company. It is established by top management, who must address all aspects to lessen the instance of errors and ensure the development of a feasible corporate policy. Inadequate managerial competence in certain fields and individual characteristics of management can induce unforeseen difficulties that jeopardize the company's likelihood of survival (Ooghe, Waeyaert 2004)
5. **Company characteristics**: reference here is made to the size, maturity, industry, and a company's flexibility in readjusting to environmental changes. Past literature focuses on two characteristics which have been shown to be associated with company failure; these are age and size. Fichman and Levinthal (1991) contend that the first years of existence render greater vulnerability to companies. This is further supported by the argument that newly founded companies must work hard in gaining external legitimacy by developing solid exchange relationships with stakeholders (Burgelman 1991; Kale, Arditi 1998). Moreover, smaller companies have restricted financial resources to counteract market contractions, as well as enduring a greater predicament in equalling larger organisations when it comes to career development opportunities (Kale, Arditi 1998).

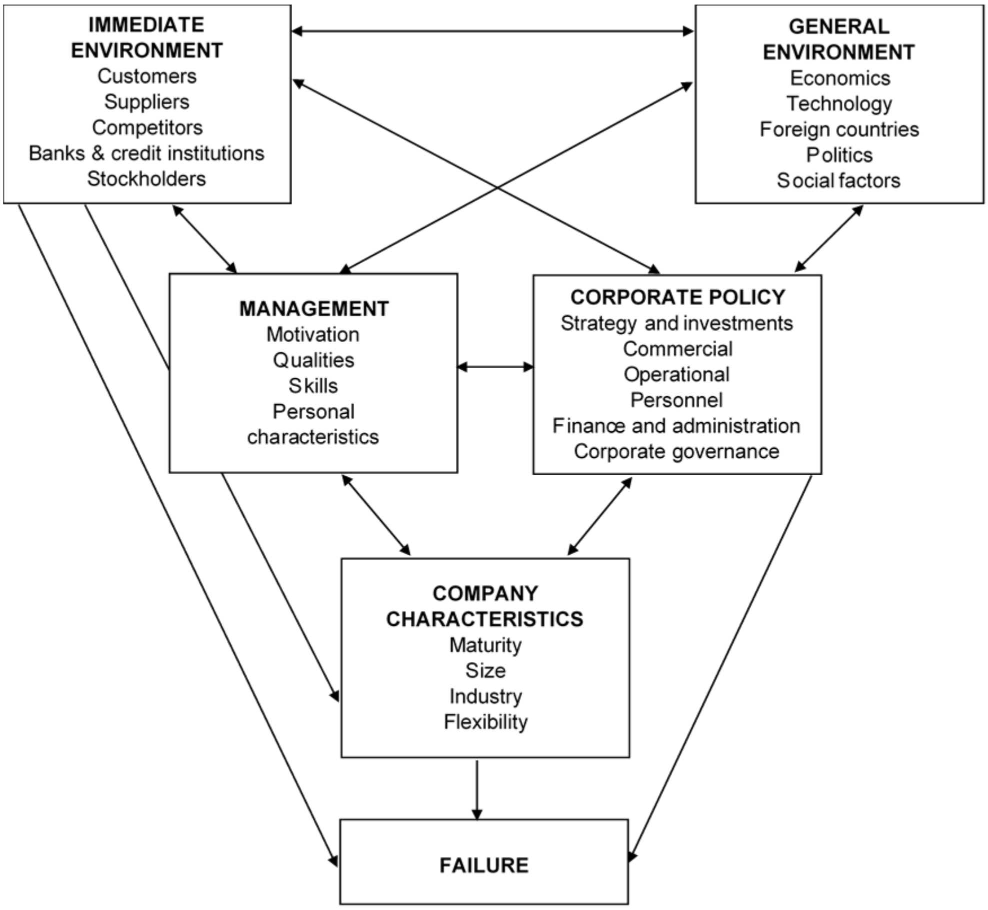

Figure 2.2 - Conceptual failure model of possible causes of bankruptcy
(Source: Ooghe, Prijcker 2008, p. 225)

2.2.2 Corporate Failure Phases

Argenti (1976) concluded that there are a number of consecutive prominent failure phases which are endured by an entity before it will ultimately declare the failure of its commercial activity.

Figure 2.3 depicts the failure process as described by Argenti (1976) from which it is evident that failure does not occur abruptly, but rather is the consequence of a sequence of events. The first phase of the failure process relates to management itself. Skill shortages or pessimistic attitudes are defects which are often associated with a failing company. Moreover, lack of appropriate managerial guidance leads to errors or mistakes within strategy plans and their implementation, which will have an impact upon the company's performance indicators, resulting in their deterioration. This constitutes Phase 2 of the failure process described by Argenti (1976). It is noteworthy that unanticipated circumstances may also harm performance indicators, which further highlights the importance of effective management. Ultimately, in the instance that no immediate action is exercised, the company escalates to Phase 3, which is bankruptcy (Sharma, Mahajan 1980).

According to Laitinen (1993), the path of failure differs from one company to another depending on its age, size, or even the industry in which it operates. However, it is evident that poor management remains a prominent factor which aids in the deterioration of the company, up until its insolvency.

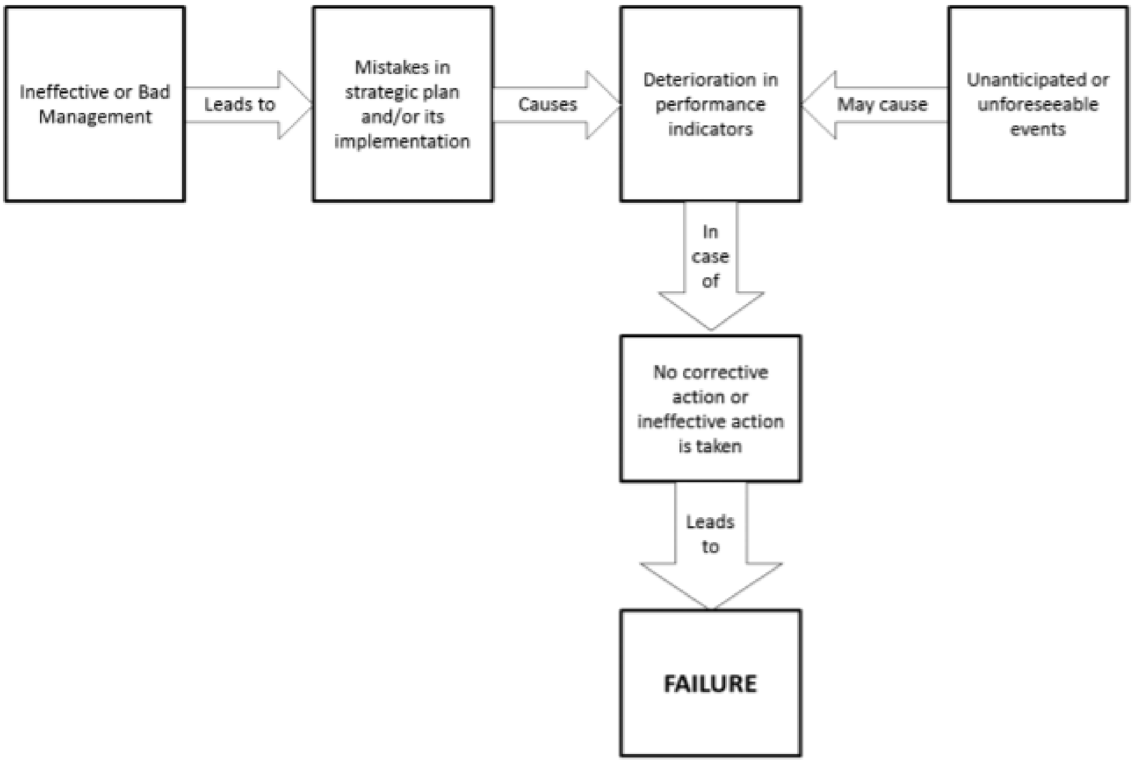

Figure 2.3 - The failure process
(Source: Sharma, Mahajan 1980, p. 81)

2.3 Corporate Failure and the Going Concern Assumption

The various aspects and causes formerly highlighted jeopardise the ability of a company to sustain its operations for the foreseeable future. This may cause failure in meeting the standard of going concern. International Accounting Standard (IAS) 1, '*Presentation of Financial Statements*', stipulates that it is the responsibility of the management to assess a company's competence to continue as a going concern. Moreover, the financial statements of a company should be prepared on such basis, unless the management is aware of certain events or conditions which prove otherwise. In instances where uncertainties that may cast compelling doubts upon the company's capability to continue as a going concern are present, adequate disclosures in the financial statements should be made (International Accounting Standards Board 2012).

In order to ascertain the proper implementation of the going concern assumption, financial statements are subject to a yearly audit, whereby the main objective is for the auditors to give an opinion as to the compliance of the financial statements with established regulations. International Standard on Auditing (ISA) 570, '*Going Concern',* spells out the responsibility imposed upon the auditor to gather sufficient appropriate audit evidence from which conclusions can be made as to whether the going concern assumption has been correctly implemented. In addition, the responsibility is extended further to assure that adequate disclosure is identified and listed in the instance of existing events or conditions that may cast compelling doubts upon the company's capability to continue as a going concern (International Federation of Accountants 2006).

2.4 Models for Predicting Corporate Failure

Several signals and warning signs can aid in the prediction as well as the prevention of financial distress. Amongst many others, financial statement analysis is one approach that can be utilised for this prediction. This accounting-based analysis focuses on the information derived through financial ratios. These ratios may be categorised and defined as profitability ratios; asset management efficiency ratios; risk, short-term cash management, and debt ratios; and stock market data, as described by Samuels, Brayshaw, and Craner (1999) and supported by Kidane (2004).

Models based on financial statement ratios are further subdivided into four major consecutive models, namely univariate analysis models, MDA models, logit and probit models, and ANNs.

The overview of the major historical developments of the quantitative models discussed hereunder is essential for understanding the context from which the models tested for the purpose of this study were established.

2.4.1 Univariate Analysis

Fitzpatrick (1932) may have conducted the oldest study with regard to the analysis of financial ratios for the sole purpose of predicting corporate failure. Univariate analysis was applied in this study, where a total of thirteen financial ratios were put under scrutiny and their relationship with failure was examined independently from the values derived by the remaining chosen ratios (Falzon 2011). However, numerous academics contradict the conclusions reached that such a model has exhibited any significant relations with failure (Bellovary et al. 2007).

2.4.1.1 Beaver (1966)

Beaver (1966) produced one of the most seminal papers in bankruptcy prediction. It employs a univariate model comprising a total of thirty variables to distinguish solvent companies from those which were bankrupt at the time. Through the use of a paired-sample consisting of seventy-nine listed failed firms during the period 1954-1964 alongside their non-failed counterparts, Beaver (1966) tested the predictive ability of these thirty financial ratios. This was done by the use of financial information extracted from company accounts dated five years prior to the failure of the defaulted companies.

Through his analysis, it was evident that although the mean ratios relating to the non-failed category differ slightly from the actual observations, significant deviations occurred within the failed category over the five-year period that was put under scrutiny. By confirming the existence of a compelling discrepancy between the two categories, the next step was to determine which ratios yield the utmost predictive power.

The percentage of misclassification for each variable employed based upon a priori assumption was derived through the application of a dichotomous classification technique. The financial ratio yielding the smallest percentage error was the cash flow to total debt variable, followed by the net profit to total assets variable. This concluded that they are the best predictors out of the total thirty tested, amounting to only 10% and 12% percentage errors respectively (Falzon 2011).

2.4.2 Multiple Discriminate Analysis

Multivariate analysis or MDA is a statistical technique which considers multiple statistical variables and forges a relationship amongst them. Experimental variables are manipulated to observe the effect on the outcome variable, which eventually may be classified under two or more qualitative terms, for instance, failed and non-failed.

According to Laitinen and Kankaanpaa (1999), three distinct phases exist in the MDA techique. The first stage relates to the prediction of the coefficient of variations, which is then followed by the measurement of every single discriminant relating to the sample score. In the final phase, classification of the outcomes into their distinct cases is carried out in accordance with the results derived.

2.4.2.1 Altman Z-score Model (1968)

The Altman's Z-score Model, first introduced in 1968, is perceived as being one of the most accurate MDA techniques. To complement these affirmations, Sherbo and Smith (2013) conferred that the model, although not perfect, still has plenty of application in the evaluation of future financial health of a company and the predictive capability of bankruptcy two years in advance. The equation originally proposed by Altman is:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5$$

Equation 2.1 - Original Altman Z-score Model

Description:

Z = Bankruptcy Index

X_1 = Working Capital/Total Assets

X_2 = Retained Earnings/Total Assets

X_3 = Earnings Before Interest and Tax (EBIT)/Total Assets

X_4 = Market Value (MV) of Equity/Book Value (BV) of Total Liabilities
X_5 = Sales/Total Assets

As described by Altman (1968) the scores that compute a Z-Score of less than 1.81 identify a high possibility of bankruptcy, while scores greater than 2.675 signify financial soundness. Z-Scores which lie between these two values are presumed to be within the grey area or else the zone of ignorance, indicating that the company is experiencing financial complications.

Further amendments to the original Z-score Model have been done in recent years to enhance the applicability of the model in line with the existent dynamic corporate landscape. For instance, modifications were done to incorporate the different parameters associated with companies that are privately-owned. This modification interchanged the utilisation of the MV of Equity figure with its BV. In addition, the model was further expanded to consider developing countries, emerging market entities, and non-manufacturing companies (Altman 2000). This latter Z''-score Model retained the first four ratios as the original model with the exclusion of the last variable relating to *Sales/Total Assets* activity ratio. The newly proposed model is as follows:

$$Z'' = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$$

Equation 2.2 - Altman's Z"-score Model

Description:
Z" = Bankruptcy Index
X_1 = Working Capital/Total Assets
X_2 = Retained Earnings/Total Assets
X_3 = EBIT/Total Assets
X_4 = MV of Equity/BV of Total Liabilities

The cut-off thresholds were also amended, thus Z"-Scores less than 1.10 indicated the possibility of bankruptcy, while Z"-Scores greater than 2.60 are indicators of financial soundness. The area of ignorance is now identified by Z"-Scores which lie between these two cut-off scores (Altman 2000).

Standardisation of the model was reached by the addition of the constant term (+3.25), which was derived from the median score of tested bankrupt American companies. Furthermore, this score was consequently translated to Standard and Poor's (S&P) ratings (Table 2.1), making the bond rating equivalent to the Z"-Score essential for investors (Altman, Hotchkiss 2006).

<table>
<tr><th rowspan="11">Safe Zone</th><th>Rating</th><th>Z" Score Threshold</th><th>Rating</th><th>Z" Score Threshold</th><th rowspan="6">Grey Area</th></tr>
<tr><td>AAA</td><td>>8.15</td><td>BB+</td><td>5.65</td></tr>
<tr><td>AA+</td><td>8.15</td><td>BB</td><td>5.25</td></tr>
<tr><td>AA</td><td>7.60</td><td>BB-</td><td>4.95</td></tr>
<tr><td>AA-</td><td>7.30</td><td>B+</td><td>4.75</td></tr>
<tr><td>A+</td><td>7.00</td><td>B</td><td>4.50</td></tr>
<tr><td>A</td><td>6.85</td><td>B-</td><td>4.15</td><th rowspan="5">Distress</th></tr>
<tr><td>A-</td><td>6.65</td><td>CCC+</td><td>3.75</td></tr>
<tr><td>BBB+</td><td>6.40</td><td>CCC</td><td>3.20</td></tr>
<tr><td>BBB</td><td>6.25</td><td>CCC-</td><td>2.50</td></tr>
<tr><td>BBB-</td><td>5.83</td><td>D</td><td><1.75</td></tr>
</table>

Table 2.1 - Correspondence between Z"-Score and S&P's ratings
(Source: Altman, Hotchkiss 2006, p. 314)

2.4.2.2 Springate's Model (1978)

The Springate's model is an evolution of the Altman's Z-score Model, developed by Gordon Springate in 1978. This model is ratio-based, utilising MDA in the selection of four influential financial ratios amongst a total of nineteen. These are assumed to be capable in differentiating between companies that are presumed to be healthy and those which are presumed to be potentially insolvent. Springate's test concluded that the model has an accuracy rate of 92.5%, as cited by Husein and Pambekti (2014). The model proposed by Springate is:

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

Equation 2.3 - Springate's Model

Description:
S = Bankruptcy Index
X_1 = Working Capital/Total Assets
X_2 = EBIT/Total Assets
X_3 = Earnings before Tax/Total Current Liabilities
X_4 = Sales/Total Assets

An S-Score of more than 0.862 indicates a potentially healthy company, that is, a company which is not potentially bankrupt. Conversely, a company is predicted to potentially experience financial bankruptcy if the model yields an S-Score of less than 0.862 (Primasari 2017).

2.4.3 Logit and Probit Regression Analysis

Logit and probit models are constructed through regressions specifically by applying the logit and probit functions. One beneficial property of these generalised linear models is that the regressions derived, convert the probability 'P' into constrained values between 0 and 1. By making use of the logit and probit as link functions, a dependent variable is linked to a set of linear predictors in a manner that yields the best overall outcome for default prediction (Figure 2.4). Thus, making it possible for the results derived to be interpreted as default probabilities (Racko 2007).

The logit link function is more common in default prediction than its counterpart. However, the choice between the two link functions is based solely upon preference since it results in no significant variations within the complete model development process.

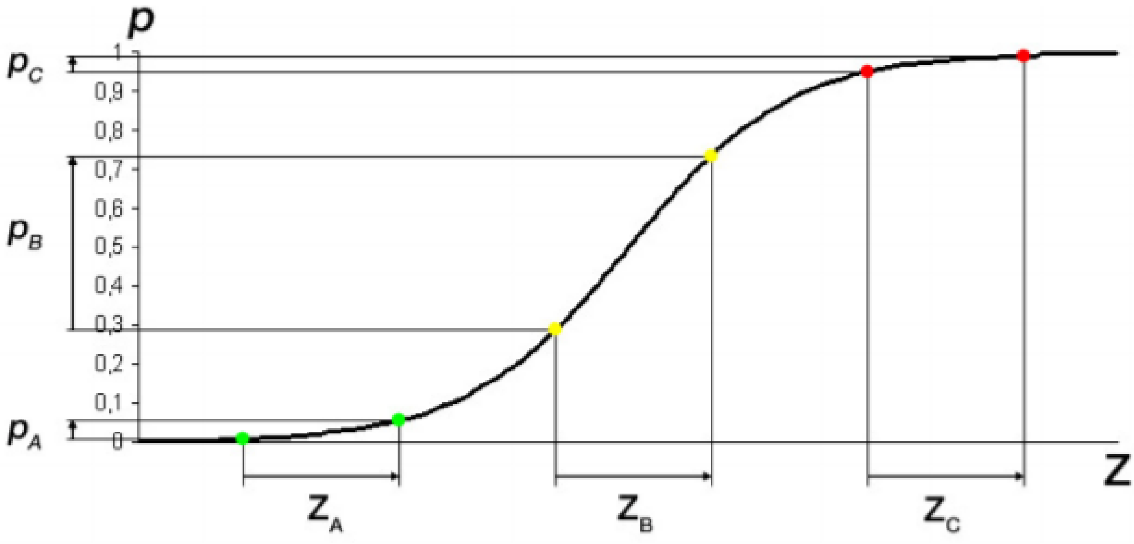

Figure 2.4 - Relationship between the independent predictors (Z) and the eventual outcome (p) in a logistic regression
(Source: Racko 2007, p. 19)

2.4.3.1 Ohlson Model (1980)

The Ohlson O-score Model is a multi-factor financial formula proposed as an alternative to the Altman Z-score Model for predicting financial distress. The aim of the model lies upon the rationale behind the pertinent link between accounting knowledge and firm value (Silvestri, Veltri 2012). The financial knowledge utilised in this model is founded within principal accounting variables such as capital and earnings (Figure 2.5). Moreover, the Ohlson O-score Model also accounts for non-accounting information that may impact a company’s stock value. However, this non-accounting information is not properly described in the original model (Rivera 2018).

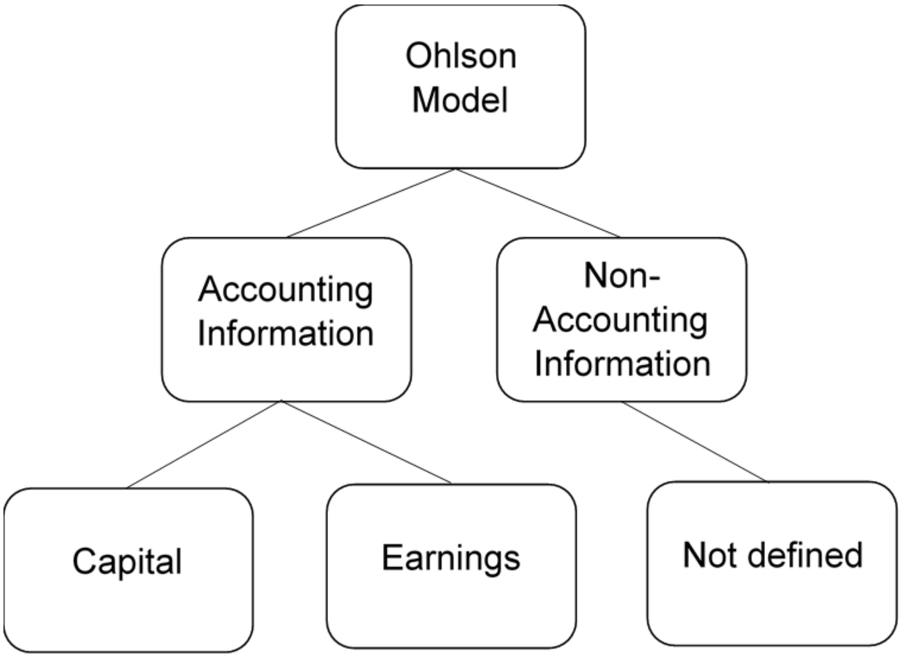

Figure 2.5 - Ohlson O-score Model accounts for non-accounting information to influence a company stock value
(Source: Rivera 2018, p. 3)

Through the use of logit statistical methods, Ohlson developed a nine variable model which is believed to overcome the weaknesses generated by the MDA method employed by Altman. The developed model is:

$$O = -1.32 - 0.407X_1 + 6.03X_2 - 1.43X_3 + 0.0757X_4 - 2.57X_5 - 1.83X_6 + 0.285X_7 - 1.72X8 - 0.521\ X_9$$

Equation 2.4 - Ohlson O-score Model

Description:

O = Bankruptcy Index

X_1 = Size (Log [Total Assets/Gnp Index])

X_2 = Debt Ratio (Total Liabilities/Total Assets)

X_3 = Working Capital/Total Assets

X_4 = Current Liabilities/Current Assets

X_5 = Total Liabilities exceed Total Assets

X_6 = Return on Assets

X_7 = Funds provided by operations/Total Liabilities

X_8 = Net Income was Negative for the last two years

X_9 = Delta Net Income/Sum of Absolute Net Income

As described by Rivera (2018), an O-Score less than 0.38 indicates non-financial distress, whereas an O-Score greater than 0.38 signifies financial distress.

2.4.3.2 Zmijewski's Model (1984)

Zmijewski (1984) contributed further to the expansion of corporate failure prediction by using probit analysis for the development of a model utilising ROA, leverage and liquidity ratios. As opposed to other bankruptcy prediction models, Zmijewski's model, although it also makes use of financial ratio analysis, provides the greatest differences from the Altman's Z-score Model in respect to the financial indicators included within the model. The model that was successfully developed is:

$$X = -4.336 - 4.513X_1 + 5.679X_2 + 0.004X_3$$

Equation 2.5 - Zmijewski's X-score Model

Description:

X = Bankruptcy Index

X_1 = Net Income/Total Assets

X_2 = Total Debt/Total Assets

X_3 = Current Assets/Current Liabilities

The resulting X-Score is presented in the form of a probability of default (P). This probability is explained by the formula:

$$P = \frac{1}{(1 + exp -X)}$$

Equation 2.6 - Probability of default (P)

As cited by Karas and Pavla (2019), a company is to be considered as financially distressed if its probability exceeds 0.5, that is, if the X-Score is greater than or equal to 0.5. This means that companies that yield an X-Score less than 0.5 are presumed to be financially sound.

2.4.4 Artificial Neural Networks Model

The idea behind ANNs is based upon the foundations of the physiology of the nervous system to the extent that this technique is utilised to mimic the way human neurons function. The technique implemented for neural network prediction is termed ‘generalisation’, which implies that once the network is functionally ready, new data is inputted from which eventually the network will predict the outcome (Odom, Ramesh 1990).

In relation to bankruptcy prediction, various academics have analysed the predictive performance of ANNs with particular reference to other traditional predictive techniques such as the Altman’s Z-score Model (Boritz et al. 1993). However, this predictive technique is often criticised for the lack of logical explanation behind its conclusions.

> “Neural networks appear best suited for rather straightforward discrimination and classification problems involving complex natural or physical relationships, rather than tasks requiring reasoning through complex issues using value-based human judgment.” (Boritz et al. 1993, p. 96)

2.5 Empirical Studies

Several academic works testing the predictive power of these bankruptcy models within different jurisdictions are notable, with some even comparing one model to another in the hope of identifying the best overall predictive accuracy.

One research led by Talebnia, Karmozi, and Rahimi (2016) aimed at investigating the two models proposed by Zavgren (1985) and Springate (1978) within Iran’s exchange market. The main coefficients of the two models were adjusted according to statistical techniques of logit and MDA to better reflect the commercial structure and condition of Iranian companies. The outcomes indicated that the adjusted Springate’s Model was superior in identifying a company’s financial health within the bankruptcy year.

Similarly, Elsa and Alodia (2017) examined the predictive power of the Altman Model and the Ohlson Model upon companies listed on the Indonesian Stock Exchange. The focal point of the study was whether logit analysis, as incorporated within the Ohlson Model, superceded the accuracy rate derived through models formulated using MDA. It was, in fact, concluded that the Ohlson Model and the logit analysis have a higher accuracy rate for manufacturing companies in Indonesia. This study is complemented by Moghadam (2009) who reached the same conclusions when testing the predictive capabilities of these two models on listed companies in the Tehran Stock Exchange.

However, both aformentioned studies were contradicted by Karamzadeh (2012), who concluded that the original Altman Model (1968) can better predict corporate failure of Iranian listed companies. The tests resulted in 74.4%, 64.4%, and 50% accuracy rates respectively for three-years prior to failure, indicating higher prediction accuracies than those reported by the application of the Ohlson Model.

Several other studies tested different bankruptcy model sets regardless of their statistical foundations. Fatmawati (2012) evaluated the accuracy rate of the Altman, Zmijewski, and Springate models in prediciting company delisting within the Indonesian Stock Exchange. Out of the three, the Zmijewski Model (1984) was proven to be the most accurate. These conclusions were further affirmed by Husein and Pambekti (2014) in which their study concluded that, although all the models can be utilised for bankrupcty prediction, the model of Zmijewski is the most pertinent in predicting financial distress. This is presumed to be the resulting outcome of a model which has greater weighting on the debt ratio as an indicator of financial distress.

2.6 Criticism of Models

Accounting and finance academics have actively investigated corporate failure forecasting since the seminal studies of Beaver (1966; 1968) and Altman (1968). However, it must be acknowledged that these models are not devoid of notable critique.

According to Hillegeist, Keating, Cram, and Lundstedt (2004) and Gharghori, Chan, and Faff (2006), the diverse accounting ratios incorporated within the Altman Z-score Model (1968) cast significant doubt on the model's predictive ability. The reason is that it is unclear whether the financial statements used for the application of this model are in fact reliable contributors for bankrupcty prediction. In fact, Lin (2015) acknowledged that the ratio *Sales/Total Assets* within the Altman's Model has little contribution to the overall predictive result.

Moreover, Altman's Model has been under scrutiny for the fact that it relies solely on one variable, *MV of Equity/BV of Total Liabilities*, as an assumption to identify symptoms of failure.

Judgement has also been passed upon the fact that the variable sets that make up the various models fail to incorporate proxies for non-financial conditions that expedite corporate failure. Grice and Dugan (2001) argue that corporate failure is usually a combination of financial stress and other conditions and emphasise the importance of recognising that these models do not capture all situations that may induce failure.

Moreover, the distinction between the terms 'bankruptcy' and 'financial distress' has also ignited disputes amongst academics. Even though prediction models, such as the Zmijewski Model (1984), were developed for default prediction, their applicability is not clearly specified. It is not evident whether these models are explicitly utilised for the identification of companies that are likely to face bankruptcy, or whether the sole purpose is for highlighting those companies which are simply facing financial difficulty. This distinction is important as, while companies that face financial distress are more likely to declare bankruptcy, most financially distressed companies are not likely to end in insolvency (Grice, Dugan 2001). This point was further stressed by Gilbert, Menon, and Schwartz (1990) who depicted that financial dimensions which isolate bankruptcy and healthy companies differ from those that isolate bankrupt and distressed companies.

2.7 Conclusion

Corporate failure has been a subject of interest for nearly half a century, generating abundant interest paired with ample controversy. The evolution of bankruptcy prediction models in pursuit of increased sophistication has raised questions regarding their accuracy as well as their applicability within different contexts. Furthermore, despite numerous existing literatures, a theory-gap is evident when it comes to their relevance within the Maltese dynamic.

The next chapter will discuss the research methodology adopted in the study.

Chapter 3
Research Methodology

3.1 Introduction

This chapter provides an overview of the research methodology applied in order to fulfil the objectives of the study. Initially, a description of the preliminary research undertaken is outlined in Section 3.2, followed by a detailed explanation of how the sample data was collected in Section 3.3. Section 3.4 and Section 3.5 present an overview of the research procedure and strategy applied, while Section 3.6 sets out the methods used in the collection and analysis of the data obtained. Section 3.7 outlines the statistical techniques employed for the purpose of this study. Finally, a brief explanation of how any limitations encountered were managed is also disclosed in Section 3.8, and Section 3.9 concludes the chapter.

Figure 3.1 hereunder, illustrates the structure of this chapter.

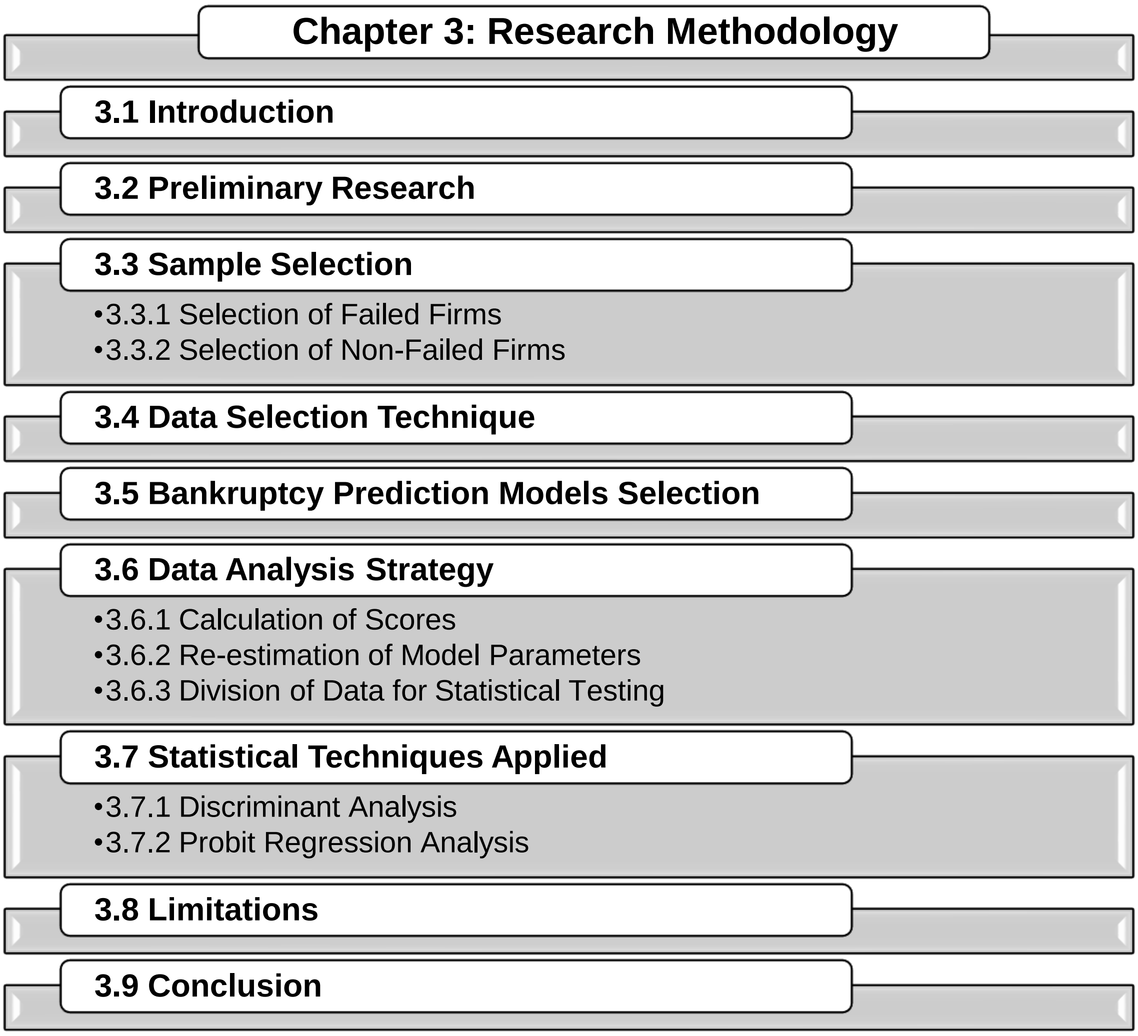

Figure 3.1 - Overview of Chapter 3

3.2 Preliminary Research

Feasibility of the research question was determined by the execution of a preliminary study. This involved obtaining knowledge of existing literature about the matter, getting authorisation to access financial information needed, as well as seeking approval from local authorities to utilise the necessary workstations. This preliminary research proved to be vital in ensuring that the compulsory data to meet the research objectives of the study could be gathered.

3.3 Sample Selection

The population for this research comprises all Maltese SMEs registered with the local company authority, the Malta Business Registry (MBR). The research sample was constructed according to predetermined criteria, which were both general and specific. General criteria encompass features that must be satisfied by the two categories. These included:

1. **All companies had to be small in size.**

Globally, smaller firms are more inclined to experience financial distress as opposed to their larger counterparts. Further, provided that approximately 99.8% of local companies are small in size (European Commission 2019), this criterion provided practicality to the study. For the scope of this research, the term ‘SME’ shall incorporate all those companies which are defined as either micro, small, or medium-sized in parallel with the European Union (EU) definition.

Figure 3.2 illustrates how companies are categorised into size components in accordance with the maximum thresholds set for employee headcount, annual turnover figure, and the annual balance sheet total. To qualify as an SME, a firm must adhere to the employee headcount ceiling, the turnover ceiling, and/or the balance sheet ceiling. It is reference to these three pivotal components that the determination is made of the three types of enterprise covered by the SME definition.

Enterprise category	Headcount: annual work unit (AWU)	Annual turnover	or	Annual balance sheet total
Medium-sized	< 250	≤ EUR 50 million	or	≤ EUR 43 million
Small	< 50	≤ EUR 10 million	or	≤ EUR 10 million
Micro	< 10	≤ EUR 2 million	or	≤ EUR 2 million

Figure 3.2 - EU ceiling threshold for categorising SMEs
(Source: European Commission 2015, p. 11)

By definition this includes all those companies which are identified as small by virtue of Article 185(1)(a) of the local Companies Act. Such companies are eligible to file abridged financial statements restricted to stipulated criteria[1]. Therefore, all selected companies which filed abridged financial statements are presumed to meet the definition of an SME as stipulated by both the Companies Act and the EU. Companies which filed full financial statements were carefully analysed by comparing them to the thresholds established under the EU definition and included in the sample only if they met the stipulated maximum thresholds illustrated in Figure 3.2.

2. **Financial statements (Statement of Financial Position and Income Statement) had to be publicly available for at least three consecutive periods.**

One important characteristic of a bankruptcy prediction model is its ability to promptly anticipate corporate failure. Having an early prognosis of an alarming financial position will enable prompt corrective action to be undertaken. By evaluating a consecutive three-year period rather than focusing on a single year, increased significance of a company's financial stand is acquired.

3. **All companies were expected to operate in the foreseeable future when the last financial statements were filed.**

It was imperative to select companies with the aforementioned characteristic. This is since the capability of a corporate failure prediction model is rendered

[1] Refer to Appendix 1

useless when tested on a company which is knowingly anticipating financial distress in the near future.

In addition, a set of specific criteria was employed for the further categorisation of each selected company. The sample was split into two categories: Category 1 comprising failed firms, whereas Category 2 comprising firms which are still in operation. The predetermined specific criteria for each respective category are discussed hereunder.

3.3.1 Selection of Failed Firms

A list of companies which were insolvent at the time of their dissolution was extracted from the MBR in December 2019. This list comprised three-thousand distinct companies. The selection process was then based upon the specified criteria hereunder over and above the general criteria set.

1. **The company had to be in fact insolvent.**

An insolvent company is a company that, to present date, has filed a declaration for voluntary dissolution and winding up (referred to as Form B1) without a declaration of solvency (referred to as Form B2). This is parallel with the definition of a 'failed firm'[2] for the scope of this research[3].

2. **The companies selected must have had their financial statements filed with the Registry of Companies for at least three consecutive years before filing their declaration of voluntary dissolution and winding up.**

This criterion enables the proper evaluation of final results generated by existing bankruptcy prediction models. The reason is that most of these models, particularly the one proposed by Altman, have been stipulated to be able to predict potential financial distress up to two years ahead of its occurrence.

[2] Refer to Section 1.2.1

3. **The memorandum of association of each company selected had to be publicly available.**

The memorandum of association was also made available through the MBR system. It had to clearly identify the nature of operations undertaken by the company, or alternatively, the industry in which the company operates. This last criterion eased the subsequent selection of Category 2 companies as these would be matched according to industry.

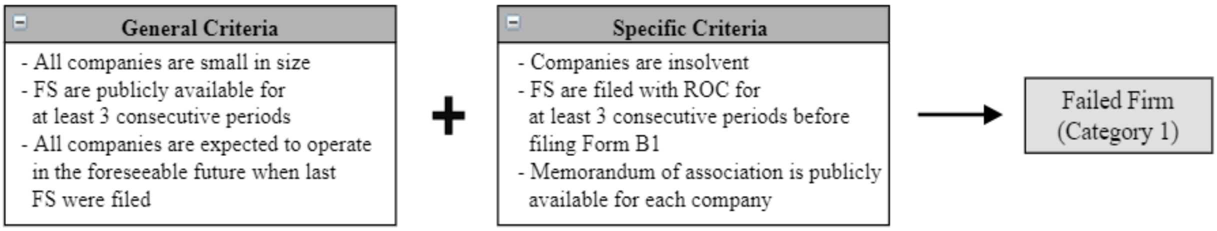

Figure 3.3 - Predetermined criteria for Category 1: Failed Firms

3.3.2 Selection of Non-Failed Firms

The selection process for the sample belonging to non-failed firms followed the general criteria discussed above, as well as other specific predeterminants.

1. **A non-failed firm was selected for every failed firm chosen in Category 1.**
2. **Each non-failed company must have publicly available financial statements for the same three-year period as its corresponding failed firm.**

The matching process was done in accordance to company size and industry. Further to this, the same three-year period was also selected for each company pair. The implementation of such selection strategy ensured that divergences in statistical findings of each pair will not be a consequence of variations in size and industry elements but rather attributed only to the failing or non-failing disposition of the companies.

This procedure was made possible through data available from databases operated by the Malta Business Book and when necessary the Yellow Pages website, both of which categorise companies according to the industry in which they operate. When multiple companies satisfied these two criteria, one was randomly chosen for the pairing.

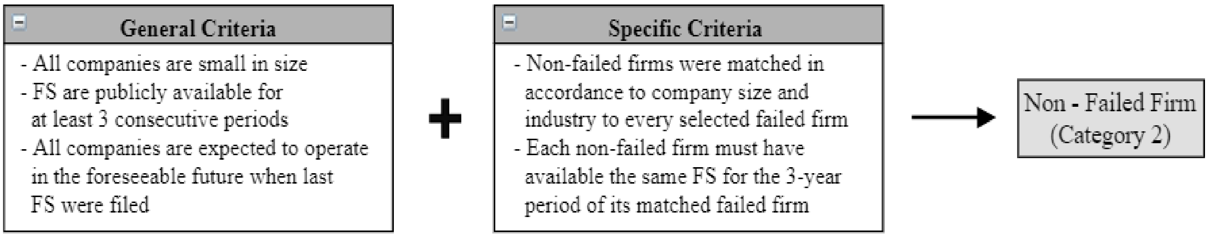

Figure 3.4 - Predetermined criteria for Category 2: Non-Failed Firms

The selection process yielded twenty-eight failed companies and twenty-eight corresponding non-failed companies meeting all stipulated criteria, thus enabling a paired-sample design[4]. It is necessary to clarify that the sample size does not represent the total population size.

3.4 Data Collection Technique

Secondary data[5] was extracted from publicly available financial statements of each selected company in the sample. Three consecutive periods were chosen for each company and the data was extracted accordingly. The periods were chosen as the last three financial statements submitted by the respective company before filing their declaration of voluntary dissolution and winding up. When this was not the case, the required data was extracted from the latest three-year period which satisfied this criterion.

The suitability of the secondary data was determined through a detailed evaluation of the audit report presented with the financial statements of the selected companies. The objective of this evaluation was to ensure that all financial statements selected were in fact prepared on a going concern basis and that the auditor did not issue an adverse audit opinion. This provides reasonable assurance that the secondary data utilised for the purpose of this study is free from material misstatement.

[4] Refer to Appendix 2
[5] Refer to Appendix 3

3.5 Bankruptcy Prediction Models Selection

The selection of corporate failure prediction models for the scope of the study relied solely upon the availability of financial data. By virtue of the local Companies Act 1995, local entities are required to file financial statements in accordance to their nature and size. Private exempt companies are obliged to file an abridged balance sheet and notes thereto, whereas other small-sized companies are also to file an abridged profit and loss account. All other companies are required to file a full set of financial statements in accordance with International Financial Reporting Standards (IFRSs) as adopted by the EU.

Given that a significant proportion of companies selected relate to small-sized firms by virtue of the local Companies Act, the most effective models in parallel with the scope of the study were the revised Altman Z"-score Model (2000)[6] and the Zmijewski's X-score Model (1984)[7]. The revised Altman Z"-score Model (2000) was selected from the MDA sphere of statistical techniques rather than the original model prescribed by Altman (1968) because the revised model omits the variable of *Sales/Total Assets*. Since most of the companies selected are in fact obliged to file abridged accounts, the annual turnover figure was not available for most firms in the sample.

Conversely, the most viable model emerging through logit and probit regression analysis is that of Zmijewski (1984) referred to as the Zmijewski's X-score Model. The underlying reason for this selection relates to the fact that this model provides the greatest variable differences from the Altman's Z"-score Model (2000) while still incorporating financial indicators that can be computed with the available data. Selecting two corporate failure prediction models which are distinct in nature enables generalised conclusions on whether one spectrum of bankruptcy models is better than the other in predicting situations of financial distress in the local dynamic.

[6] Refer to Equation 2.2
[7] Refer to Equation 2.5

3.6 Data Analysis Strategy

3.6.1 Calculation of Scores

The required data was extracted from the financial statements of each selected company and inputted in Microsoft Excel. The dependent variables, that is, the resulting scores were computed through the same software. The extracted data was inputted into the original models selected without any changes to reflect a distinctive geographical sample.

The resulting scores were expressed first as a percentage of correctly classified failed and non-failed companies and then evaluated through the use of Receiver Operating Characteristic (ROC) curves and the Area Under Curve (AUC) values[8]. These two approaches were implemented to assess the accuracy rate of the two models.

3.6.2 Re-estimation of Model Coefficients

The selected bankruptcy prediction models were originally developed using American data. Therefore, using these models without any modification to consider a distinctive geographical data set would presume to generate inconclusive results. For this reason, the logged data in Microsoft Excel was inputted in a Statistical Package for the Social Sciences (SPSS) to enable statistical testing that would reflect a distinctive geographical data set.

The statistical testing incorporated the same statistical techniques exercised to formulate the original models selected for this study, namely discriminant analysis and probit regression analysis. More specifically, the statistical tests incorporated all the data extracted from local financial statements pertaining to one, two, and three-years before bankruptcy for each categorical group – failed and non-failed companies. This procedure enabled the development of newly estimated parameters to be multiplied with each of the financial ratios included in the original models respectively.

[8] Refer to Appendix 4

However, unlike their original correspondents, the statistical testing considered all three-year observations, whereas the original models were based only on a single year analysis. This resolution was reached due to a restricted sample employed by the study. Further, considering a three-year timeline would suggest greater ability in predicting default earlier than the year before bankruptcy. The single year analysis, specifically that relating to one-year prior to default, was used only to better justify the relationship between the independent variables and the probability of default.

3.6.3 Division of Data for Statistical Testing

To ensure the effectiveness of the statistical testing employed, the sample constructed was split into two sets, namely the training/known set and the test/unknown set. Such sample divisibility was done randomly, resulting in the training data set to include 78.6% of the total sample data and the remaining 21.4% were allocated to the test data set.

The training data set was utilised to build up the model, meaning that relevant calculations were run on this particular data set to re-estimate the model parameters. The remaining companies not utilised for the parameter re-estimation were used to validate the model built. More specifically, the test set was used to monitor how well the model performs on a wider set of data, while contributing to increased knowledge on false positives and negatives.

3.7 Statistical Techniques Applied

The statistical techniques employed for the re-estimation of model coefficients are discussed hereunder. These techniques were applied in line with the purpose of this study.

3.7.1 Discriminant Analysis

Discriminant analysis was used for the formulation of a discriminant function which parallels the model developed by Altman (2000). The same financial ratios incorporated in the Altman's Z"-score Model (2000) were employed. This enabled the formulation of a discriminant function including a linear combination of independent variables with associated parameters that better reflect the local geographical environment. More specifically, each independent variable was plotted against the group variable. This enabled the classification of the most significant financial variables in predicting corporate default after which the accuracy of the test was determined through residual analysis.

3.7.2 Probit Regression Analysis

Probit regression analysis was used for the formulation of a probit model which parallels the model developed by Zmijewski (1984). Similar to the procedure applied for the MDA model, identical financial ratios incorporated in the Zmijewski’s X-score Model (1984) were employed, and their equivalent parameters were re-estimated to better reflect the local geographical setting. This procedure enabled the evaluation of the relationship between the binary response variable (1 for failed groups and 0 for non-failed groups) and the independent variables, namely, the financial ratios. More specifically, the procedure measured the relationship between the incorporated financial ratios of the model and their overall influence in predicting the possibility of bankruptcy. Further, the prediction accuracy rate of the test was validated through residual analysis.

3.8 Limitations

The primary limitation to the research design was the limited number of companies included. This is a consequence of both the Maltese geographical area, as well as the sample criteria that must be implemented to carry out the research within a prescribed timeframe. As a result, the generalisation of the gathered findings may be controversial. However, a three-year period was evaluated for each company included within the sample, providing added significance to the concluding results.

Secondly, deliberate assumptions had to be made to prevent the unnecessary downsizing of the sample chosen. These assumptions included:

1. The operating profit or loss figure was assumed to represent EBIT in most cases. When this figure was not provided, profit for the year was used instead.
2. The MV of equity was assumed to be the same figure which was presented in the balance sheet statement when no further information was provided for in the notes to the financial statements.

3.9 Conclusion

This section presented an overview of the research methodology which was employed to fulfil the objectives of the research question. A detailed explanation was also given of the research strategy applied alongside the methods implemented for the effective collection and evaluation of the data set constructed.

The following chapter will highlight the relevant findings acquired from the application of the research procedures and strategy discussed overhead together with an interpretation of these findings.

Chapter 4
Research Findings

4.1 Introduction

This chapter sets out the findings of the empirical analysis. Initially, the accuracy rate of the two selected bankruptcy prediction models is analysed in Section 4.2. Section 4.3 presents the results obtained from the statistical testing employed by discriminant analysis, while Section 4.4 discloses the results generated by probit regression analysis. Section 4.5 concludes the chapter.

Figure 4.1 hereunder, illustrates the structure of this chapter.

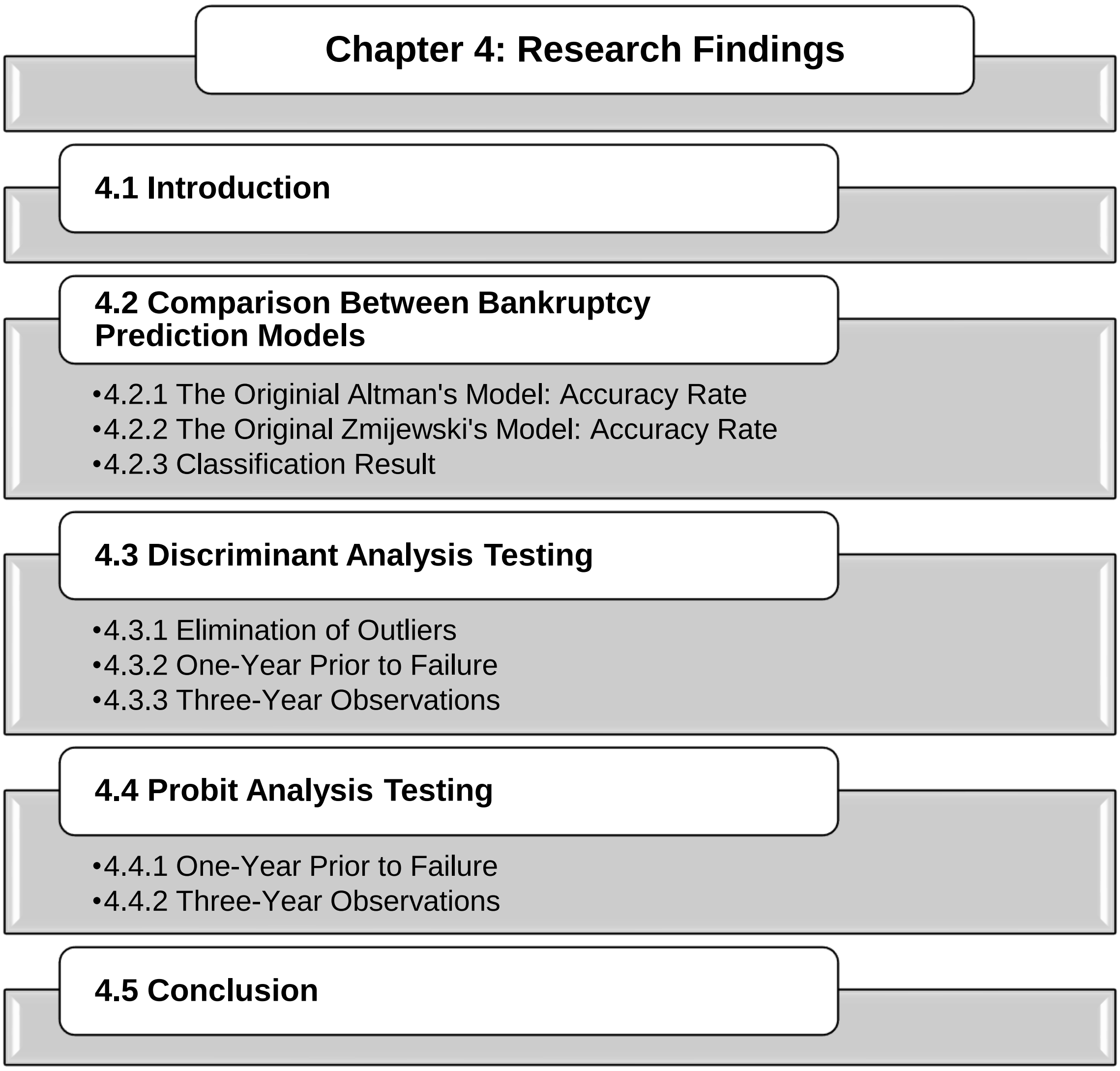

Figure 4.1 - Overview of Chapter 4

4.2 Comparison Between Bankruptcy Prediction Models

The data extracted from publicly available financial statements was inputted into the Altman's Z"-score Model (referred to from hereon as 'Model 1') and the resulting Z"-Scores classified the selected companies as either being in default or not, according to the thresholds[9] set by Altman (2000). The procedure was repeated for the Zmijewski's X-score Model (referred to from hereon as 'Model 2'), where the resulting X-Scores were categorised according to the thresholds[10] set by Zmijewski (1984).

The computed scores were calculated through Microsoft Excel, and no adjustments were made to the original models selected. More specifically, the extracted data from the financial statements of each selected company was inputted into the two selected corporate failure prediction models without any changes to reflect a distinctive geographical sample.

Two approaches were implemented to assess the accuracy rate of the selected models. First, the accuracy of the respective model was expressed as a percentage of correctly classified failed and non-failed companies. The predictive ability was further assessed through the use of ROC curves and AUC values[11].

4.2.1 The Original Altman's Model: Accuracy Rate

Model 1 was first assessed and the accuracy percentage for each of the three years prior to bankruptcy can be seen in Table 4.1 below. The total percentage of correctly classified companies in their respective categories, failed and non-failed, for the period T+1 was 78.43%. This means that Model 1 was able to correctly predict as defaulted, twenty-one companies out of a total of twenty-eight failed companies. Similarly, Model 1 correctly predicted as non-failed, nineteen companies out of a total of twenty-eight operating companies.

For the more distant periods, the accuracy percentages decrease each year, being just 64.58% for the T+3 period. It is evident from Table 4.1 that the

[9] Refer to Section 2.4.2.1
[10] Refer to Section 2.4.3.2
[11] Refer to Appendix 4

performance of Model 1 deteriorated when fitted with data pertaining to two years and three years prior to company failure. Further, Table 4.1 illustrates that the accuracy percentage rates were more significant closer to the year of actual default. In fact, the rate of accuracy reported a sharp increase by roughly 13% between period T+3 to period T+1. More specifically, the performance of Model 1 in correctly classifying the local sample increased greatly when fitted with the latest company data.

Given that only a small proportion of the evaluated companies fell into the area of ignorance[12] (grey zone), their impact was excluded from the aggregate percentage. Further, such exclusion eases comparability with results obtained from Model 2 since the Zmijewski's X-score Model (1984) does not incorporate the grey zone interval for the evaluation of its final outcomes.

Years Prior Failure	Actual		Total[13]	Predicted				Accuracy	
	Failed	Non-Failed		Failed	Grey Zone	Non-Failed	Grey Zone	Number	%
T+3	28	28	**48**	16	2	15	6	**31**	64.58%
T+2	28	28	**53**	17	0	18	3	**35**	66.04%
T+1	28	28	**51**	21	2	19	3	**40**	78.43%
Total	84	84	**152**	54	4	52	12	**106**	
Mean									**69.68%**

Table 4.1 - Correctly classified percentage rate for Model 1

The accuracy rate of Model 1 was further assessed by generating a ROC curve (Figure 4.2), where the sensitivity rate is plotted against 1 minus the specificity rate. More specifically, this can be interpreted as the true positive rate plotted as a function of the false positive rate[14]. The overall performance of the tested model can thus be interpreted from the curvature of the plotted graph. In fact, the plotted

[12] The area of ignorance, or grey zone, is one of the cut-off points set by Altman (1968) to predict a company's possibility of failure. A computed Z-Score that falls within the ignorance zone indicates an existing possibility of bankruptcy for the company within the next two years.
[13] Note that these total figures represent the summation of failed and non-failed companies, less those companies that fell into the area of ignorance (grey area).
[14] Note that for the purpose of this study, a true positive relates to a defaulted firm being predicted as failed, whereas a false positive relates to a non-failed firm being predicted as failed.

ROC curve for Model 1 shows a fair overall performance by the tested model since the plotted ROC curve bows out towards the top of the y-axis. This further indicates that the model is generating a higher rate of true positives overall.

This conclusion can be further supported by computing the area under the plotted ROC curve since the AUC value indicates how well Model 1 can differentiate between the failed and non-failed categories. In fact, the resulting AUC value of 0.695 (Table 4.2) indicates that the model tested incorporates a good measure of separability between the two diagnostic categories.

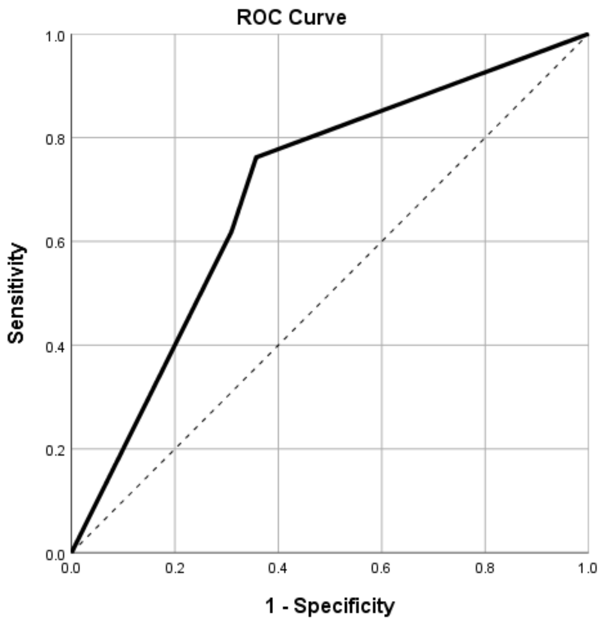

Figure 4.2 - Plotted ROC curve for Model 1

Area Under the Curve				
Area	Std. Error	P-value	95% Confidence Interval	
			Lower Bound	Upper Bound
.695	.041	.000	.614	.776

Table 4.2 - AUC value for Model 1

4.2.2 The Original Zmijewski's Model: Accuracy Rate

The accuracy percentage for each of the three years prior to company default was then computed for Model 2 (Table 4.3). The total percentage of correctly classified companies in their respective categories for the period T+1 was

67.86%. This indicates that Model 2 was able to correctly predict as defaulted, twenty-five companies out of a total of twenty-eight failed companies. Similarly, Model 2 correctly predicted as non-failed, thirteen companies out of a total of twenty-eight operating companies.

Similar to the results obtained by Model 1, the more distant periods yielded lower accuracy percentages each year, being just 64.29% for the T+3 period. Table 4.3 illustrates how the performance of Model 2 deteriorated when fitted with data pertaining to two years and three years prior to company failure. However, although evidence shows that accuracy percentage rates were more significant closer to the year of actual default, the increase in the rate of accuracy was gradual. In fact, the accuracy rate increased by roughly 2% each year, leading up to failure.

Years Prior Failure	**Actual**		**Total**	**Predicted**		**Accuracy**	
	Failed	**Non-Failed**		**Failed**	**Non-Failed**	**Number**	**%**
T+3	28	28	**56**	25	11	**36**	64.29%
T+2	28	28	**56**	26	11	**37**	66.07%
T+1	28	28	**56**	25	13	**38**	67.86%
Total	84	84	**168**	76	35	**111**	
Mean							**66.07%**

Table 4.3 - Correctly classified percentage rate for Model 2

The plotted ROC curve (Figure 4.3) and the computed AUC value (Table 4.4) adds further to Model 2's testing performance. The AUC value, standing at 0.667, indicates that the model tested incorporates a good measure of separability between the two diagnostic categories. Yet an immense inequality in the silhouette of the plotted ROC curve is perceptible when compared to the ROC curve generated for Model 1. In fact, the curvature of the plotted graph for Model 2 is closer to the bottom left corner of the y-axis, indicating a decreased overall accuracy of the tested model when compared to that of Model 1. This discrepancy emanates from the fact that Model 2 had a much higher rate of false positives when compared to the rate expressed for Model 1. In fact, it is evident from Table

4.3 that Model 2 failed to classify a high proportion of non-failed firms in their correct category.

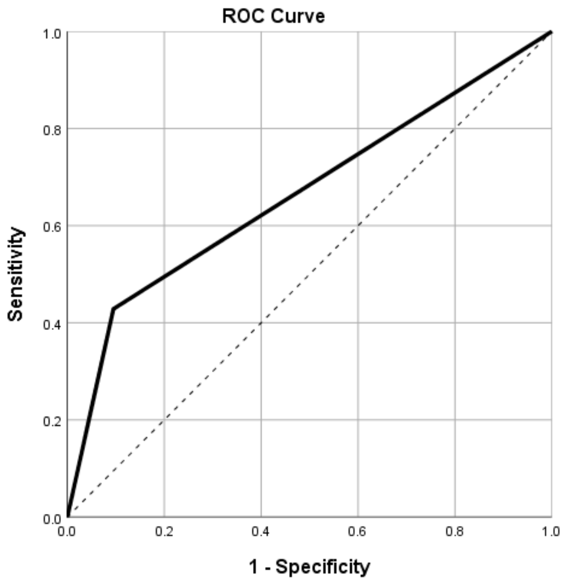

Figure 4.3 - Plotted ROC curve for Model 2

Area Under the Curve				
Area	Std. Error	P-value	95% Confidence Interval	
			Lower Bound	Upper Bound
0.667	0.042	0.000	0.584	0.749

Table 4.4 - AUC value for Model 2

4.2.3 Classification Result

Average classification results show that Model 1 is presumed to have a marginally better performance in correctly classifying local companies, when compared to the performance of Model 2 (Table 4.5). This result is further supported by a higher computed AUC value for Model 1, indicating that this model incorporates a better measure of separability between the two diagnostic categories.

However, by acknowledging the fact that no re-estimation of the models' coefficients was carried out to factor in a geographically distinctive sample, this classification result is presumed to be inconclusive.

Year	Accuracy	
	Altman Z”-score	**Zmijewski X-score**
T+3	64.58%	64.29%
T+2	66.04%	66.07%
T+1	78.43%	67.86%
Average	**69.68%**	**66.07%**

Table 4.5 - Average classification result of the models

4.3 Discriminant Analysis Testing

The data extracted from publicly available financial statements was inputted in SPSS to run a discriminant analysis. Discriminant analysis is the same statistical technique used to develop the Altman’s Z”-score Model (2000). In fact, the same financial ratios incorporated within the Altman’s Z”-score Model (2000) were also used for this statistical test. This procedure resulted in a linear combination of independent variables with associated parameters that better reflect the local geographical dataset. More specifically, the data extracted from publicly available financial statements was used for the formulation of a discriminant function specifically developed for the local sample selected.

Further, statistical testing using the discriminant analysis was carried out on a training set and a test set. The training data set[15] comprised of 78.6% of the total sample data selected for the purpose of this study. The companies selected for the training data set were randomly chosen. The training data set comprised of twenty-one failed companies and twenty-three non-failed companies. The remaining 21.4% of the original dataset, the test set[16], was used to monitor the effectiveness of the statistical test. More specifically, the test data set comprised of the remaining companies not selected as part of the training data set.

[15] The training data set comprises a total of forty-four failed and non-failed companies from a sample of fifty-six companies.

[16] The test data set comprises of the remaining twelve failed and non-failed companies not selected for the training data set, from a sample of fifty-six companies.

4.3.1 Elimination of Outliers

When using MDA, high multicollinearity was detected between the independent variables. The reason is that MDA proves to be highly sensitive to outliers. For this reason, multiple independent variables were rejected by the statistical test. The only two independent variables which reported no correlation were *Working Capital/Total Assets* and *MV of Equity/BV of Liabilities,* and thus were accepted by the statistical test. The remaining variables, *Retained Earnings/Total Assets* and *EBIT/Total Assets,* were rejected due to high correlation and eliminated from the discriminant function. This resulted in an overall weak predictive accuracy rate[17] generated by the model fitted using discriminant analysis.

Two cases were identified as being strong violators of the homoscedasticity assumption[18], and thus were eliminated from the data set. Both cases were identified as being non-failed companies. For this reason, the training data set was adjusted and now included twenty-one failed companies and twenty-one non-failed companies[19]. The procedure was repeated without the two outliers identified, resulting in unbiased results. In fact, after the elimination of these two outliers, the statistical test accepted all the independent variables for the discriminant function.

4.3.2 One-Year Prior to Failure

Three independent statistical tests[20] were employed for each of the years leading up to company default. Identical accuracy rates resulted for each of the three-years when statistical tests were validated by the test data set. Due to word limitations, only the analysis using observations for the year prior to bankruptcy will be discussed.

The discriminant function coefficients generated through discriminant analysis for each independent variable can be shown in Table 4.6. It is critical to mention that

[17] Refer to Appendix 5
[18] MDA assumes homogeneity of variances, that is, variances among different groups are equal.
[19] Note that after the elimination of outliers, the training data set comprises of forty-four failed and non-failed companies from a sample of fifty-four companies, that is, 77.7% of the total sample data selected for the purpose of this study.
[20] Refer to Appendix 6

the probability of default is denoted by a negative value for the discriminant function, while the opposite category, the probability of non-default, is denoted by a positive one. Both coefficients for *Working Capital/Total Assets* and *EBIT/Total Assets* generated positive coefficients (0.377 and 1.344 respectively), indicating an inverse relationship with the probability of default. More specifically, an increase in Working *Capital/Total Assets* or an increase in *EBIT/Total Assets* generated a higher Z-Score. As opposed to this, the variables for *Retained Earnings/Total Assets* and *MV of Equity/BV of Liabilities* generated a negative parameter (-0.396 and -0.694 respectively), indicating a direct relationship to the probability of default. More specifically, an increase in either *Retained Earnings/Total Assets* or *MV of Equity/BV of Liabilities* resulted in a lower Z-Score computed by the discriminant function.

It is important to note that the Box's M test[21] (Table 4.7) indicated that the observed covariances still reject the homoscedasticity assumption, since significance of test is less than 0.05. This test was also affected as a result of deviations from multivariate normality. However, the canonical discriminant function held all the independent variables since the correlation decreased upon the elimination of the outliers.

Canonical Discriminant Function Coefficients	
	Function
Working Capital / Total Assets_1	.377
Retained Earnings / Total Assets_1	-.396
EBIT / Total Assets_1	1.344
MV of Equity / BV of Liabilities_1	-.694
(Constant Term)	.291

Table 4.6 - MDA test: discriminant function coefficients (one-year prior)[22]

[21] The Box's M test is a multivariate statistical measure utilised to test the assumption of homoscedasticity of variances.

[22] Thus, Z_1 = 0.291 + 0.377*(Working Capital/Total Assets)* – 0.396*(Retained Earnings/Total Assets)* + 1.344*(EBIT/Total Assets)* – 0.694*(MV of Equity/BV of Liabilities).*

Test Results		
Box's M		55.224
F	**Approx.**	4.922
	df1	10
	df2	7649.402
	P-value	.000

Table 4.7 - MDA test: Box's M test (one-year prior)

By testing for equality of the group means (Table 4.8), results indicate that the only independent variable which contributes significance in predicting corporate failure is *EBIT/Total Assets* (0.082). All other independent variables generated a significance value greater than 0.10, indicating that they are statistically insignificant to the model. The Wilks' Lambda test contribute further to this concluding result as *EBIT/Total Assets* generated the smallest value, standing at 0.926. This means that the independent variable of *EBIT/Total Assets* incorporates the greatest discriminatory ability in separating data into the diagnostic categories.

Test of Equality of Group Means					
	Wilks' Lambda	**F**	**df1**	**df2**	**P-value**
Working Capital / Total Assets_1	.997	.117	1	40	.735
Retained Earnings / Total Assets_1	1.000	.000	1	40	1.000
EBIT / Total Assets_1	.926	3.193	1	40	.082
MV of Equity / BV of Liabilities_1	1.000	.002	1	40	.965

Table 4.8 - MDA test: variable significance (one-year prior)

4.3.3 Three-Year Observations

Statistical testing was further employed using all three-year observations extracted from financial statements. For the purpose of this study, this testing procedure proved to have more significance in quantifying the predictive power of the model.

Table 4.9 below illustrates the parameter estimates generated through discriminant analysis and further highlights the independent variable having the most predictive power in distinguishing between the two diagnostic categories. In fact, it is evident that the variable of *EBIT/Total Assets* was the best predictor of corporate failure in comparison to the other independent variables. The reason is that it is the only variable generating a constant positive coefficient for all the three years leading up to failure (0.436, 0.905 and 0.551 respectively). The remaining three variables produced high multicollinearity along separate years. Even though they were not eliminated from the test, further interpretability of these variables is restricted in this setting.

Canonical Discriminant Function Coefficients	
	Function
Working Capital / Total Assets_1	.834
Retained Earnings / Total Assets_1	-.313
EBIT / Total Assets_1	.436
MV of Equity / BV of Liabilities_1	-2.482
Working Capital / Total Assets_2	-2.830
Retained Earnings / Total Assets_2	2.218
EBIT / Total Assets_2	.905
MV of Equity / BV of Liabilities_2	2.622
Working Capital / Total Assets_3	.652
Retained Earnings / Total Assets_3	-.721
EBIT / Total Assets_3	.551
MV of Equity / BV of Liabilities_3	3.283
(Constant Term)	-.191

Table 4.9 - MDA test: discriminant function coefficients (three-year observations)

In addition, Tables 4.10 and 4.11 below analyse how efficiently the estimated discriminant model fits the sampled data. The MDA test indicates an overall canonical correlation[23] of 0.683, indicating a fairly accurate representation of the data set incorporated. Further, the chi-square test illustrated that the association between the actual outcome and the predicted outcome is not an attribute of chance, since the p-value is less than the 0.05 level of significance. This indicates

[23] Canonical correlation analysis is a statistical measure of associations among variable groups.

that the fitted discriminant function possesses strong discriminatory ability in splitting data into the correct groupings.

Model Fit				
Function	**Eigenvalue**	**% of Variance**	**Cumulative %**	**Canonical Correlation**
1	.875	100.0	100.0	.683

Table 4.10 - MDA test: canonical correlation (three-year observations)

Model Fit				
Test of Function(s)	**Wilks' Lambda**	**Chi-square**	**df**	**P-value**
1	.533	21.374	12	.045

Table 4.11 - MDA test: chi-square test (three-year observations)

The discriminant analysis generated 85.71% accuracy rate in correctly classifying companies in their failed and non-failed categories, set upon the known data set for observations for the three years prior to bankruptcy. Specifically, out of forty-two companies, the test correctly classified sixteen failed companies and twenty non-failed companies (Table 4.12). The test showed a higher accuracy rate in correctly classifying companies that are still in operation in their respective grouping (95.2%) than for firms in bankruptcy (76.2%).

Despite the significant evidence that the three-year observations improved prediction on the known data, opposing results were reported when testing the fitted model on the unknown data set. In fact, the overall accuracy rate dropped to 66.66% (Table 4.13). However, the findings highlighted a slight increase in accuracy rate when it comes to correctly predicting defaulted companies, standing at 80%. Conversely, the accuracy rate for correctly predicting non-failed companies worsened, dropping to 57.1%.

Grouped Cases Correctly Classified					
			Predicted Group Membership		Total
			No	Yes	
Failed	No	Count	20	1	21
		% within Failed	95.2%	4.8%	100%
	Yes	Count	5	16	21
		% within Failed	23.8%	76.2%	100%
Total		Count	25	17	42
		% within Failed	59.5%	40.5%	100%

Table 4.12 - MDA training data set: cross tabulation (three-year observations)

Grouped Cases Correctly Classified					
			Predicted Group Membership		Total
			No	Yes	
Failed	No	Count	4	3	7
		% within Failed	57.1%	42.9%	100%
	Yes	Count	1	4	5
		% within Failed	20.0%	80.0%	100%
Total		Count	5	7	12
		% within Failed	41.7%	58.3%	100%

Table 4.13 - MDA test data set: cross tabulation (three-year observations)

4.4 Probit Analysis Testing

The same data extracted from publicly available financial statements was inputted in SPSS and run again using probit regression analysis. Probit regression analysis is the same statistical technique used to develop the Zmijewski's X-score Model (1984). In fact, the same financial ratios incorporated within the Zmijewski's X-score Model (1984) were also used for this statistical test. Similar to the statistical testing described in Section 4.3, the procedure resulted in a linear combination of independent variables with associated parameters that better reflect the local geographical dataset. More specifically, the data extracted from publicly available financial statements was used for the formulation of a regression function specifically developed for the local sample selected. This developed regression function represents the relationship between the binary response variable (1 for failed groups and 0 for non-failed groups) and the independent variables, namely, the financial ratios.

Similar to the previous statistical test, the development of new parameters was enabled through the use of a training set, which comprised of 78.6% of the total sample data. The test set (remaining 21.4%) was then used to better analyse the model fit. However, unlike the MDA approach, in the probit regression analysis the whole sample was used since probit regression has low sensitivity to outliers, and thus their existence does not significantly alter the originated results.

4.4.1 One-Year Prior to Failure

Three independent statistical tests[24] were again employed for each of the years leading up to company default; however due to word count limitations, only the analysis using observations for the year prior to bankruptcy will be discussed. The data pertaining to one-year prior to failure generated the highest accuracy rate in distinguishing between the two categorical groupings.

Parameter estimates generated through probit regression analysis for each independent variable can be shown in Table 4.14. It is critical to mention that through the use of probit analysis, the probability of default is modelled against the predictors, and thus these parameter estimates represent marginal effects. Since both parameters for *Net Income/Total Assets* and *Total Debt/Total Assets* generated positive coefficients (1.076 and 0.012 respectively), this indicates an increase in the computed score. More specifically, an increase in *Net Income/Total Assets* or an increase in *Total Debt/Total Assets* decreases the probability of default since a higher score is associated with a lower probability of bankruptcy. Conversely, *Current Assets/Current Liabilities* generated a negative

[24] Refer to Appendix 7

parameter (-0.021), indicating a lower overall score. Thus, an increase in *Current Assets/Current Liabilities* further increases the probability of bankruptcy.

Furthermore, each independent variable was tested to analyse its individual effect upon the overall fitted model. It was highlighted that none of the three independent variables have any discernible effect in predicting the probability of default. The reason is that all p-values were greater than the 0.05 level of significance (Table 4.15). However, the variable of *Net Income/Total Assets* generated the smallest p-value, standing at 0.081.

Parameter Estimates						
Parameter	**B**	**Std. Error**	**95% Wald Confidence Interval**		**Hypothesis Test**	
			Lower	**Upper**	**Wald Chi-Square**	**df**
(Constant Term)	.126	.2130	-.292	.543	.348	1
Net Income / Total Assets_1	1.076	.6176	-.134	2.287	3.036	1
Total Debt / Total Assets_1	.012	.0208	-.028	.053	.360	1
Current Assets / Current Liabilities_1	-.021	.0414	-.103	.060	.269	1

Table 4.14 - Probit test: parameter estimates (one-year prior)[25]

Tests of Models Effects			
	Wald Chi-Square	**df**	**P-value**
(Constant Term)	.348	1	.555
Net Income / Total Assets_1	3.036	1	.081
Total Debt / Total Assets_1	.360	1	.549
Current Assets / Current Liabilities_1	.269	1	.604

Table 4.15 - Probit test: test of model effects (one-year prior)

[25] Thus, X_1 = 0.126 + 1.076*(Net Income/Total Assets)* + 0.012*(Total Debt/Total Assets)* – 0.021*(Current Assets/Current Liabilities).*

4.4.2 Three-Year Observations

Statistical testing was repeated using all three-year observations, to enable better analysis of the overall predictive power of probit analysis.

Table 4.16 below presents the parameter estimates generated through probit analysis. The conclusions from the analysis using observations for the year prior to bankruptcy are supported by this probit analysis. Findings show that the variable *Net Income/Total Assets* is the best predictor for the probability of default when compared to the other tested variables. The reason is because *Net Income/Total Assets* is the only variable which generated a constant positive parameter for all the three years leading up to company default (1.751, 0.247, and 2.459 respectively).

Parameter Estimates						
Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test	
			Lower	Upper	Wald Chi-Square	df
(Constant Term)	.031	.4164	-.785	.847	.005	1
Net Income / Total Assets_1	1.751	1.0753	-.356	3.859	2.652	1
Total Debt / Total Assets_1	.029	.0223	-.014	.073	1.737	1
Current Assets / Current Liabilities_1	1.744	.6609	.448	3.039	6.960	1
Net Income / Total Assets_2	.247	3.2971	-6.216	6.709	.006	1
Total Debt / Total Assets_2	.906	1.3318	-1.704	3.517	.463	1
Current Assets / Current Liabilities_2	-1.911	.7070	-3.297	-.525	7.305	1
Net Income / Total Assets_3	2.549	1.4892	-.370	5.467	2.929	1
Total Debt / Total Assets_3	- 1.010	1.3339	-3.624	1.605	.573	1
Current Assets / Current Liabilities_3	.465	.2307	.013	.917	4.058	1

Table 4.16 - Probit test: parameter estimates (three-year observations)

In addition, Table 4.17 hereunder further examines the discrepancies resulting from the expected values under the fitted model when compared to the observed values. The probit statistical test indicates a deviance[26] of 41.79, yet SPSS failed to generate the associated p-value. For this reason, it is uncertain whether the deviations generated by the model fitted using probit analysis are statistically significant. Despite this, it is presumed that the probit fitted model reported significant deviations from the observed data set given the small value generated when the deviations are divided by the degrees of freedom[27] (value/df equal to 1.229).

Similar to the aforementioned statistical measure, SPSS failed to generate the associated p-value for the Pearson chi-square test[28], and thus statistical significance of the result was not permitted. Despite this, given the small value generated when the chi-square value is divided by the degrees of freedom (value/df equal to 2.555), it is further presumed that the model fitted using probit analysis does not provide an accurate representation of the data set selected for the purpose of this study.

However, this does not withhold the fact that the probit fitted model was found to possess fairly strong capability in separating the data set into the two diagnostic groupings of failed and non-failed. This conclusion is supported by the Omnibus test (Table 4.18) which reported a p-value less than the 0.05 level of significance, standing at 0.024. This indicates that the fitted model outperforms the null hypothesis, and thus the re-estimated model was found to improve the correct classification of data.

[26] The deviance goodness of fit test is a statistical measure of how accurate the predictions generated by the fitted model are to the observed results.
[27] Degrees of freedom represent the number of independent values that can vary in a statistical test without violating the associated constraints.
[28] The Pearson chi-square test is a non-parametric statistical measure used to identify whether the association between the actual outcome and the predicted outcome of an observed distribution is an attribute of chance.

Goodness of Fit			
	Value	df	Value/df
Deviance	41.794	34	1.229
Pearson Chi-Square	86.857	34	2.555
Akaike's Information Criterion (AIC)	61.794		
Bayesian Information Criterion (BIC)	79.636		

Table 4.17 - Probit test: goodness of fit test (three-year observations)

Omnibus Test		
Likelihood Ratio Chi-Square	df	P-value
19.112	9	.024

Table 4.18 - Probit test: Omnibus test (three-year observations)

The probit analysis generated 84.09% accuracy rate in correctly classifying companies in the two diagnostic categories, set upon the known data set for all three-year observations. Specifically, out of forty-four companies, the test correctly classified seventeen failed companies and a further twenty non-failed companies (Table 4.19).

Despite the significant evidence that the three-year observations improved prediction on the known data set, the unknown test data generated negligible results in supporting these conclusions. In fact, there was minimal improvement in the accuracy rate, standing at 83.33%, with no evident enhancement in the failed category (Table 4.20). In fact, the evidence shows that the accuracy rate for predicting true positives deteriorated significantly, dropping to 60%, whereas the fitted model was not able to correctly predict any of the non-failed companies in their respective grouping.

Grouped Cases Correctly Classified					
			Predicted Category Value		Total
			No	Yes	
Failed	No	Count	17	4	21
		% within Failed	81.0%	19.0%	100%
	Yes	Count	3	20	23
		% within Failed	13.0%	87.0%	100%
Total		Count	20	24	44
		% within Failed	45.5%	54.5%	100%

Table 4.19 - Probit training data set: cross tabulation (three-year observations)

Grouped Cases Correctly Classified					
			Predicted Category Value		Total
			No	Yes	
Failed	No	Count	7	0	7
		% within Failed	0.0%	100%	100%
	Yes	Count	2	3	5
		% within Failed	40.0%	60.0%	100%
Total		Count	9	3	12
		% within Failed	75.0%	25.0%	100%

Table 4.20 - Probit test data set: cross tabulation (three-year observations)

4.5 Conclusion

This section presented the predominant research findings of this study together with an interpretation of these findings. The following chapter will provide an in-depth discussion of the imperative points highlighted through these findings.

Chapter 5
Discussion of Findings

5.1 Introduction

This chapter discusses the findings of this study and compares these findings to prior literature. Initially, the independent variables incorporated in the statistical testing are discussed, followed by their significance to the probability of default in Section 5.2. Section 5.3 presents the predictive accuracy of both the MDA test and the probit test, followed by the validation of each fitted model, while Section 5.4 determines which of the two statistical tests is best at predicting bankruptcy in the Maltese setting. Section 5.5 concludes the chapter.

Figure 5.1 hereunder, illustrates the structure of this chapter.

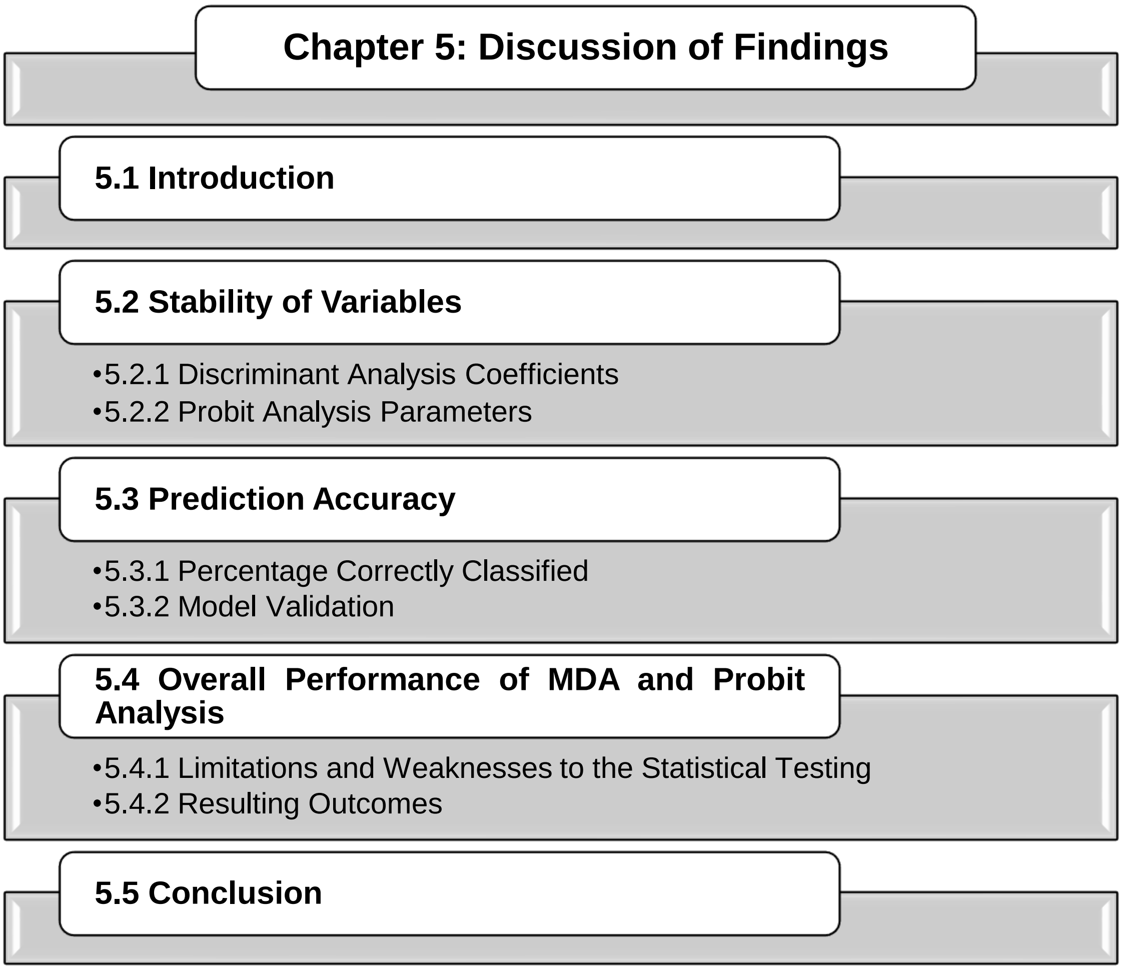

Figure 5.1 - Overview of Chapter 5

5.2 Stability of Variables

The independent variables employed in the two statistical tests are discussed below. Further, the stability of each re-estimated coefficient is reported and justifications for their relationship to the probability of failure, are sought. Given the high degree of time series correlation among the independent variables, the single year analysis, specifically that relating to one-year prior to default, is discussed.

5.2.1 Discriminant Analysis Coefficients

Table 5.1 reports the coefficients of the original Altman's Z"-score Model (2000) compared to the re-estimated discriminant function coefficients for the local sample data set selected in line with the purpose of this study. The results illustrate a significant difference between the coefficients of the original and those of the re-estimated model. This is in line with expectations since the two datasets have different characteristics.

Further to the difference in coefficients, a difference in sign is also evident. Two out of the four independent variables employed, particularly *Retained Earnings/Total Assets* and *MV of Equity/BV of Liabilities,* have a negative sign while in the original model these variables had a positive sign. This indicates that these variables have an opposite impact on the resulting Z-Score. The remaining independent variables, although differing greatly in value, generate positive coefficients like those of the original model. As a result, the findings suggest that the coefficients of Altman's Model (2000) are time sensitive and unstable. This conclusion regarding the respective accounting-based model is further supported by Kidane (2004), who concludes that the predictive accuracy rate of the Altman Model is confined to a specific industry as well as time horizon. Moreover, Singh and Mishra (2016) further confirmed this by comparing the Altman Model to a re-estimated model in the context of predicting the probability of failure of Indian manufacturing companies, in which the same findings were obtained.

MDA Model		
Variable	**Altman's Z"-score Model (2000)[29]**	**Re-Estimated Model[30]**
(Constant Term)	3.25	0.291
Working Capital / Total Asset	6.56	0.377
Retained Earnings / Total Assets	3.26	-0.396
EBIT / Total Assets	6.72	1.344
MV of Equity / BV of Liabilities	1.05	-0.694

Table 5.1 - MDA models: coefficient comparison

Further, the findings obtained report that *EBIT/Total Assets* is the best predictor of corporate default amongst Maltese companies[31]. This accounting ratio is a measure of the Return on Total Assets (ROTA) of the company. More specifically, it is a measure of the company's ability to utilise its acquired assets to generate earnings.

The reported results are in line with expectations, given the fact that an increase in the profitability ratio results in a reduction in the probability of default. In fact, these results are in line with both those concluded through the original model and also with the modified models, where the *EBIT/Total Assets* ranked first as the highest contributor to the discriminant function for category separation (Altman 1968; 1993; 2000). However, Singh and Mishra (2016) contradict these results. Even though the respective financial ratio was still found to be of significance to the overall discriminant function, it ranked last amongst the contributors. Furthermore, Zammit's (2005) research on the explanatory power of conventional accounting ratios within the Maltese context concluded that local companies holding insufficient working capital were more at risk of experiencing financial distress. This implies that the financial ratio of *Working Capital/Total Assets* may be a better contributor in identifying the probability of default for Maltese SMEs. In fact, although for the purpose of this study the latter independent variable was not found to be significant, it generated the second lowest p-value.

[29] Refer to Equation 2.2
[30] Refer to Table 4.6
[31] Refer to Table 4.8

5.2.2 Probit Analysis Parameters

Table 5.2 reports the coefficients of the original Zmijewski's X-score Model (1984) compared to the re-estimated parameters considering the local sample data set. The results, like those produced by the MDA statistical testing, illustrate a significant difference between the parameters of the original and those of the re-estimated model. This is in line with expectations since the two sample data sets used for the development of each respective model have two considerably different geographical data sets.

Further, differences in signs for the re-estimated parameters are also evident. The ratio *Total Debt/Total Assets* is the only re-estimated coefficient which generated the same sign as that of the original model. These results provide evidence that, similar to the Altman Model, the coefficients employed within the Zmijewski's X-score Model (1984) are sensitive to the concept of time and lack stability. This conclusion regarding the Zmijewski's accounting-based model is further supported by Grice and Dugan's (2001) study, where the Zmijewski's X-score Model (1984) was also found to be time sensitive to the extent that it was expected to significantly alter predictive accuracies when applied to time periods distinct from those used to develop the original model.

Probit Model		
Variable	**Zmijewski's X-score Model (1984)**[32]	**Re-Estimated Model**[33]
(Constant Term)	-4.336	0.126
Net Income / Total Asset	-4.513	1.076
Total Debt / Total Assets	5.679	0.012
Current Assets / Current Liabilities	0.004	-0.021

Table 5.2 - Probit models: coefficient comparison

With regard to the significance of variables, the re-estimated probit model failed to highlight any statistically significant parameters which were able to separate the selected data set into the correct groupings[34]. The independent variable of

[32] Refer to Equation 2.5
[33] Refer to Table 4.14
[34] Refer to Table 4.15

Net Income/Total Assets generated the smallest p-value in comparison to the other variables employed within the regression model (standing at 0.081). Even though the p-value was greater than the 0.05 level of significance, it was accepted as having some effect on the fitted regression model.

The financial ratio *Net Income/Total Assets* is a measure of the ROTA of the company, and thus aims at quantifying the company's ability to utilise its acquired assets to generate earnings. This indicates that the reported results are in line with expectations since it is anticipated that an increase in magnitude of this ratio will further decrease the probability of company default. These findings are supported by Singh and Mishra (2016), whose study reported that the ratio of *Net Income/Total Assets* was found to be one of the statistically significant contributors to the overall re-estimated probit model. Further, it is critical to highlight that this financial ratio also identifies as a profitability ratio, similar to the significant variable identified for the re-estimated MDA model. This signifies more the contribution of profitability ratios in predicting financial distress amongst Maltese SMEs.

Conversely, Zammit (2005) concluded that both the working capital ratio and the current ratio, or more specifically *Current Assets/Current Liabilities,* proved to have significant explanatory power in predicting bankruptcy potential amongst Maltese firms. Even though the independent variable of working capital is not incorporated within the Zmijewski's X-score Model (1984), and thus was excluded from the probit statistical test, the current ratio was not found to be significant to the probability of default when the probit model was fitted on the selected local data set.

5.3 Predictive Accuracy

The findings highlighted that both statistical tests employed have proved to possess strong discriminatory ability in classifying the financial statements selected for the sample data set into their failed and non-failed groupings. This conclusion was reached through the statistical testing carried out which incorporated all three-year observations.

5.3.1 Percentage Correctly Classified

The discriminant analysis statistical test reported improvement in the overall predictive accuracy rate when strong outliers were eliminated. Table 5.3 hereunder illustrates the predictive accuracy rates generated when the built model was run on the training data set as well as when the same developed model was then run on the test data set. The total percentage of correctly classified companies in their respective categories, failed and non-failed for the year prior to failure was 69%. This means that the built model was able to correctly predict twenty-nine companies out of a total of forty-two companies. For the more distant periods, the accuracy percentage spiked significantly, holding an accuracy rate of 76.19% for the model fitted on data pertaining to three-years prior to failure. However, it is evident that the overall better predictive accuracy was reached upon fitting the model using all three-year observations, standing at 85.71%. More specifically, the three-year model was capable of correctly classifying thirty-six companies out of a total of forty-two in their respective groupings.

Despite these promising results, the statistical test employed using discriminant analysis reported a weak performance when run on the test data set. In fact, for each of the individual three years, the accuracy rate dropped to 58.33%. Even though the three-year model still reported the highest overall predictive accuracy rate (66.66%), this was a significant deterioration when compared to the accuracy rate generated when the model was applied on the known data set. As a result, it is evident that the MDA statistical test possesses uncertain capability in correctly categorising Maltese companies outside the sample data set selected for the purpose of this study.

Discriminant Analysis Test				
Years Prior Failure	**Training Data Set**		**Test Data Set**	
	Accuracy		**Accuracy**	
	Number	**%**	**Number**	**%**
Three-years	**32**	76.19%	**7**	58.33%
Two-years	**29**	69.00%	**7**	58.33%
One-year	**29**	69.00%	**7**	58.33%
Three-year model	**36**	85.71%	**8**	66.66%

Table 5.3 - Discriminant analysis test accuracy rate

The probit analysis test reported significant predictive accuracy without any adjustments made to the training data set. Table 5.4 hereunder illustrates the predictive accuracy rates generated when the built model was run on the training data set as well as when the same developed model was then run on the test data set. The total percentage of correctly classified companies in their respective categories, failed and non-failed, for the year prior to failure was 75%. More specifically, the built model was able to correctly predict thirty-three companies out of a total of forty-four local companies. For the more distant periods, the accuracy percentages decrease each year, with a significant deterioration in the accuracy rate for the model fitted on data pertaining to two-years prior to company failure. However, overall better predictive accuracy was reached upon fitting the model using all three-year observations, standing at 84.09%. More specifically, the three-year model was capable of correctly classifying thirty-seven local companies out of a total of forty-four in their respective groupings.

The fitted models showed minimal improvements when run using test data for each of the three individual years. This indicates that the models fitted using probit regression analysis possess some discriminatory ability when using test data. The greatest accuracy was reported by the model fitted on data pertaining to three-years prior to default, standing at 66.66%. However, the three-year model still reported the highest predictive accuracy rate (83.33%), correctly classifying ten Maltese companies out of a total of twelve companies in their diagnostic category.

Probit Analysis Test				
Years Prior Failure	Training Data Set		Test Data Set	
	Accuracy		Accuracy	
	Number	%	Number	%
Three-years	**28**	63.64%	**8**	66.66%
Two-years	**20**	45.45%	**4**	33.33%
One-year	**33**	75.00%	**9**	75.00%
Three-year model	**37**	84.09%	**10**	83.33%

Table 5.4 - Probit analysis test accuracy rate

5.3.2 Model Validation

Training and test error rates were used to quantify the performance of the statistical testing employed for the prediction of corporate failure. For the purpose of this study, the test error rate was used since this rate proves to be more useful in estimating the overall predictive capability of the model.

For the purpose of this study, a Type 1 error is identified when the fitted model incorrectly classified a failed company. More specifically, this type of error occurred when the model allocated a failed company to the non-failed category. Conversely, a Type 2 error is identified when the fitted model incorrectly classified a non-failed company. More specifically, a Type 2 error occurred when the model allocated a company which was still in operation to the failed category.

With the exception of the model fitted using data pertaining to one-year prior to default, the MDA statistical test generated a Type 1 error rate which was less than the Type 2 error rate (Table 5.5). This indicates that the statistical testing employed using discriminant analysis was more accurate in categorising a defaulted firm rather than a non-failed firm. More specifically, there were more non-failed firms classified as failed rather than failed firms which were grouped in the non-failed category.

It is important to clarify that the MDA statistical tests were employed using a data set which reported degrees of correlation between the independent variables even though this was lessened by the elimination of two significant outliers[35]. Furthermore, the models fitted rejected the homoscedasticity assumption and reported deviations from multivariate normality[36]. For this reason, such violations of the statistical assumptions implemented by the discriminant analysis technique may bias significance tests and the estimated rates of error. Even though deviations from the normality assumptions are more susceptible when using the MDA technique within the fields of finance and economics, it is of great importance to determine the extent of these violations and their lasting impact on the classification results (Eisenbeis 1977).

Test Error Rate		
MDA Statistical Test	**Type 1 Error**	**Type 2 Error**
Three-years prior failure	8.33%	33.33%
Two-years prior failure	8.33%	33.33%
One-year prior failure	25.00%	16.67%
Three-year model	8.33%	25.00%

Table 5.5 - Discriminant analysis: test error rate

As opposed to the error rates generated for the MDA statistical test, the probit approach presented differing results. It is evident from Table 5.6 that different individual years reported different results. The model fitted using data pertaining to one-year prior to company failure reported a Type 1 error rate greater than that of Type 2. This indicates that the respective fitted model was more accurate in categorising a non-failed firm rather than a defaulted firm. Conversely, results for the model fitted using data pertaining to two-years prior to failure indicates that it performed better in categorising failed companies since the Type 1 error rate is less than the Type 2 error rate.

The greatest difference is evident in the results generated by the model fitted using all three-year observations, where no Type 2 errors were identified. More specifically, the model built on all three-year observations proved to possess the highest accuracy in separating non-failed firms into their correct groupings while still possessing some flaws in correctly grouping failed firms. It is important to clarify that the Type 1 error rate is identical for all the models fitted using probit

[35] Refer to Section 4.3.1
[36] Refer to Appendix 6

regression analysis since all the models incorrectly classified the same number of failed companies, and thus such an occurrence was an attribute of chance.

Test Error Rate		
Probit Statistical Test	**Type 1 Error**	**Type 2 Error**
Three-years prior failure	16.67%	16.67%
Two-years prior failure	16.67%	50.00%
One-year prior failure	16.67%	8.33%
Three-year model	16.67%	0.00%

Table 5.6 - Probit analysis: test error rate

The presumed cost of a Type 1 error is unlikely to be equivalent to that generated by a Type 2 cost (Boritz et al. 1993). The Type 1 error rate proves to have more significance for the purpose of this study since a good corporate failure prediction model must possess greater ability in correctly grouping a failing company in its respective category. However, the relative cost of mismatches rests greatly on the distinct users of the financial statements. Since different players within the financial environment are impacted differently by estimation deviations. More specifically, a commercial bank is impacted less by the cost of a Type 2 error when compared to company management. “The firm could unfairly lose reputation and credit as the error in labelling becomes a self-fulfilling prophesy” (Zavgren 1985, p. 42).

The trade-off between the two types of error rests upon a predetermined cut-off value. Given the limited sample employed for this research, the lesser conservative cut-off value of 0.5 was set for both statistical tests employed. Further, numerous related empirical studies employed an identical cut-off rate, for instance, Falzon (2011).

5.4 Overall Performance of MDA and Probit Analysis

The overall performance of the two statistical tests employed for the purpose of this study is discussed hereunder. More specifically, the restrictive traits of the chosen statistical tests are highlighted, and justifications for their impact on the findings of this research are discussed. This is followed by a comparison of results generated by the MDA fitted model and of results generated by the probit model respectively.

5.4.1 Limitations and Weaknesses to the Statistical Testing

The statistical test implemented using discriminant analysis reported high degrees of correlation amongst the independent variables, resulting in the rejection of multiple variables[37]. As a result, the overall predictive accuracy of the test was badly impacted. The results indicated the presence of strong violators to the MDA assumptions, given the high sensitivity of MDA to outliers. In fact, the degree of correlation decreased after the identification and elimination of two significant outliers, resulting in the canonical discriminant function to accept all the incorporated independent variables.

The elimination of these two cases was still insufficient for the fitted model to satisfy all statistical assumptions presumed by discriminant analysis. In fact, the fitted models for each of the individual three years, as well as the one pertaining to all three-year observations, all rejected the homoscedasticity assumption and indicated deviations from multivariate normality[38]. Given the limited sample data selected for the purpose of this study, further elimination of outliers was not practical, and only the outliers which were presumed to be strong violators were dropped from the sample. For this reason, the performance of the MDA statistical test was confined to the adjusted data set selected for the purpose of this study, and thus generalised conclusions may be rendered inappropriate. A larger sample data set may have contributed to better overall performance reported by the statistical technique, as more outliers could easily be eliminated without restricting the available data on which to fit the MDA model.

Like the MDA statistical technique, the model fitted using probit analysis also reported high correlation amongst the independent variables employed. Despite this, the statistical test generated overall significant prediction accuracy rates when run on the unadjusted sample data set, except for the model fitted to data pertaining to two-years prior to company failure. However, this does not withhold the fact that the deterioration in accuracy rate may be easily related to the company data extracted from financial statements for the second year prior to

[37] Refer to Section 4.3.1
[38] Refer to Appendix 6

failure[39] rather than a reflection of the statistical test's performance. These results further support the robustness of the probit analysis technique when it comes to outliers. For this reason, all sample data was used in the probit fitted model.

Further, the goodness of fit test reported an overall weak model fitted on data pertaining to all three-years observations. This test reported relatively high discrepancies in the expected values under the model when compared to the values being observed. As a result, similar to the MDA statistical test, the performance of the probit statistical test was confined to the sample data set selected for the purpose of this study, and thus generalised conclusions may be rendered inappropriate.

5.4.2 Resulting Outcomes

Given the different statistical assumptions employed by the two statistical techniques selected for the purpose of this study, no clear-cut conclusion can be reached as to which fitted model performs better in predicting potential financial distress of Maltese SMEs. This is further restrained by the distinct set of financial ratios incorporated within the two fitted models. Despite this, the evidence obtained from the resulting findings favours the probit regression technique as having the better predictive ability of potential bankruptcy in the Maltese context.

The models fitted using probit regression analysis reported higher accuracy rates in correctly classifying Maltese companies in their respective grouping when compared to the models fitted using discriminant analysis. Furthermore, significant accuracy rates were reported despite not adjusting the sample data set for potential outliers. This further highlighted the robustness of this statistical technique within the local context. Notwithstanding this, it is to be noted that probit models reported minimal improvement when applied on the test data set. However, these improvements in accuracy were only associated with the non-failed category, that is, the fitted model is presumed to generate better accuracy at correctly classifying non-failed companies in their respective grouping when applied on test data. Conversely, the MDA statistical test reported an overall weak

[39] Refer to Appendix 3

performance when applied on test data, rendering its predictive capability dubious if it had to be used on a sample which is distinct from that used for the purpose of this study.

Despite the contradicting results reported by the empirical analysis undertaken, it was highlighted that profitability ratios are significant contributors to the prediction of corporate default amongst Maltese entities. The ratios of profits to total assets were found to possess high discriminatory ability in predicting the possibility of financial distress when applied to the local sample selected. This indicates that the ability of Maltese SMEs to effectively utilise their acquired assets to generate earnings is a distinctive characteristic of the local economic environment for distinguishing between financially sound entities and those which may be at risk of default.

5.5 Conclusion

This chapter provided an in-depth discussion of the findings presented in Chapter 4. This discussion compared the results of this study to prior literature and ascertained which of the bankruptcy models is best suited for Maltese companies.

The final chapter will present a summary of the research conducted, followed by recommendations for further research that will support this study.

Chapter 6
Conclusions

6.1 Introduction

This chapter sets out the conclusions of this study. Section 6.2 presents an overview of the study carried out. Section 6.3 sets out the conclusions reached from the main findings obtained, while Section 6.4 puts forward a list of recommendations based on the conclusions of the study. Finally, suggestions for further research are provided for in Section 6.5, while Section 6.6 provides the concluding remarks.

Figure 6.1 hereunder, illustrates the structure of this chapter.

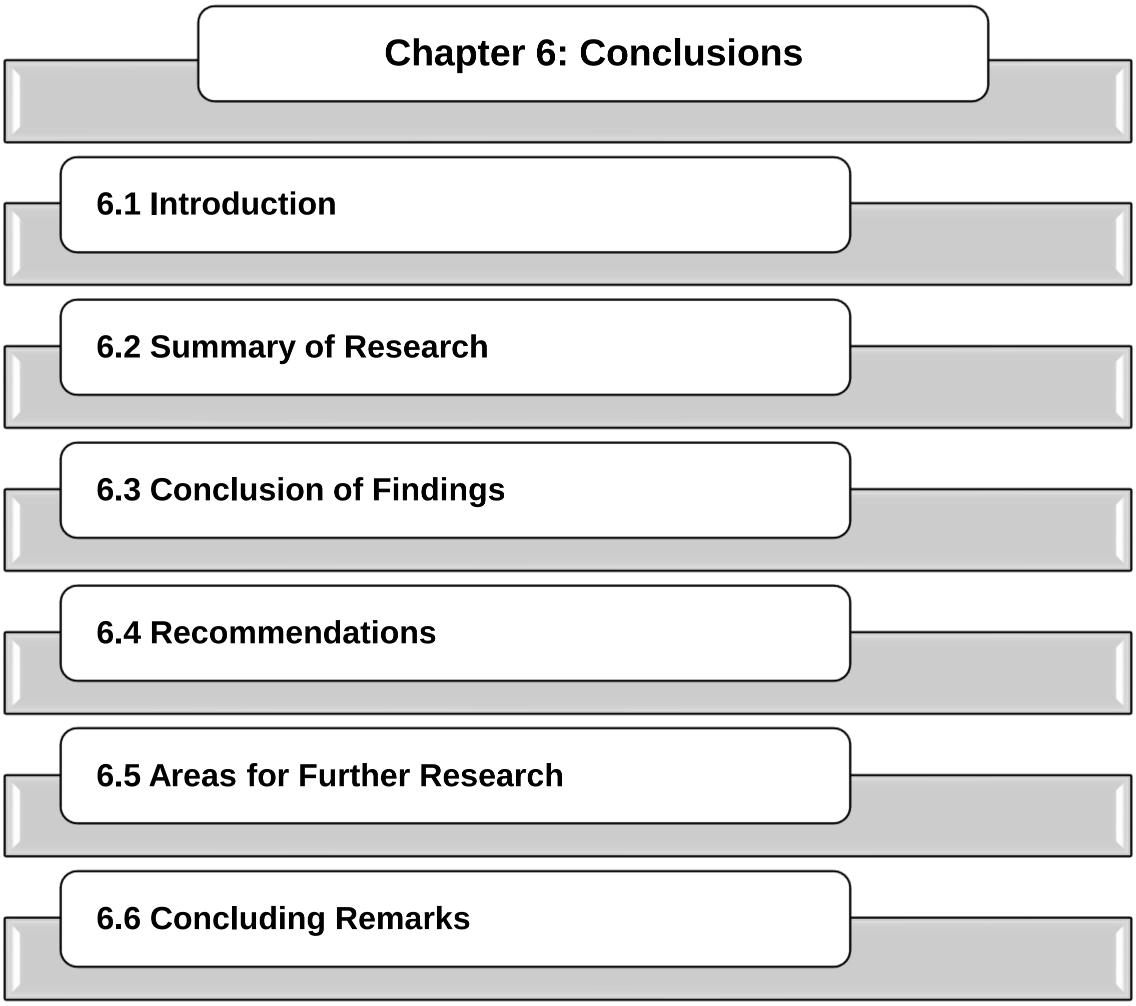

Figure 6.1 - Overview of Chapter 6

6.2 Summary of Research

The central objective of this research is to determine the accuracy of different bankruptcy models developed through different statistical techniques within the Maltese context. An attempt was made to understand which Maltese financial traits best predict the potential for bankruptcy. Moreover, the study aimed at acquiring an understanding of the statistical techniques that best incorporate the identified local traits into an effective bankruptcy prediction model suited for Maltese SMEs. The required information was extracted from the financial statements of local SMEs selected for the purpose of this study, and statistical testing was conducted to examine the explanatory power of accounting ratios in the prediction of corporate failure.

The study commenced by giving an overview of the literature pertinent to the subject area. The numerous interpretations of the term ‘corporate failure’ were discussed with reference made to the presumed roots of failure as well as the path that leads to it. The study further highlighted relevant accounting and auditing provisions set to lessen the adverse impacts of bankruptcy. Furthermore, an overview of the major corporate failure prediction models developed throughout the years was also given, alongside findings retrieved through various empirical studies conducted in the hope of testing the predictive accuracy rate of these models. Additionally, information was also provided about the limitations associated with these default prediction models and about numerous uncertainties associated with their applicability to different settings.

A quantitative approach was employed to gather the necessary data to fulfil the aims of the study. The population for this research comprised of Maltese SMEs registered with the Maltese Business Registry. A paired-sample design was practical for the purpose of this study, and this was constructed according to a set of both general and specific predetermined criteria. The latter enabled the selection of twenty-eight failed companies and twenty-eight corresponding non-failed companies. Based on the availability of data, two bankruptcy prediction models were selected and applied to the local data set to assess their predictive accuracy.

Further, statistical testing using discriminant analysis and probit regression analysis was carried out. This enabled modifications to the selected models to better reflect a distinctive geographical data set, and eventually assess the predictive accuracy of each respective statistical technique within the local context. All financial data was extracted from publicly available financial statements of each selected SME in the sample, pertaining to the last three consecutive years before the defaulted companies filed their declaration of voluntary dissolution and winding up.

The following is an overview of the main findings of the empirical analysis, which address the objectives set for the purpose of this study:

1. **The accuracy of different bankruptcy models developed through different statistical techniques**

   Given that a significant proportion of companies selected for the purpose of this study related to small-sized firms by virtue of the local Companies Act, the most effective models in parallel with the scope of the study were the revised Altman Z”-score Model (2000) and the Zmijewski’s X-score Model (1984). The revised Altman Z”-score Model (2000) was selected from the MDA sphere of statistical techniques, while the Zmijewski’s X-score Model (1984) was the most viable model emerging through probit regression analysis. The selection of these corporate failure prediction models relied solely upon the availability of financial data extracted from the financial statements of each selected company.

   The two original models were fitted on the sample dataset, without adjusting for the geographically distinct setting. As a result, even though average classification reported that the Altman’s Z”-score Model (2000) has a marginally better performance in correctly classifying local companies, this result was presumed to be inconclusive.

2. **Evaluating the explanatory power of the financial ratios making up the chosen bankruptcy models**

   The study aimed to evaluate the explanatory power of the financial ratios making up the two selected bankruptcy prediction models when applied within the local context. More specifically, the study aimed at identifying which of these financial ratios has the greatest discriminatory ability in predicting financial distress amongst Maltese SMEs.

   In this respect, the empirical analysis has revealed that profitability ratios are the most significant contributors to the prediction of corporate default amongst Maltese entities. All other financial ratios tested were found to be insignificant. These results contradicted numerous conclusions reached by local researchers that aimed at identifying the contributors to the prediction of financial distress in Malta. Further, numerous financial ratios were found to have an opposite impact on the resulting prediction when compared to other studies, both local and foreign. These differences could be associated to the distinctive Maltese characteristics as well as to the period for which financial data was extracted. One limitation to the research design was the limited number of companies included. Therefore, a larger number of observations might have generated different findings better reflecting the local economic environment.

3. **Identifying the bankruptcy model most suited for Maltese SMEs**

   Finally, the study aimed at identifying the statistical technique which best incorporates the identified local characteristics into an effective bankruptcy prediction model suited for Maltese SMEs. A definitive conclusion as to which fitted model performs better in predicting potential financial distress of Maltese SMEs was not possible due to the distinctive statistical assumptions employed by the MDA and the probit statistical techniques. This was further restrained by the different set of financial ratios incorporated within the two fitted models. Despite this, the evidence obtained from the empirical analysis favours the models fitted using the probit regression technique as having the better predictive accuracy.

6.3 Conclusion of Findings

Results indicate that the application of both the Altman Z"-score Model (2000) and the Zmijewski's X-score Model (1984) have the ability to provide some indication for bankruptcy potential within the Maltese context. However, they cannot be applied to local companies without any modification due to being developed on a different geographical sample. Despite this, the financial ratios incorporated in each of the respective models proved to be acceptable contributors to the overall prediction of bankruptcy amongst Maltese SMEs.

A clear-cut conclusion with regard to which fitted model performs better in predicting potential bankruptcy in Malta was difficult to reach. This was a result of the distinct statistical assumptions employed by both the discriminant analysis technique and the probit analysis technique. Additionally, the different sets of financial ratios incorporated within the two fitted models further restrain a definitive conclusion. Notwithstanding this, the evidence from the empirical analysis carried out favours the probit regression technique as having the higher accuracy for predicting corporate failure in the Maltese context. The robustness of this statistical technique within the local context was further highlighted by its ability to report high predictive accuracy despite being developed on a sample data set which was not adjusted for potential outliers.

Another important finding of the empirical analysis is that profitability ratios are the most significant contributors to the prediction of corporate default amongst Maltese entities. Out of the numerous independent variables tested, the ratio of profits to total assets was found to possess the strongest discriminatory ability in classifying the financial statements selected for the sample data set into their failed and non-failed groupings. This clearly indicates that the ability of local companies to effectively utilise their acquired assets to generate earnings is a distinguishing characteristic that can flag out Maltese SMEs which may be at risk of default.

6.4 Recommendations

Below are recommendations resulting from the findings of this study:

1. **The development of a corporate failure prediction model using probit regression analysis as a statistical technique**

Even though a definitive conclusion as to which fitted model performs better in predicting potential financial distress of Maltese SMEs was not possible, the evidence obtained from the empirical analysis favours the models fitted using the probit regression technique as having the better predictive accuracy. In light of this, bankruptcy models developed using the probit statistical technique are recommended. This will ensure the development of a statistical model that best incorporates the identified local traits into a corporate failure prediction model.

2. **The incorporation of conventional accounting ratios in bankruptcy prediction models which better reflect the distinctive characteristics of the local economic environment**

The ratios of profits to total assets were the only financial ratios which reported discriminatory ability in predicting financial distress when applied to the local sample selected. In this respect, it is advised that a corporate failure prediction model specifically developed for Maltese entities should incorporate profitability ratios amongst others. This will ensure practicality in the development of a corporate failure prediction model, as the model would incorporate the identified local traits as predictors for potential default.

3. **Periodic reviews of bankruptcy prediction models developed specifically for the Maltese economic environment**

Irrespective of the effectiveness of a corporate failure prediction model, its predictive capability will deteriorate as the economic environment changes and evolves. In fact, the coefficients of both the Altman's Z"-score Model (2000) and the Zmijewski's X-score Model (1984) were found to be unstable and sensitive to time changes. For this reason, it is recommended that models developed to handle bankruptcy forecasting should be reviewed periodically. This will ensure that bankruptcy prediction models which are specifically developed for use within the local context better reflect the present economic setting and generate unbiased results.

6.5 Areas for Further Research

The study aimed at strengthening the forecasting ability for potential bankruptcy within the Maltese context by testing the statistical technique that best incorporates local traits into an effective bankruptcy prediction model. Managerial judgements, credit approvals, as well as the wider economic environment of Malta can benefit profoundly from the practical application of a corporate failure prediction model specifically developed for Maltese SMEs. Several empirical studies are suggested hereunder, that can further extend the research undertaken in this dissertation.

1. **Testing other algorithms and techniques that may better predict the probability of default amongst Maltese SMEs**

Due to the limited data and a constrained time frame, the models fitted using discriminant analysis and probit regression respectively were only validated on the test data set established for the purpose of this study. For this reason, their bankruptcy prediction ability was confined to the sample selected. Their application to a wider set of data distinct from that chosen for the purpose of this study would evaluate further their predictive accuracy and consequently their applicability to the Maltese corporate environment.

Further, due to time constraints, statistical testing was restricted to only two statistical techniques, namely the MDA technique and the probit regression technique. Researchers could further investigate the development of corporate failure prediction models using different statistical methodologies other than those utilised for the purpose of this study. By using logistic regression analysis or else ANNs, further evaluation is rendered possible in selecting the model with the highest predictive ability.

2. **Investigating the explanatory power of conventional accounting ratios and their relation to predicting financial distress amongst Maltese entities**

The empirical analysis highlighted that not all financial ratios included in the models selected by Altman's Z"-score Model (2000) and Zmijewski's X-score Model (1984) were found to have discriminatory ability when tested within the Maltese setting. Numerous other accounting ratios that can easily be computed from the extracted financial data could be employed as independent variables in the prediction models. Other financial ratios may include the *Acid-Test Ratio*[40] or the *Proprietary Ratio*[41]. Degrees of correlation between the selected independent variables should be first evaluated in order to refrain from including financial ratios that assess identical concepts in the same model. By incorporating the most significant financial ratios within the bankruptcy prediction model, better overall predictive accuracy should be generated.

3. **Developing industry-specialised bankruptcy prediction models that incorporate the distinctive characteristics present within the Maltese economic environment**

The empirical analysis could be further extended by testing for Maltese financial traits that best forecast the potential for bankruptcy in specific industries. The study can incorporate larger groups of data divided into clusters in accordance with the specific industry in which the selected companies operate, and statistical testing can be carried out for each cluster identified. This will enable better assessment of model validation by using numerous other models, both parametric and non-parametric. Moreover, the robustness of the model and parameter stability can be better analysed, resulting in industry-specific developed models for predicting bankruptcy for Maltese SMEs.

[40] The acid-test ratio is an estimation of whether the entity has sufficient short-term assets at its disposal to cover its short-term debt, that is, current assets less inventory divided by current liabilities.

[41] The proprietary ratio is an indicator of financial stability that provides an estimation of the company's capital amount that is used to support its financial well-being, that is, shareholder's equity divided by total tangible assets.

6.6 Concluding Remarks

The applicability and performance of bankruptcy prediction models rely heavily on the statistical techniques implemented for their development. Numerous local analysts and researchers have investigated different approaches in the hope of identifying the model that provides the highest accuracy. However, many failed to test which statistical technique best incorporates local traits into an effective bankruptcy prediction model suited for Maltese SMEs.

The study concluded that the development of a model using the probit regression technique best incorporates the identified local traits into an effective bankruptcy prediction model for Maltese entities. Even though further research in this area is imperative to substantiate the applicability of such statistical technique in different time horizons, these findings should provide a better understanding of which Maltese economic characteristics can identify SMEs which may be at risk of default.

References

ALLEN, D. E., and CHUNG, J. (1998). A Review of Choice of Model and Statistical Techniques in Corporate Distress Prediction Studies. *Accounting Research Journal, 11*(1), 245-269.

ALTMAN, E. I. (2000). Predicting Financial Distress of Companies: Revisting the Z-Score and ZETA* Models. *New York University*, pp.26-50 doi:10.4337/9780857936097.00027.

ALTMAN, E. I. (1993). *Corporate Financial Distress and Bankruptcy: A Complete Guide to Predicting and Avoiding Distress and Profiting From Bankruptcy.* 2nd ed., New York: John Willey and Sons. Inc.

ALTMAN, E. I. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *The Journal of finance, 23*(4), 589-609. Available: https://www.jstor.org/stable/2978933.

ALTMAN, E. I., and HOTCHKISS, E. (2006). Predict and Avoid Bankruptcy, Analyse and Invest in Distressed Debt. In *Corporate Financial Distress and Bankruptcy.* 3rd ed., New Jersey: John Willey & Sons. Inc., pp. 265-280.

ALTMAN, E. I., SABATO, G., and WILSON, N. (2008). The Value of Qualitative Information in SME Risk Management [Semantic Scholar], [Online]. Available: http://pages.stern.nyu.edu/~ealtman/SME_EA_GS_NW.pdf [19 March, 2020].

ARGENTI, J. (1976). *Corporate Collapse: The Causes and Symptoms.* London: McGraw-Hill.

AZZOPARDI, D. (2007). *Corporate Failure Prediction Models: The Perception of Maltese Stockbrockers.* (Unpublished M.A. Dissertation): University of Malta.

BEAVER, W. H. (1968). The Information Content of Annual Earnings Announcements. *Journal of Accounting Research, 6*, 67-92.

BEAVER, W. H. (1966). Financial Ratios as Predictors of Failure. *Journal of Accounting Research, 4*, 71-11. Available: https://www.jstor.org/stable/2490171.

BELLOVARY, J. L., GIACOMINO, D. E., and AKERS, M. D. (2007). A Review of Bankruptcy Prediction Studies: 1930-Present. *Journal of Financial Education, 33*, 1-42.

BORITZ, J. E., KENNEDY, D. B., and ABLUQUERQUE, A. M. (1993). Predicting Corporate Failure Using a Neural Network Approach. *Intelligent Systems in Accounting, Finance and Management, 4*, 95-111.

BRADLEY III, D. B., and RUBACH, M. J. (2002). *Trade Credit and Small Businesses: A Cause of Business Failures?* (Unpublished Report): University of Central Arkansas.

BRUNO, A. V., and LEIDECKER, J. K. (1988). Causes of New Venture Failure: 1960s vs. 1980s. *Business Horizons, 31*(6), 51-56. doi:https://doi.org/10.1016/0007-6813(88)90024-9.

BURGELMAN, R. A. (1991). Intraorganizational Mortality: Liabilities of Newness and Adoloscence. *Organization Science, 2*(3), 239-262.

EISENBEIS, R. (1977). Pitfalls in the Application of Discriminant Analysis in Business, Finance, and Economics. *Journal of Finance, 32*(3), 875-900.

ELSA, I., and ALODIA, C. I. (2017). The Analysis of Altman Model and Ohlson Model in Predicting Financial Distress of Manufacturing Companies in the Indonesia Stock Exchange. *Indian-Pacific Journal of Accounting and Finance, 1*(1), 51-63.

EUROPEAN COMMISSION (2019). *SBA Fact Sheet - Malta.* Luxembourg: Publications Office of the European Union.

EUROPEAN COMMISSION (2015). *User Guide to the SME Definition.* Luxembourg: Publications Office of the European Union. Available: https://businessenhance.gov.mt/en/schemes/Documents/Reference%20

Documents/SME%20Definition%20-%20User%20Guide.pdf [15 March, 2020].

FALZON, S. (2011). *The Power of Selected Corporate Failure Prediction Models in the Local Context.* Accountancy. (Unpublished M.A. Dissertation): University of Malta.

FATMAWATI, M. (2012). Penggunaan The Zmijewski Model, The Altman Model, Dan The Springate Model Sebagai Prediktor Delisting. *Jurnal Keuangan dan Perbankan, 16*(1), 56-65. Available: https://jurkubank.wordpress.com/.

FICHMAN, M., and LEVINTHAL, D. A. (1991). Honeymoon and Liability of Adolescence: A New Perspective on Duration Dependence in Social and Organizational Relationships. *Academy of Management Review, 16*(2), 442-468.

FITZPATRICK, P. J. (1932). A Comparison of Ratios of Successful Industrial Enterprises with those of Failed Firm. *Certified Public Accountant, 12*, 598-605, 656-662, 727-731.

FRANCALANZA, C. A., and BORG, B. (2000). Small Business Failure and the Maltese Commercial Environment. *Bank of Valletta Review, 22* (Autumn 2000), 28-43.

GHARGHORI, P., CHAN, H. W., and FAFF, R. (2006). Investigating the Performance of Alternative Default-Risk Models: Option-Based versus Accounting-Based Approaches. *Australian Journal of Management, 31*(2), 207-234.

GILBERT, L. R., MENON, K., and SCHWARTZ, K. B. (1990). Predicting Bankrupcty for Firms in Financial Fistress. *Journal of Business Finance and Accounting, 17*(1), 161-171.

GRICE, J. S., and DUGAN, M. T. (2001). The Limitations of Bankrupcty Prediction Models: Some Cautions for the Researcher. *Review of Quantitative Finance and Accounting, 17*(2), 151-166.

HILLEGEIST, S., E, K., CRAM, D., and LUNDSTEDT, K. (2004). Assessing the Probability of Bankruptcy. *Review of Accounting Studies, 9*(1), 5-34.

HUSEIN, M. F., and PAMBEKTI, G. T. (2014). Precision of the Models of Altman, Springate, Zmijewski, and Grover for Predicting the Financial Distress. *Journal of Economics, Business and Accountancy, 17*(3), 405-416. doi:10.14414/jebav.14.1703010.

INTERNATIONAL ACCOUNTING STANDARDS BOARD (2012). *IAS 1 - Presentation of Financial Statements*. Available: http://www.ifrs.org/Documents/IAS1.pdf [12 September, 2019].

INTERNATIONAL FEDERATION OF ACCOUNTANTS (2006). *IAS 570 - Going Concern*. Available: https://www.ifac.org/system/files/downloads/a031-2010-iaasb-handbook-isa-570.pdf [12 September, 2019].

KALE, S., and ARDITI, D. (1998). Business Failures: Liabilities of Newness, Adolescence and Smallness. *Journal of Construction Engineering anf Management, 24*(6), 279-302.

KARAMZADEH, M. S. (2012). Application and Comparison of Altman and Ohlson Models to Predict Bankrupcty of Companies. *Research Journal of Applied Sciences, Engineering and Technology, 5*(6), 2007-2011.

KARAS, M., and PAVLA, S. (2019). Predicting Bankruptcy in Construction Business: Traditional Model Validation and Formulation of a New Model. *Journal of International Studies, 12*(1), 283-296. doi:10.14254/2071-8330.2019/12-1/19.

KIDANE, H. W. (2004). *Predicting Financial Distress in IT and Services Companies in South Africa.* University of the Free State , Business Management . (Unpublished M.A Dissertation): University of the Free State, Republic of South Africa. Available: http://hdl.handle.net/11660/1117.

LAITINEN, E. K. (1993). Financial Predictors for Different Phases of the Failure Process. *Omega, Elsevier, 21*(2), 215-228.

LAITINEN, T., and KANKAANPAA, M. (1999). Comparative Analysis of Failure Prediction Methods: The Finnish Case. *European Accounting Review, 8*(1), 67-92.

LEVRATTO, N. (2013). From Failure to Corporate Bankruptcy: A Review. *Journal of Innovation and Entrepreneurship, 2*(20), 1-15. Available: https://innovation-entrepreneurship.springeropen.com/articles/10.1186/2192-5372-2-20.

LIN, H. (2015). Default Prediction Model for SME's: Evidence from UK Market Using Financial Ratios. *International Journal of Business and Management, 10*(2), 81-106. doi:10.5539/ijbm.v10n2p81.

MOGHADAM, A. G., GHOLAMPOUR, M. M., and ZADEH, F. N. (2009). Review of the Prediction Power of Altman and Ohlson Models in Predicting Bankrupcty of Listed Companies in Tehran Stock Exchange. *Knowledge and Development, 16*(28), 176-192.

MOSSMAN, C. E., BELL, G. G., SWARTZ, L. M., and TURTLE, H. (1998). An Empirical Comparison of Bankruptcy Models. *Financial Review, 33*(2), 35-54.

ODOM, M. D., and RAMESH, S. (1990). A Neural Network Model for Bankruptcy Prediction. *International Joint Conference on Neural Networks, 2*, 163-168. doi:10.1109/IJCNN.1990.137710.

OOGHE, H., and PRIJCKER, S. D. (2008). Failure Processes And Causes of Company Bankruptcy: A Typology. *Management Decision, 46*(2), 223-242. doi:10.1108/00251740810854131.

OOGHE, H., and WAEYAERT, N. (2004). Oorzaken Van Faling: Literatuuroverzicht En Conceptueel Verklaringsmodel. *Economisch en Sociaal Tijdschrift, 57*(4), 367-393.

PLATT, H. D., and PLATT, M. B. (2002). Predicting Corporate Financial Distress: Reflections on Choice-Based Sample Bias. *Journal of Economics and Finance, 26*, 184-199. doi:https://doi.org/10.1007/BF02755985.

PRIMASARI, N. S. (2017). Analysis Altman Z-Score, Grover Score, Springate and Zsmijewski as Financial Distress Signaling: Empirical Study of Consumer Goods Industry in Indonesia. *Accounting and Management Journal, 1*(1), 23-42. doi:10.13140/RG.2.2.34759.39844.

RACKO, P. (2007). *Statistical Credit Risk Models.* (Unpublished M.A. Dissertation): University of Vienna. doi:10.25365/thesis.210**.**

RIVERA, S. I., ROMAN, J., and SCHAEFER, T. (2018). An Application of the Ohlson Model to Explore the Value of Big Data for AT&T. *Academy of Accounting and Financial Studies, 22*(1), 1-9. doi:1528-2635-22-1-103.

SAMUELS, J., BRAYSHAW, R., and CRANER, J. (1999). Financial Statement Analysis in Europe. *The International Journal of Accounting, 34*(4), 615-617.

SHARMA, S., and MAHAJAN, V. (1980). Early Warning Indicators of Business Failure. *Journal of Marketing, 44*, 80-89.

SHERBO, A., and SMITH, A. (2013). The Altman Z-Score Bankruptcy Model at Age 45: Standing the Test of Time? *American Bankrupcty Institute Journal, 32*(11), 41-86.

SILVESTRI, A., and VELTRI, S. (2012). A Test of the Ohlson Model on the Italian Stock Exchange. *Accounting and Taxtion, 4*(1), 83-94.

SINGH, B. P., and MISHRA, A. K. (2016). Re-estimation and Comparisons of Alternative Accounting Based Bankruptcy Prediction Models for Indian Companies. *Financial Innovation, 2*(6), 1-28.

SPRINGATE, G. L. (1978). *Predicting the Possibility of Failure in a Canadian Firm: A Discriminant Analysis.* (Unpublished M.A. Dissertation): Simon Fraser University, Canada.

TALEBNIA, G., KARMOZI, F., and RAHIMI, S. (2016). Evaluating and Comparing the Ability to Predict the Bankruptcy Prediction Models of Zavgren and Springate in Companies Accepted in Tehran Stock Exchange. *Marketing and Branding Research, 3*, 137-143.

VASSALLO, Y. M. (2016). *An Analysis of Corporate Failure and Related Weaknesses in the Maltese Scenario.* Accountancy . (Unpublished M.A. Dissertation): University of Malta.

VELLA, A. (2004). *The Relation within the Maltese Context of Springate's Z-Score Measure and Non-Financial Measures of Predicting Corporate Failure: An Investigation.* (Unpublished M.A. Dissertation): University of Malta.

ZAMMIT, M. (2005). *Conventional Accounting Ratios and their Relative Power in the Prediction of Corporate Failure: A Local Investigation.* (Unpublished M.A. Dissertation): University of Malta.

ZAVGREN, C. (1985). Assessing the Vulnerability to Failure of American Industrial Firms: A Logistic Analysis. *Journal of Business Finance & Accounting, 12*(1), 19-45.

ZMIJEWSKI, E. M. (1984). Methodological Issues Related to the Estimation of Financial Distress Prediction Models. *Journal of Accounting Research, 22*, 59-82. doi:10.2307/2490859.

ZWEIG, M., and CAMPBELL, G. (1993). Receiver-Operating Characteristic (ROC) Plots: A Fundamental Evaluation Tool in Clinical Medicine. *Clinical Chemistry, 39*(4), 561-577.

<u>Acts of Parliament</u>

Companies Act 1995 (c.386). Malta. Available: http://www.justiceservices.gov.mt/DownloadDocument.aspx?app=lom&itemid=8853 [24 March, 2020].

Insolvency Act 1986 (c.XI). United Kingdom. Available: http://www.legislation.gov.uk/ukpga/1986/45/contents [25 March, 2020].

Appendix 1

Article 185(1)(a) of Companies Act

Overview

Enclosed in this section is an extract of Article 185(1)(a) of the local Companies Act, where the stipulated criteria referred to in Section 3.3 are listed for the filing of abridged financial statements.

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least one director of the company or the company secretary and forwarded to the Registrar for registration within forty-two days after the date to which it is made up. Where the annual return is forwarded to the Registrar by electronic means it may be signed by one director or the company secretary or by an individual specifically authorised for such purpose by the memorandum, or by a resolution of the board of directors, or by an extraordinary resolution of the company. The signature of such annual return shall be by means of an electronic signature duly recognised by the Registrar.

(3) If default is made in complying with the provisions of this article, every officer of the company who is in default shall be liable to a penalty, and, for every day during which the default continues, to a further penalty.

Exemptions for certain small companies. *Amended by: IV. 2003.81; L.N. 391 of 2005; L.N. 425 of 2007; IX. 2008.27; XXXI. 2015.16.*

185. (1) Companies which on their balance sheet dates do not exceed the limits of two of the three following criteria:

- balance sheet total: four million euro (4,000,000);
- turnover: eight million euro (8,000,000);
- average number of employees during the accounting period: fifty (50);

shall in this Chapter be designated as "small companies" and shall be exempted from the requirement imposed by article 177. When advantage is taken of this exemption the information required in paragraph 3 of the Sixth Schedule regarding the acquisition by a company of its own shares shall be given in the notes to the accounts.

(2) Private companies which on their balance sheet dates do not exceed the limits of two of the three following criteria:

- balance sheet total: forty-six thousand six hundred euro (46,600);
- turnover: ninety-three thousand euro (93,000);
- average number of employees during the accounting period: two (2);

shall be exempted from the provisions of Chapter IX of Title I of Part V and from the requirements imposed by article 179 and the Third Schedule.

(3) Where on its balance sheet date other than its first balance sheet date, a company exceeds or ceases to exceed the limits of two of the three criteria indicated in sub-articles (1) and (2), that fact shall affect the application of the derogation provided for in those sub-articles only if it occurs in two consecutive accounting periods.

(4) The balance sheet total referred to in this article shall be calculated by taking the amount of total assets shown in the balance sheet drawn up in accordance with generally accepted accounting principles and practice.

Figure A.1.1 - Extract of Article 185(1)(a) of the local Companies Act

Appendix 2

Paired-Sample Design

Introduction

Enclosed in this section is the paired-sample design referred to in Section 3.3.2

Overview of the Paired-Sample Design

For every failed firm, a corresponding non-failed firm was selected. This matching process was done in accordance to company size and industry. Further to this, the same three-year period was also selected for each company pair.

Table A.2.1 below illustrates the twenty-eight sets of companies and their respective nature of operations, as well as the period chosen for each pair.

Failed Firms (Category 1)	Non-Failed Firms (Category 2)	Period	Nature of Operations
5050 Poker Ltd	Merkur Interactive Malta P.L.C	2009 2010 2011	Online Gaming
Aka Investment Holdings Limited	Ben Estates Ltd	2013 2014 2015	Estate Agents
Avery Dennison Holdings (Malta) Limited	A.G. Investments Limited	2006 2007 2008	Investment Services
Bowtie Confectionery Limited	Dolceria Italiana Limited	2004 2005 2006	Manufacture/Wholesale (Food)
Cassar Stores Company Limited	Euro Appliances Company Limited	2009 2010 2011	Wholesale/Retail (Domestic Appliances)
Europ-Star Limited	DC Aviation Limited	2013 2014 2015	Aircraft Charter
Fredonia Company Limited	Filtons Clothing Company Limited	2012 2013 2014	Manufacture/Retail (Clothing)
Good Look Marble Works Limited	Belair Real Estate Ltd	2012 2013 2014	Property Letting

I.C.C Limited	B.T.I Limited	2001 2002 2003	Manufacture/Production (Uniforms)
J.A. Aluminium Limited	A&C Alumium Limited	2009 2010 2011	Aluminium Apertures and Fixtures
JL Investments Malta Limited	Rabelink International Freight (Malta) Limited	2014 2015 2016	Shipping Agents
JP Baldaszti Holding Limited	MPS Limited	2011 2012 2013	Marketing/Advertising
Latency Engineering Blue Limited	SC Engineering Supply Ltd	2014 2015 2016	Engineering Services
Lighthouse Toys Limited	Tradeways Limited	2001 2002 2003	Manufacture/Retail (Toys)
Marine Asset Management Ltd	Petecraft Limited	2010 2011 2013	Seacraft Charter
Media Entertainment Ventures International Limited	Professional Marketing Services Limited	2007 2008 2009	Marketing/Advertising
Naviga Ltd	Sailpower Limited	2007 2008 2009	Boat Leasing and Charter
Nextweb Limited	William J. England & Son Limited	2004 2005 2006	Computer Networks
NGN Europe Limited	Connect Limited	2014 2015 2016	Telecommunication Systems
Nick Demicoli Construction Co. Ltd	Blokrete Limited	1997 1998 1999	Property Construction

Personal Exchange International Limited	Cash Point (Malta) Limited	2013 2014 2015	Remote Gaming
Pno Casino Limited	Tain Betting Promotion Limited	2014 2015 2016	Online Gaming
Prestige Printers Ltd	Merlin Publishers Limited	2005 2006 2007	Publishers
Smart Digital Network Limited	Smart Technologies Software Limited	2006 2007 2008	Retail (Electronic Equipment)
Suffolk Limited	Busy Bee Limited	2005 2006 2007	Catering Services
The Best of Malta (Travel & Tourism) Ltd	Tristar Travel Ltd	2003 2004 2005	Travel Agency
Wavebet International Limited	Co-Gaming Limited	2012 2013 2014	Online Betting
Woodline Limited	Desira Woodworks Ltd	2004 2005 2006	Manufacture (Furniture)

Table A.2.1 – Paired-sample selected

Appendix 3
Secondary Data

Introduction

Enclosed in this section is the secondary data extracted from the publicly available financial statements of each selected local company in the sample, as referred to in Section 3.4.

Overview of the Extracted Sample Data

The sample data enclosed hereunder relate to the financial data required to compute the two selected bankruptcy prediction models[42] evaluated by this study. The financial knowledge relates to figures stipulated in publicly available financial statements of both failed and non-failed companies. Furthermore, the same financial data was extracted for each of the three-year period chosen for every pair selected, as illustrated in the paired-sample design[43].

It is critical to mention that financial information extracted pertained to years prior to Malta's accession to the EU, as well to periods afterwards. For this reason, some of the figures extracted are denoted in the Maltese Lira (LM), while others are denoted in Euro (€). The differences in currency had no effect on the findings obtained.

[42] Refer to Section 3.5, Equation 2.2 and Equation 2.5
[43] Refer to Appendix 2

Failed Group	5050 Poker Ltd			AKA Investment Holdings Limited			Avery Dennison Holdings (Malta) Limited		
Year Prior to Failure	1 year	2 years	3 years	1 year	2 years	3 years	1 year	2 years	3 years
	€	€	€	€	€	€	€	€	€
Current Assets	400,111	1,003,917	179,892	153,902	71,094	58,089	15,135,633	15,062,061	14,991,218
Current Liabilities	421,995	941,793	197,709	91,351	138,366	130,289	118,772	69,145	36,440
Retained Earnings	(42,542)	(35,377)	(70,013)	1,992	(16,914)	(30,175)	166,741	142,796	104,658
EBIT	(7,324)	34,376	(36,539)	26,464	17,624	15,117	(35,832)	(21,641)	(8,324)
Total Assets	419,453	1,025,875	179,892	1,851,883	1,789,329	1,796,578	16,785633	16,712,061	16,641,218
MV of Equity	40,000	40,000	40,000	10,000	10,000	10,000	16,500,120	16,500,120	16,500,120
Total Liabilities	421,995	1,021,252	209,905	1,832,891	1,816,753	1,816,753	118,772	69,145	36,440
Net Income	(7,165)	34,636	(36,493)	18,906	13,261	11,242	23,945	38,138	51,455

Non-Failed Group	Merkur Interactive Malta P.L.C.			Ben Estates LTD			A.G. Investments Limited		
Year Prior to Failure	1 year	2 years	3 years	1 year	2 years	3 years	1 year	2 years	3 years
	€	€	€	€	€	€	€	€	€
Current Assets	6,135	12,739	19,848	83,306	36,240	11,561	421,305	272,236	124,160
Current Liabilities	2,894	26,200	27,414	128,037	81,560	66,638	836,775	668,431	266,455
Retained Earnings	(47,134)	(38,461)	(32,566)	71,234	48,238	3,539	59,296	58,976	22,701
EBIT	(7,167)	(5,932)	(11,323)	35,990	69,380	18,871	320	2,617	9,543
Total Assets	6,135	12,739	19,848	344,685	285,920	255,534	3,213,069	3,143,610	1,231,049
MV of Equity	25,000	25,000	25,000	21,500	21,500	21,500	349,406	349,406	150,000
Total Liabilities	28,269	26,200	27,414	251,951	216,182	230,495	2,804,367	2,735,228	1,058,348
Net Income	(8,673)	(5,895)	(11,288)	22,996	44,699	11,899	320	2,617	9,543

Failed Group	Bowtie Confectionery LTD			Cassar Stores Company Limited			Europ-Star Limited		
Year Prior to Failure	1 year	2 years	3 years	1 year	2 years	3 years	1 year	2 years	3 years
	LM	LM	LM	€	€	€	€	€	€
Current Assets	45	43,746	45,833	2,188	22,136	28,857	534,459	1,485,967	1,261,612
Current Liabilities	165,571	190,651	176,030	2,204	24,488	32,704	611,762	1,470,049	1,241566
Retained Earnings	(184,879)	(161,920)	(145,235)	(2,345)	(1,781)	(3,241)	(205,878)	(94,941)	(90,451)
EBIT	(22,300)	(14,874)	(11,492)	(564)	1,460	(2,874)	(85,926)	67,828	12,052
Total Assets	23,567	71,606	73,760	2,188	25,036	31,792	575,884	1,545,104	1,321,115
MV of Equity	21,000	21,000	21,000	2,329	2,329	2,329	170,000	170,000	20,000
Total Liabilities	197905	212,526	197,905	2,204	24,488	32,704	611,762	1,470,049	1,391,566
Net Income	(22959)	(166,685)	(13,249)	(564)	1,460	(2,874)	(110,937)	(4,490)	(2,197)

Non-Failed Group	Dolceria Italiana Limited			Euro Appliances Company Limited			DC Aviation Limited		
Year Prior to Failure	1 year	2 years	3 years	1 year	2 years	3 years	1 year	2 years	3 years
	LM	LM	LM	€	€	€	€	€	€
Current Assets	27,840	30,394	23,304	169,209	160,622	158,936	272,780	314,178	251,713
Current Liabilities	51,414	59,286	47,938	1,644,215	1,643,094	1,642,467	253,719	313,081	321,268
Retained Earnings	(2,576)	(5,702)	(7,355)	(1,522,835)	(1,530,301)	(1,531,360)	31,040	(35,335)	(56,509)
EBIT	4,809	1,653	8,395	(1,470)	(2,859)	53,423	98,186	34,091	(28,527)
Total Assets	58,838	63,584	54,681	169,209	160,622	158,936	340,375	327,746	314,759
MV of Equity	10,000	10,000	10,000	2,329	2,329	2,329	50,000	50,000	50,000
Total Liabilities	51,414	59,286	52,036	1,689,715	1,688,594	1,687,967	259,335	313,081	321,268
Net Income	3,126	1,653	8,395	7,466	1,059	54,373	68,375	21,174	(20,794)

Failed Group	Fredonia Company Limited			Good Look Marble Works Limited			I.C.C Limited		
Year Prior to Failure	1 year	2 years	3 years	1 year	2 years	3 years	1 year	2 years	3 years
	€	€	€	€	€	€	LM	LM	LM
Current Assets	35,790	72,145	60,915	100	56	12	198,890	177,341	175,448
Current Liabilities	66,738	95,870	76,557	97,050	99,157	100,435	261,865	195,727	426,340
Retained Earnings	(30,115)	(30,026)	(21,629)	(30,646)	(31,786)	(31,864)	(246,988)	(251,122)	(262,639)
EBIT	(7,430)	(8,400)	(9,758)	8,806	7,574	5,433	22,335	31,644	28,784
Total Assets	36,623	73,185	62,269	66,404	67,604	68,804	220,497	208,406	214,566
MV of Equity	4,660	4,660	4,660	233	233	233	31,400	31,400	31,400
Total Liabilities	66,738	95,870	76,557	97,050	99,157	100,435	424,406	195,727	426,340
Net Income	(7,430)	(8,400)	(9,758)	907	78	323	241	7,624	2,231

Non-Failed Group	Filtons Clothing Company Limited			Belair Real Estate LTD			B.T.I. Limited		
Year Prior to Failure	1 year	2 years	3 years	1 year	2 years	3 years	1 year	2 years	3 years
	€	€	€	€	€	€	LM	LM	LM
Current Assets	143,019	115,724	122,316	235,406	156,381	45,805	331,551	321,879	315,148
Current Liabilities	69,708	50,337	65,695	242,074	237,181	145,941	265,338	253,101	213,801
Retained Earnings	96,410	88,560	79,868	333,137	224,245	168,957	3,440	2,935	35,470
EBIT	7,850	8,690	2,311	131,237	96,678	78,167	505	(32,535)	3,063
Total Assets	211,541	184,320	190,986	908,172	843,118	743,919	348,778	336,036	329,271
MV of Equity	45,423	45,423	45,423	1,998	1,998	1,998	40,000	40,000	40,000
Total Liabilities	69,708	50,337	65,695	559,889	603,728	559,817	305,338	293,101	253,801
Net Income	7,850	8,690	2,311	108,892	55,288	41,217	505	(32,535)	3,063

Failed Group	J.A. Aluminium Limited			JL Investments Malta Limited			JP Baldaszti Holding Limited		
Year Prior to Failure	**1 year**	**2 years**	**3 years**	**1 year**	**2 years**	**3 years**	**1 year**	**2 years**	**3 years**
	€	**€**	**€**	**€**	**€**	**€**	**€**	**€**	**€**
Current Assets	193,456	323,492	322,900	4,237,102	15,457,473	11,820,175	7,030	173,622	70,015
Current Liabilities	149,513	226,193	229,276	35,845,015	46,664,722	45,803,399	149,321	105,949	71,800
Retained Earnings	(107,436	(56,287)	(47,514)	(5,691,607)	(6,394,351)	(9,029,019)	(331,264)	0	(2,025)
EBIT	(51,149)	(8,773)	(2,691)	554,695	2,618,158	(4,112,737)	(331,339)	273,026	(2,027)
Total Assets	190,712	335,941	340,397	30,154,408	40,271,536	36,775,545	66,186	235,122	66,186
MV of Equity	18,635	18,635	18,635	1,165	1,165	1,165	240	240	240
Total Liabilities	279,513	373,953	369,276	35,854,015	46,664,722	45,803,399	397,210	234,882	71,800
Net Income	(51,149)	(8,773)	(2,691)	702,579	2,634,668	(3,951,069)	(331,264)	177,548	(2,025)

Non-Failed Group	A & C Aluminium Limited			Rabelink International Freight (Malta) Limited			MPS Limited		
Year Prior to Failure	**1 year**	**2 years**	**3 years**	**1 year**	**2 years**	**3 years**	**1 year**	**2 years**	**3 years**
	€	**€**	**€**	**€**	**€**	**€**	**€**	**€**	**€**
Current Assets	54,973	46,421	50,345	86,094	67,992	71,918	1,716,249	2,456,786	1,936,364
Current Liabilities	88,250	77,138	81,013	61,727	46,264	49,892	1,614,962	2,325,302	1,649,447
Retained Earnings	(92,910)	(92,361)	(90,163)	13,672	7,522	2,998	55,489	102,647	300,813
EBIT	(3,869)	(1,795)	6,206	8,069	4,555	11,194	(47,158)	(198,166)	(174,023)
Total Assets	277,402	258,376	264,453	98,693	77,080	76,184	1,905,465	2,662,161	2,203,059
MV of Equity	23,294	23,294	23,294	23,294	23,294	23,294	232,937	232,937	232,937
Total Liabilities	176,459	156,884	160,762	61,727	46,264	49,892	1,616,574	2,326,112	1,668,841
Net Income	(3,869)	(1,795)	6,206	6,150	4,524	11,394	(47,158)	(198,166)	(174,023)

Failed Group	Latency Engineering Blue Limited			Lighthouse Toys Limited			Marine Asset Management LTD		
Year Prior to Failure	1 year	2 years	3 years	1 year	2 years	3 years	1 year	2 years	3 years
	€	€	€	LM	LM	LM	€	€	€
Current Assets	2,187,920	4,056,147	3,321,120	110,186	132,720	141,866	23,370	204,120	880,162
Current Liabilities	2,482,398	2,101,771	1,948,268	255,084	241,195	249,816	291,580	286,705	1,914,137
Retained Earnings	(238,060)	285,357	0	(285,033)	(241,105)	(233,696)	(2,380,782)	(1,918,708)	(1,074,742)
EBIT	(402,001)	435,281	3,730,742	(31,291)	6,681	3,202	105,029	(159,587)	(66,838)
Total Assets	2,187,920	4,056,147	3,321,120	147,421	177,460	193,490	2,692,774	3,207,200	1,736,162
MV of Equity	1,200	1,200	1,200	101,510	101,510	101,510	1,250	1,250	1,250
Total Liabilities	2,482,398	3,700,481	3,221,998	272,624	258,735	267,356	5,072,306	5,124,658	2,809,654
Net Income	(364,787)	256,544	2,424,982	(43,928)	(7,409)	(11,759)	(462,074)	(843,966)	(722,066)

Non-Failed Group	SC Engineering Supply LTD			Tradeways Limited			Petecraft Limited		
Year Prior to Failure	1 year	2 years	3 years	1 year	2 years	3 years	1 year	2 years	3 years
	€	€	€	LM	LM	LM	€	€	€
Current Assets	502,530	414,237	343,999	303,487	324,819	311,745	138,986	127,996	82,283
Current Liabilities	192,711	164,164	168,896	96,705	222,752	212,981	160,503	164,570	116,930
Retained Earnings	11,122	11,019	10,757	52,443	46,143	43,857	17,091	8,995	15,581
EBIT	14,604	13,418	152	6,300	2,286	1,842	28,970	(6,586)	(17,913)
Total Assets	981,078	858,476	733,067	375,098	397,548	380,180	299,389	289,476	238,058
MV of Equity	200,000	200,000	200,000	20,000	20,000	20,000	1,165	1,165	1,165
Total Liabilities	769,956	647,457	522,310	302,655	331,405	316,323	260,259	279,316	221,312
Net Income	103	262	152	6,300	2,286	1,842	28,970	(6,586)	(17,913)

Failed Group	Media Entertainment Ventures International Limited			Naviga LTD			Nextweb Limited		
Year Prior to Failure	1 year	2 years	3 years	1 year	2 years	3 years	1 year	2 years	3 years
	€	€	€	€	€	€	LM	LM	LM
Current Assets	17,619	17,616	49,718	508,112	560,232	264,823	238,659	178,271	118,447
Current Liabilities	209,246	252,316	199,120	80,979	80,179	236,312	266,818	265,449	322,711
Retained Earnings	(190,835)	(220,229)	(150,602)	(1,084)	(199)	(1,281)	(472,023)	(342,250)	(275,636)
EBIT	31,396	(66,428)	(18,723)	(885)	2,786	(1,281)	(129,773)	(66,614)	2,421
Total Assets	19,611	33,287	49,718	508,112	560,232	264,823	344,241	302,392	262,127
MV of Equity	1,200	1,200	1,200	1,165	1,165	500	257,000	107,000	107,000
Total Liabilities	209,246	252,316	199,120	508,031	559,266	265,604	470,179	448,557	341,678
Net Income	29,394	(69,627)	(66,782)	(885)	2,786	(2,984)	(129,773)	(66,614)	2,421

Non-Failed Group	Professional Marketing Services Limited			Sailpower Limited			William J. England & Son Limited		
Year Prior to Failure	1 year	2 years	3 years	1 year	2 years	3 years	1 year	2 years	3 years
	€	€	€	€	€	€	LM	LM	LM
Current Assets	222,144	204,176	167,259	592,383	760,179	89,488	8,749	10,904	11,798
Current Liabilities	147,685	165,759	135,023	509,953	774,702	73,304	1,885	4,648	6,113
Retained Earnings	55,288	47,136	39,879	(4,768)	571	(593)	2,604	2,470	2,373
EBIT	12,546	11,165	5,465	(5,339)	1,952	7,777	134	97	931
Total Assets	235,439	227,327	194,623	605,185	777,602	93,812	9,489	12,118	13,486
MV of Equity	1,165	1,165	1,165	100,000	2,329	1,000	5,000	5,000	5,000
Total Liabilities	178,986	179,026	153,579	509,953	774,702	93,405	1,885	4,648	6,113
Net Income	8,155	7,257	3,473	(5,339)	1,952	18,116	134	97	931

Failed Group	NGN Europe Limited			Nick Demicoli Construction Co. LTD			Personal Exchange International Limited		
Year Prior to Failure	1 year	2 years	3 years	1 year	2 years	3 years	1 year	2 years	3 years
	€	€	€	LM	LM	LM	€	€	€
Current Assets	10,972	495,599	351,971	48,890	74,102	83,210	15,219,611	9,019,377	17,785,263
Current Liabilities	776,867	626,166	475,757	23,369	25,729	67,603	14,558,971	14,023,912	20,919,305
Retained Earnings	(765,895)	(131,567)	(124,986)	13,532	13,632	15,512	(5,153,047)	(7,444,556)	(7,851,716)
EBIT	(635,328)	(678)	(3,496)	(100)	(1,880)	6,430	2,519,118	412,253	(6,527,304)
Total Assets	10,972	495,599	351,971	48,980	74,102	83,215	17,056,473	9,329,905	18,218,108
MV of Equity	1,200	1,200	1,200	100	100	100	500,000	500,000	500,000
Total Liabilities	776,867	626,166	475,757	35,348	60,370	67,603	14,558,971	14,023,912	23,419,275
Net Income	(635,328)	(6,781)	(3,496)	(100)	(1,880)	4,017	2,291,509	407,160	(6,533,646)

Non-Failed Group	Connect Limited			Blokrete Limited			Cash Point (Malta) Limited		
Year Prior to Failure	1 year	2 years	3 years	1 year	2 years	3 years	1 year	2 years	3 years
	€	€	€	LM	LM	LM	€	€	€
Current Assets	9,233	6,149	16,194	1,121,251	820,344	702,945	7,166,388	5,400,841	4,837,526
Current Liabilities	50,623	55,705	60,491	1,353,256	1,065,882	1,349,931	5,210,812	17,309,674	14,600,917
Retained Earnings	(41,856)	(50,022)	(44,763)	486,738	338,794	414,761	(8,564,828)	(7,299,670)	(4,582,958)
EBIT	8,166	(5,296)	733	206,347	(14,388)	1,968	(2,686,530)	(4,736,105)	(9,907,638)
Total Assets	9,233	6,149	16,194	2,079,721	1,689,425	2,035,360	12,425,984	10,296,296	10,300,591
MV of Equity	466	466	466	500	500	500	15,780,000	280,000	280,000
Total Liabilities	50,623	55,705	60,491	1,592,483	1,350,131	1,620,099	5,210,812	17,309,674	14,600,917
Net Income	8,166	(5,259)	904	147,944	(75,967)	(69,501	(1,265,158)	(2,716,712)	(4,582,958)

Failed Group	PNO Casino Limited			Prestige Printers LTD			Smart Digital Network Limited		
Year Prior to Failure	1 year	2 years	3 years	1 year	2 years	3 years	1 year	2 years	3 years
	€	€	€	LM	LM	LM	€	€	€
Current Assets	6,832,838	5,770,144	321,115	14	134	254	22,178	5,149	8,927
Current Liabilities	13,597,568	10,406,356	100,425	6,846	120	120	193,212	77,409	28,736
Retained Earnings	(5,960,011)	(3,027,710)	690	(8,832)	(1,986)	(1,866)	(201,069)	(70,445)	(37,164)
EBIT	(2,939,301)	(3,028,400)	58,411	(6,846)	(120)	(120)	(36,974)	(33,281)	(37,164)
Total Assets	7,877,557	7,598,656	321,115	14	134	254	99,702	46,037	55,059
MV of Equity	220,000	220,000	220,000	2,000	2,000	2,000	18,000	18,000	41,929
Total Liabilities	13,597,568	10,406,356	100,425	6,846	120	120	99,702	98,482	74,223
Net Income	(2,932,301)	(3,028,400)	37,967	(120)	(120)	(120)	(36,974)	(33,281)	(37,164)

Non-Failed Group	Tain Betting Promotion Limited			Merlin Publishers Limited			Smart Technologies Software Limited		
Year Prior to Failure	1 year	2 years	3 years	1 year	2 years	3 years	1 year	2 years	3 years
	€	€	€	LM	LM	LM	€	€	€
Current Assets	3,817,413	3,694,753	3,692,615	261,105	385,470	283,740	225,126	170,046	77,229
Current Liabilities	3,832,927	3,441,548	2,964,720	100,819	138,521	105,528	64,016	91,659	10,450
Retained Earnings	(5,040,269)	(4,165,218)	(3,615,734)	75,366	298,256	270,582	294,798	205,660	75,366
EBIT	(873,852)	(549,131)	42,844	27,674	42,878	48,833	89,138	30,104	50,935
Total Assets	3,919,658	3,876,330	3,948,986	765,541	801,586	706,955	494,300	347,399	86,316
MV of Equity	2,500,000	2,500,000	2,500,000	100,000	100,000	100,000	500	1,165	1,165
Total Liabilities	3,832,927	3,441,548	2,964,720	205,100	260,413	160,074	198,337	140,574	10,450
Net Income	(875,051)	(549,484)	42,852	27,674	42,878	48,833	89,138	30,104	50,935

Failed Group	Suffolk Limited			The Best of Malta (Travel &Tourism) LTD			Wavebet International Limited		
Year Prior to Failure	1 year	2 years	3 years	1 year	2 years	3 years	1 year	2 years	3 years
	LM	LM	LM	LM	LM	LM	€	€	€
Current Assets	69,986	23,770	32,105	121,976	80,889	133,422	5,943,974	12,347,833	9,486,589
Current Liabilities	358,424	317,969	301,245	250,033	224,810	253,887	4,423,417	8,579,832	9,300,596
Retained Earnings	309,360	(319,929)	(294,656)	(127,765)	(144,767)	(119,522)	(3,816,748)	(1,554,766)	(53,485)
EBIT	(56,432)	(98,668)	(24,557)	17,175	(25,048)	(95,493)	(2,261,982)	(1,501,281)	(33,544)
Total Assets	99,064	48,040	56,589	126,033	88,325	145,629	5,948,719	12,367,116	9,527,111
MV of Equity	50,000	50,000	50,000	1,000	1,000	1,000	5,342,056	5,342,050	280,000
Total Liabilities	358,424	317,969	301,245	253,798	232,092	264,151	4,423,417	8,579,832	9,300,596
Net Income	10,569	(25,273)	(24,633)	16,002	(25,245)	(95,493)	(2,261,982)	(1,501,281)	(33,544)

Non-Failed Group	Busy Bee Limited			Tristar Travel LTD			Co-Gaming Limited		
Year Prior to Failure	1 year	2 years	3 years	1 year	2 years	3 years	1 year	2 years	3 years
	LM	LM	LM	LM	LM	LM	€	€	€
Current Assets	307,694	259,389	209,897	77,134	79,621	59,102	9,594,381	4,073,768	6,790,537
Current Liabilities	415,814	236,368	181,696	74,241	74,160	55,553	15,093,897	11,690,512	13,037,931
Retained Earnings	672,996	618,161	537,067	11,142	9,057	7,492	(3,785,451)	(7,637,373)	(5,798,500)
EBIT	54,835	81,094	(13,796)	2,085	1,565	2,627	1,888,334	(1,839,335)	(3,150,934)
Total Assets	1,159,212	924,386	873,056	94,383	92,217	72,045	11,588,446	4,333,139	7,439,431
MV of Equity	5,000	5,000	5,000	9,000	9,000	9,000	280,000	280,000	200,000
Total Liabilities	481,216	301,225	330,989	74,241	74,160	55,553	15,093,897	11,690,512	13,037,931
Net Income	54,835	81,094	(13,976)	2,085	1,565	2,627	3,851,922	(1,838,873)	(3,150,5540)

Failed Group	Woodline Limited		
Year Prior to Failure	1 year	2 years	3 years
	LM	LM	LM
Current Assets	377,421	526,059	502,867
Current Liabilities	478,155	759,612	693,415
Retained Earnings	(309,050)	(152,859)	(110,977)
EBIT	(192,008)	(38,204)	(9,813)
Total Assets	754,036	910,531	888,554
MV of Equity	140,000	80,000	80,000
Total Liabilities	923,086	983,390	919,531
Net Income	(156,191)	(41,882)	(17,900)

Non-Failed Group	Desira Woodworks LTD		
Year Prior to Failure	1 year	2 years	3 years
	LM	LM	LM
Current Assets	6,645	9,005	36,583
Current Liabilities	55,868	44,125	46,125
Retained Earnings	(49,028)	35,861	(26,872)
EBIT	(13,167)	(8,989)	(12,078)
Total Assets	115,609	124,416	128,450
MV of Equity	30,000	30,000	30,000
Total Liabilities	134,637	130,277	125,322
Net Income	(13,167)	(8,989)	(12,078)

Appendix 4
ROC Curve and the AUC Value

Introduction

This section provides a brief explanation of the ROC curve and the AUC value, as referred to in Section 3.6.1. This approach was used to assess the accuracy rate of the selected bankruptcy prediction models.

Overview of the ROC curve and the AUC value

The Receiver Operating Characteristic curve or ROC curve yields practicality in the probability prediction of a binary outcome. The curve plots the true positive rate (sensitivity) against the false positive rate (1 minus specificity) for numerous cut-off points between the values of 0 and 1. Each point on the plotted curve depict a sensitivity/specificity combination corresponding to a specific threshold. A test which includes no overlap of distributions is presumed to have perfect discrimination, or a 100% sensitivity and a 100% specificity. This indicates that the overall accuracy of the tested model is proportionate to how much the plotted ROC curve bows out to the top left corner of the graph, i.e. the y-axis (Zweig, Campbell 1993). An example of a test showing high overall accuracy can be shown by the plotted ROC curve in Figure A.4.1 below.

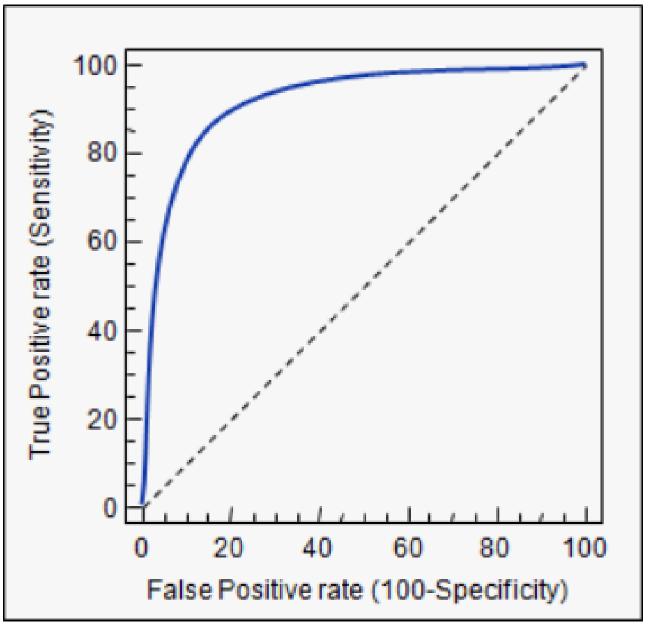

Figure A.4.1 - Plotted ROC curve

The AUC value represents the area under the ROC curve, and it puts into quantifiable terms the performance rating of the model tested. An AUC value of 0.5 indicates that the model has no class separation capacity, which will be accompanied by the ROC curve coinciding with the diagonal. On the other hand, a model test with a good measure of separability has an AUC of 1, in which case, the plotted curve will reach the top left corner of the plot. As a result, a high AUC value for a plotted ROC curve, indicates a better overall performance of the model tested.

Appendix 5
Identified Outliers in MDA Test

Introduction

Enclosed in this section are the initial outcomes generated through discriminant analysis testing, as referred to in Section 4.3.1. High multicollinearity issues between the independent variables were detected leading to multiple variables being rejected by the statistical test. Further, two specific cases were identified as being strong violators of the homoscedasticity assumption and thus were eliminated from the data set.

Overview of the Identified Outliers in MDA Test

The data extracted from publicly available financial statements was inputted in SPSS to enable statistical testing to be employed using discriminant analysis. At first sight, high multicollinearity issues were highlighted amongst the four independent variables (Table A.5.1). The only two independent variables which reported no correlation were *Working Capital/Total Assets* and *MV of Equity/BV of Liabilities.*

Furthermore, the Box's M test (Table A.5.2) indicated that the observed covariances rejected the homoscedasticity assumption since significance of test is less than 0.05. This further indicated that variances amongst the different parameters are unequal. As a result, the discriminant analysis rejected the highly correlated variables (Table A.5.3), being *Retained Earnings/Total Assets* and *EBIT/Total Assets* and incorporated only the remaining two uncorrelated independent variables in its testing.

Pooled Within-Groups Matrices				
Correlation	**Working Capital / Total Assets_1**	**Retained Earnings / Total Assets_1**	**EBIT / Total Assets_1**	**MV of Equity / BV of Liabilities_1**
Working Capital / Total Assets_1	1.000	1.000	1.000	.049
Retained Earnings / Total Assets_1	1.000	1.000	1.000	.046
EBIT / Total Assets_1	1.000	1.000	1.000	.046
MV of Equity / BV of Liabilities_1	.049	.046	.046	1.000

Table A.5.1 - MDA test: correlation matrices (including outliers)

Test Results		
Box's M		291.951
F	**Approx.**	92.339
	df1	3
	df2	444257.937
	Sig.	.000

Table A.5.2 - MDA test: Box's M test (including outliers)

Variables Failing Tolerance Test			
	Within-Groups Variance	**Tolerance**	**Minimum Tolerance**
Retained Earnings / Total Assets_1	9041.989	.000	.000
EBIT / Total Assets_1	5437.545	.001	.001

Table A.5.3 - MDA test: tolerance test (including outliers)

The discriminant function coefficients generated through discriminant analysis for the two accepted independent variables respectively can be shown in Table A.5.4. It is critical to mention that the probability of default is denoted by a negative value for the discriminant function while the opposite category is denoted by a positive one. Thus, since the coefficient for *Working Capital/Total Assets* generated a positive coefficient (0.010), it contributes to a lower probability of failure. More specifically, an increase in Working *Capital/Total Assets* decreases the probability of default. Conversely, the variable *MV of Equity/BV of Liabilities* generated a negative parameter (-0.035) indicating a direct relationship to the probability of default.

Canonical Discriminant Function Coefficients	
	Function
Working Capital / Total Assets_1	.010
MV of Equity / BV of Liabilities_1	-.035
(Constant Term)	.233

Table A.5.4 - MDA test: discriminant function coefficients (including outliers)[44]

The discriminant analysis test incorporating only two independent variables generated a poor accuracy rate in correctly classifying companies in their failed

[44] Thus, Z_1 = 0.233 + 0.010*(Working Capital/Total Assets)* - 0.035*(MV of Equity/BV of Liabilities).*

and non-failed categories, standing at 52.3% (Table A.5.5). Specifically, out of forty-four companies, the test correctly classified all non-failed companies, yet only matched two failed companies in their correct groupings. Given the imperial deviance in generating true positives, the model was not fitted on a wider set of data. In fact, it was tested for significant outliers which were strong violators of the homoscedasticity assumption. As a result, two cases were identified as being great disruptors to the overall accuracy of the fitted model (Figure A.5.1) and were thus eliminated from the data set.

The discriminant analysis test was then repeated with the adjusted data set showing a great improvement in overall accuracy rates[45].

Grouped Cases Correctly Classified					
			Predicted Group Membership		Total
			No	Yes	
Failed	No	Count	21	0	21
		% within Failed	100%	0.0%	100%
	Yes	Count	21	2	23
		% within Failed	91.3%	8.7%	100%

Table A.5.5 - MDA training data set: cross tabulation (including outliers)

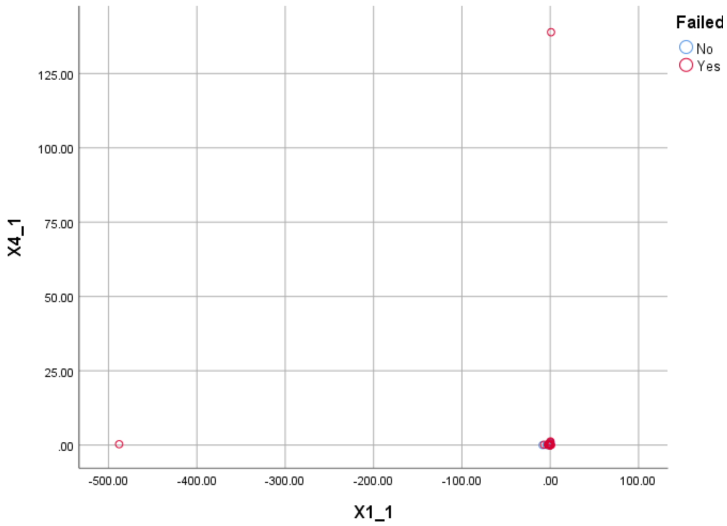

Figure A.5.1 - Identified violators of the homoscedasticity assumption

[45] Refer to Appendix 6

Appendix 6

MDA Independent Statistical Tests

Introduction

Enclosed in this section are the outcomes of the three individual MDA statistical tests employed for each of the years leading up to company default, as referred to in Section 4.3.2. Further, the results disclosed hereunder were generated by models run on the training and test data sets which have been adjusted according to the outliers[46] identified.

Overview of the MDA Individual Statistical Tests

The discriminant function coefficients generated through discriminant analysis for the independent variables for each independent year can be shown in Table A.6.1. It is critical to mention that the probability of default is denoted by a negative value for the discriminant function while the opposite category is denoted by a positive one. With the exception of *Working Capital/Total Assets* for both two-years and three-years prior to failure, all parameters generated a positive coefficient. This indicates that an increase in each of these parameters is presumed to generate a higher Z-Score. Conversely, the parameters which generated a negative coefficient are presumed to have a direct relationship to the probability of default. More specifically, an increase in any of these parameters will result in a lower Z-Score computed by the discriminant function.

Canonical Discriminant Function Coefficients			
	Function 1[47]	Function 2[48]	Function 3[49]
Working Capital / Total Assets	.377	-2.034	-2.369
Retained Earnings / Total Assets	-.396	1.729	2.168
EBIT / Total Assets	1.344	.873	1.061
MV of Equity / BV of Liabilities	-.694	4.822	5.984
(Constant Term)	.291	-.710	-.913

Table A.6.1 - MDA test: discriminant function coefficients (independent years)

[46] Refer to Appendix 5
[47] Refer to Table 4.6
[48] Thus, Z_2 = - 0.710 - 2.034*(Working Capital/Total Assets)* + 1.729*(Retained Earnings/Total Assets)* + 0.873*(EBIT/Total Assets)* + 4.822*(MV of Equity/BV of Liabilities).*
[49] Thus, Z_3 = - 0.913 - 2.369*(Working Capital/Total Assets)* + 2.168*(Retained Earnings/Total Assets)* + 1.061*(EBIT/Total Assets)* + 5.984*(MV of Equity/BV of Liabilities).*

It is important to note that the Box's M test (Table A.6.2) indicated that the observed covariances still reject the homoscedasticity assumption, since significance of test is less than 0.05. This is evident in all three independent models. This test was also affected as a result of deviations from multivariate normality. However, for each of the three models, the canonical discriminant function held all the independent variables since the correlation decreased upon the elimination of the outliers.

Test Results				
		Years Prior to Failure		
		1 Year[50]	2 Years	3 Years
Box's M		55.224	49.037	43.816
F	Approx.	4.922	4.370	3.905
	df1	10	10	10
	df2	7649.402	7649.402	7649.402
	P-value	.000	.000	.000

Table A.6.2 - MDA test: Box's M test (independent years)

By testing for equality of the group means (Table A.6.3), results indicate that the significance of variables in predicted failure are distinct when models are fitted using observations extracted from different time horizons. The model fitted using data pertaining to two-years prior to company default failed to report any significant relationship between the independent variables and the probability of default. This is since all the estimated coefficients generated a significance value greater than 0.10. Conversely, the model fitted using data pertaining to three-years prior to company failure identified *MV of Equity/BV of Liabilities* as being a significant contributor to the discriminant function in data separation (0.033). Unlike the reported results by the one-year fitted model, the three-year fitted model indicates that the independent variable of *MV of Equity/BV of Liabilities* incorporates the greatest discriminatory ability in separating data into the diagnostic categories.

[50] Refer to Table 4.7

Test of Equality of Group Means			
	P-value 1[51]	**P-value 2**	**P-value 3**
Working Capital / Total Assets	.735	.533	.891
Retained Earnings / Total Assets	1.000	.728	.940
EBIT / Total Assets	.082	.925	.742
MV of Equity / BV of Liabilities	.965	.118	.033

Table A.6.3 - MDA test: variable significance (independent years)

Table A.6.4 hereunder shows the predictive accuracy of the three independent MDA models when run on a known data set. More specifically, these accuracy rates are produced using the same data set from which the fitted models were developed. The discriminant analysis test for one-year and two-years prior to company failure both generated 69% accuracy rate in correctly classifying companies in their failed and non-failed categories. Specifically, out of forty-two companies, the test correctly classified eleven failed companies and eighteen non-failed companies from the latest data. For the two-years prior default, out of forty-two companies, the test correctly classified sixteen failed companies and thirteen non-failed companies. The data pertaining to three-years prior to company failure generated the highest overall accuracy rate, standing at 76.19%. Specifically, out of forty-two companies, the test correctly classified seventeen failed companies and fifteen non-failed companies in their respective groupings.

[51] Refer to Table 4.8

Grouped Cases Correctly Classified						
				Predicted Group Membership		Total
				No	Yes	
One-Year Prior Failure	Failed	No	Count	18	3	21
			% within Failed	85.7%	14.3%	100%
		Yes	Count	10	11	21
			% within Failed	47.6%	52.4%	100%
Two-Years Prior Failure	Failed	No	Count	13	8	21
			% within Failed	61.9%	38.1%	100%
		Yes	Count	5	16	21
			% within Failed	23.8%	76.2%	100%
Three-Years Prior Failure	Failed	No	Count	15	6	21
			% within Failed	71.4%	28.6%	100%
		Yes	Count	4	17	21
			% within Failed	19.0%	81.0%	100%

Table A.6.4 - MDA training data set: cross tabulation (independent years)

The test data sets for each of the three years (Table A.6.5) validated the models built. More specifically, the outputs indicated the independent performance levels of the built models when applied to the test data set. It is evident that the overall accuracy rate dropped significantly when running each of the three independent models on the test data set. In fact, the overall accuracy rate fell to 58.33% for each of the three years. Further, there was minimal improvement in the category of interest, being the default category. This is with the exception for the data pertaining to one year prior to company failure where the accuracy rate for correctly classifying failed companies deteriorated significantly.

Grouped Cases Correctly Classified						
				Predicted Group Membership		Total
				No	Yes	
One-Year Prior Failure	Failed	No	Count	5	2	7
			% within Failed	71.4%	28.6%	100%
		Yes	Count	3	2	5
			% within Failed	60.0%	40.0%	100%
Two-Years Prior Failure	Failed	No	Count	3	4	7
			% within Failed	42.9%	57.1%	100%
		Yes	Count	1	4	5
			% within Failed	20.0%	80.0%	100%
Three-Years Prior Failure	Failed	No	Count	3	4	7
			% within Failed	42.9%	57.1%	100%
		Yes	Count	1	4	5
			% within Failed	20.0%	80.0%	100%

Table A.6.5 - MDA test data set: cross tabulation (independent years)

Appendix 7

Probit Independent Statistical Tests

Introduction

Enclosed in this section are the outcomes of the three independent probit statistical tests employed for each of the years leading up to company default, as referred to in Section 4.4.1. Further, the results disclosed hereunder were generated by models run on the training and test data sets which include the total sample selected.

Overview of the Probit Individual Statistical Tests

The parameter estimates generated through probit regression analysis for the independent variables for each independent year can be shown in Table A.7.1. It is critical to mention that through probit analysis, the probability of default is modelled against the predictors, and thus these parameter estimates represent marginal effects.

Parameter estimates across the three separate years differ in magnitude as well as in sign. The parameter for *Net Income/Total Assets* generated positive coefficients for both Year 2 and Year 3, thus indicating that an increase in the ratio contribute to an overall decrease in the probability of default. This is since a higher computed score is associated with a lower probability of bankruptcy. Similarly, *Current Assets/Current Liabilities* generated a negative parameter for each of the three fitted models, indicating a lower overall score. Thus, an increase in *Current Assets/Current Liabilities* further increases the probability of bankruptcy.

Contradictory results were generated by the re-estimated parameters associated with *Total Debt/Total Assets.* While both Year 1 and Year 2 prior to company failure generated a positive coefficient for this independent variable, the model fitted on data pertaining to three-year prior to company default generated a negative parameter. This indicates that the three-year model presumes that an increase in *Total Debt/Total Assets* further increases the probability of bankruptcy.

Parameter Estimates			
	Function 1[52]	Function 2[53]	Function 3[54]
(Constant Term)	.126	.026	.030
Net Income / Total Assets_1	1.076	.367	.996
Total Debt / Total Assets_1	.012	.048	-.005
Current Assets / Current Liabilities_1	-.021	-.098	-.007

Table A.7.1 - Probit test: parameter estimates for (independent years)

Furthermore, each independent variable was tested to analyse its individual effect upon the overall fitted model. It was highlighted that none of the three independent variables have any discernible effect in predicting the probability of default. This is since all p-values for each of the three independently fitted models were greater than the 0.05 level of significance (Table A.7.2). The variable of *Net Income/Total Assets* generated the smallest p-value, standing at 0.081 for the model fitted on data pertaining to one-year prior to failure.

Test of Equality of Model Effects			
	P-value 1[55]	P-value 2	P-value 3
(Constant Term)	.555	.941	.908
Net Income / Total Assets_1	.081	.649	.232
Total Debt / Total Assets_1	.549	.667	.967
Current Assets / Current Liabilities_1	.604	.613	.711

Table A.7.2 - Probit test: test of model effects (independent years)

Table A.7.3 hereunder shows the predictive accuracy of the three independent probit models when run on a known data set. More specifically, these accuracy rates are produced using the same data set from which the fitted models were developed. The probit analysis test for data pertaining to one-year prior to

[52] Refer to Table 4.14
[53] Thus, X_2 = 0.026 + 0.367*(Net Income/Total Assets)* + 0.048*(Total Debt/Total Assets)* – 0.098*(Current Assets/Current Liabilities).*
[54] Thus, X_3 = 0.030 + 0.996*(Net Income/Total Assets)* – 0.005*(Total Debt/Total Assets)* – 0.007*(Current Assets/Current Liabilities).*
[55] Refer to Table 4.15

company default generated the highest overall accuracy rate, standing at 75.00% in correctly classifying companies in their failed and non-failed groupings. Specifically, out of forty-four companies, the test correctly classified fourteen failed companies and nineteen non-failed companies. The data pertaining to two-years prior to company failure indicated a weaker overall accuracy rate in predicting corporate failure, standing at 45.45%. Specifically, out of forty-four companies, the test correctly classified fourteen failed companies and six non-failed companies. It is important to note that the deterioration in accuracy rate may be easily related to the company data extracted from financial statements for the second-year prior to failure rather than a reflection of the statistical test's performance.

Finally, the data pertaining to three-years prior to company default generated an overall accuracy rate of 63.64% which is higher than that resulting from data of two-years before, yet slightly lesser than that generated by the latest data. Specifically, the statistical test using observations of three-years prior to bankruptcy correctly classified thirteen failed companies and fifteen non-failed companies.

Grouped Cases Correctly Classified						
				Predicted Category Value		Total
				No	Yes	
One-Year Prior Failure	Failed	No	Count	19	2	21
			% within Failed	90.5%	9.5%	100%
		Yes	Count	9	14	23
			% within Failed	39.1%	60.9%	100%
Two-Years Prior Failure	Failed	No	Count	6	15	21
			% within Failed	28.6%	71.4%	100%
		Yes	Count	9	14	23
			% within Failed	39.1%	60.9%	100%
Three-Years Prior Failure	Failed	No	Count	15	6	21
			% within Failed	71.4%	28.6%	100%
		Yes	Count	10	13	23
			% within Failed	43.5%	56.5%	100%

Table A.7.3 - Probit training data set: cross tabulation (independent years)

The test data sets for each of the three years (Table A.7.4) validated the models built. More specifically, the outputs indicated the individual performance levels of the built models when applied to the test data set. For the data pertaining to one-year prior to company default there was minimal improvement in the overall accuracy rate, with no evident enhancement in the failed category. Conversely, the two-year test data set indicated a further deterioration in accuracy rate, now standing at only 33.33%.

The fitted model for data pertaining to three-years prior to company default on the test data set showed the greatest improvement in correctly classifying companies in their diagnostic categories. The overall accuracy rate improved slightly, standing at 66.66%, and it has also shown the better performance in correctly classifying defaulted companies.

Grouped Cases Correctly Classified						
				Predicted Category Value		Total
				No	Yes	
One-Year Prior Failure	Failed	No	Count	6	1	7
			% within Failed	85.7%	14.3%	100%
		Yes	Count	2	3	5
			% within Failed	40.0%	60.0%	100%
Two-Years Prior Failure	Failed	No	Count	1	6	7
			% within Failed	14.3%	85.7%	100%
		Yes	Count	2	3	5
			% within Failed	40.0%	60.0%	100%
Three-Years Prior Failure	Failed	No	Count	5	2	7
			% within Failed	71.4%	28.6%	100%
		Yes	Count	2	3	5
			% within Failed	40.0%	60.0%	100%

Table A.7.4 - Probit test data set: cross tabulation (independent years)