A THREE-TIER APPROACH TO DETERMINE FINANCIAL DISTRESS OF COMPANIES LISTED ON THE JOHANNESBURG STOCK EXCHANGE

by

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ABSTRACT

This study presents a three-tiered approach to determine financial distress in companies listed on the Johannesburg Stock Exchange. The objective of this unique approach is to contribute to the existing knowledge base in the study of financial distress prediction. The three-tiered approach sees the development of a: (i) basic model, (ii) Merton model, and (iii) hybrid model. The basic model is further split in three phases. In the first phase the model is based on fundamental data; the second phase adds market variables; and the third phase adds macroeconomic indicators. The first phase points to various company specific ratios, the second phase points to various market based ratios and the third phase points to external economic indicators. Pioneered by Merton (1974:449), the Merton model is a structural model with its framework adopted from the Black-Scholes option pricing methodology. Therefore, the hybrid model is a combination of the basic and Merton models.

This study explores the effectiveness of a hybrid model, in which both the fundamental and market data are used as input variables. This combination is intended to enhance the predictive power of a company's default event, given that both variables convey company-specific credit risk information that is not considered by the other.

In developing the basic model, this study focuses on exploring a multinomial approach where companies are categorised in three groups: distressed, depressed and healthy. This is in line with the thinking that failure does not affect companies immediately, but is rather a process. Healthy companies go through a depression phase before they actually fail.

The statistical technique of choice for the basic and hybrid models is the multinomial logistic regression. This technique is chosen on its strength over alternatives like multi-discriminant analysis, with the nature of data being the driving force. Certain statistical tests were performed on the data, like the Kolmogorov-Smirnov and Shapiro-Wilk statistical tests of data normality. The sample of companies used in the present study is categorised as follows; 8% distressed, 14% depressed, and 78% healthy. Given that the

percentage number of companies in each category is not equal, the statistical integrity of multi-discriminant analysis would be grossly compromised.

The Merton model is based on the formula as derived by its pioneer. This mathematical formula uses five estimated variables: asset value, asset volatility, debt level, risk-free rate, and time. The fundamental assumption of structural models is that there is a cause-effect, economically motivated reason why firms default. Default is highly likely to occur when the market value of a firm's assets is insufficient to cover its liabilities in the future. This balance sheet approach to measuring risk means that the market-based models share common ground with fundamental models in credit analysis. However, a major advantage of market-based models over the fundamental approach is that they provide both timely warning of changes in credit risk and an up-to-date view of a firm's value. This view is given on the basis that market prices are indicative of future cash flows of the business.

The most important motivation to study both these models and further develop a hybrid model within the South African market is the lack of such academic research in the local academic domain. Therefore, this uniquely positions the study where the distress probability is studied by applying both fundamental and market data. This study also aims to investigate which of the two models is better at differentiating defaulting and non-defaulting firms. In this way, the study assesses the extent to which different failure prediction models may yield significantly different rankings for the same firm. Furthermore, the study explores the extent of gains (if any) that can be realised by combining the two models' predictions.

The present study is based on information sourced from the Johannesburg Stock Exchange, INET BFA, South African Reserve Bank and other relevant academic material. To be included in the sample, firms are required to have a minimum listing period of at least 24 months to ensure that the firm's market price reflects the market's collective opinion of the prospect of its business. For purposes of the fundamental data, companies are required to have existed for at least five years to be included in sample. The economic period under review in this study is 2005-2014. The 2014 cut-off is set to ensure the availability of financial statements. The study has a sample size of 100 companies, consisting of eight distressed, 14 classified as depressed, and 78 healthy.

The selection of the final set of fundamental, market and macroeconomics indicators follows a rigorous process in an attempt to ensure that only variables showing the most predictive power are included in the model. The first step in the variable selection process entails the revision of the extant literature to identify popular variables that carry a high success rate. This step led to the identification of 17 variables combined. The next step involves the application of Spearman's Rho test using the forward stepwise method on the 17 chosen ratios. The Spearman's Rho is selected on the basis of its ability to handle data that are not normally distributed. The final selected variables used in this study are five fundamental, three market and two macroeconomic indicators.

The research results of the Basic model reveal that three fundamental variables are found to be making a significant contribution in predicting financial distress. These variables are: working capital over total assets, earnings before interest and taxes over total assets and turnover over total assets. Also found in the results is the enhancement of the prediction accuracy as a result of adding market variables in the model. The macroeconomic variables were found to not make any further statistical contributions.

The Merton model discussed in chapter 8 produced 99% accuracy in predicting the financial distress. Out of the total sample, the Merton model misclassified only 1 company as financially distressed when in actual fact the same company is healthy. Some interesting and informative facts are discovered in a further analysis of this one misclassified company. That analysis is provided in chapter 8.

Once the basic and Merton models were developed, the study constructed a hybrid model. The intention was to observe whether the prediction results would improve using a hybrid model. The end results suggested an enhancement of the statistical results prediction results showed a financial distress prediction of 100%.

The study concludes on four research findings. Firstly, the financial distress model using a multinomial specification is able to distinguish between the three financial states of a company: distressed, depressed and healthy. Secondly, the prediction accuracy of a financial distress model is enhanced when combining fundamental, market and macroeconomic variables. Thirdly, the Merton model produces prediction accuracy results that are better than the basic model. Lastly, combining the variables from the basic model and the Merton model give better prediction results.

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Table 1: LIST OF DEFINITIONS

Key term	Term description
Liquidity	The degree to which a company is readily able to meet its current obligations from liquid assets.
Financial model	The representation of a computer program of key financial dimensions of a business system for purposes of simulating the impact of management decisions.
Bankruptcy	A legal process of disposing of the assets of a business or individual to satisfy creditors' claims in total or in part, and protecting the debtor(s) from further legal action.
Dichotomous	Refers to a variable that has two states, for example “defaulting” or “non-defaulting”.
Distressed	The state a company is in, if it has a negative profit after tax.
Healthy	The state a company is in, if it has a positive profit after tax.
Multiple discriminant analysis	A statistical technique that classifies an observation into one of several groups – the latter representing the different states of the discrete response variable. Each group consists of a multivariate equation that is made up of one or more independent predictor variables, but with different co-efficient that “best” discriminates between the groups.
Multivariate	Refers to the use of multiple variables.
Paired sample	A sample in which a non-defaulting firm is matched in asset size and industry classification to that of a defaulting firm.

Stepwise regression	Performs regression by removing and adding variables to identify a useful subset of the predictors. Three commonly used procedures are provided: standard stepwise regression (adds and removes variables), forward selection (adds variables), and backwards elimination (removes variables).
Test sample	A sample of companies that is used to develop the statistical equations for each of the models.
Univariate	Refers to a single variable.
Real gross domestic product	The real gross domestic product is the market value of all goods and services produced in a nation during a specific time period. Real gross domestic product measures a society’s wealth by indicating how fast profits may grow and the expected return on capital. It is labelled “real” because each year’s data are adjusted to account for changes in year-to-year prices. The real gross domestic product is a comprehensive way to gauge the health and wellbeing of an economy.
Consumer price index (CPI)	The CPI measures changes in the prices paid for goods and services by urban consumers for the specified month. The CPI is essentially a measure of individuals’ cost of living changes and provides a gauge of the inflation rate related to purchasing those goods and services.
Current Employment Statistics (CES)	CES provides comprehensive data on national employment, unemployment, and wages and earnings data.

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Corporate demise is the most undesirable development that has catastrophic ramifications for the immediately affected stakeholders, and is an event that could trigger a contagious loss to the company concerned, potentially extending to the country's economy. The global economies are becoming increasingly sensitive to early warning indicators of corporate demise and distress. This may have led to a heightened concentration on corporate ethics and governance to arrest potential risk of corporate financial distress.

The government, shareholders, financiers, potential investors, credit rating agencies, auditors, suppliers, customers and employees are immediately affected stakeholders of a corporate failure. The list could be extended to include the local communities that are benefiting through corporate social investments. The early detection of financial distress is essential for the protection of various financial and social investments. For this reason, the prediction and classification of companies to determine whether they are potential candidates for financial distress have become key topics of debate and detailed research. The interests of these stakeholders include government taxes and curbing unemployment, return on investment, timely settlement of outstanding bills, ongoing concern questions, and a level of comfort for employees and management that guarantees a stable income.

During the times of Fitzpatrick (1932:598), at the beginning of the research on financial distress prediction, there were no advanced statistical methods and mechanisms available to researchers. Often, financial distress studies were purely based on financial ratios comparison where values in failed companies were found to be poorer than those in companies that had not failed. In 1966, there was a quantum leap in the fraternity with Beaver's pioneering study introducing the application of statistical techniques to studying financial distress predictions. In his work, he presented the use of the univariate approach of multiple discriminant analysis. This development was followed by another academic paper by Altman in 1968, introducing the multivariate analysis which was an extension of

Beaver's 1966 study. Until the 1980s, multiple discriminant analysis was the dominant method of failure prediction. However, it suffered from assumptions that were violated very often. The assumption of normality of the financial ratio distributions was problematic, particularly for failing firms. During the 1980s, an alternative statistical technique made prominent by Ohlson (1980:109) emerged, which was seen as less statistically demanding compared to the multiple discriminant analysis. However, in recent years, literature reveals various alternative methodologies used in predicting financial distress.

The challenge in accurately predicting corporate failure has posed a long-standing problem in bankruptcy prediction research. To date, prediction research remains topical among academics and practitioners. The complication in estimating the company's ability to timely honour its liabilities when they fall due stems from the difficulty to distinguish the companies that will default from those that will not, prior to default (Kealhofer & Kurbat 2002:67). These authors are alluding to the reality of a default being experienced when the default actually happens. Therefore, prior to the default, the best that can be done is to estimate the probability that a firm will default. According to existing literature, these estimates are calculated through various prediction and structural models, using either financial ratio-based information or market-based information.

In an attempt to enhance the predictive power of a company's default event, the present study is proposing a hybrid model that combines two sets of information: information derived from the fundamental model and information derived from the market-based model. In the present study, it is believed that this may enhance the predictive power of the hybrid model since each approach contains company-specific credit risk information that is not considered by the other. Li and Miu (2010:819) confirm that many studies have pointed out that investors and financial institutions rarely opt for just one approach, but rather combine different sources of information to arrive at their own credit risk assessments. In particular, most closely related is the research by Chava and Jarrow (2004:537), Kealhofer and Kurbat (2002:67), Löffler (2007:38), and Shumway (2001:101). Except for the findings of Kealhofer and Kurbat (2002:67), these studies conclude that combining various failure prediction models improves the prediction of default over the use of a single measure.

The most prominent fundamental prediction models include the: multiple discriminant analysis model (Altman, 1968:589), logistic analysis model (Ohlson, 1980:109), and probit model (Zavgren, 1985:19). These fundamental models have been challenged from structural models that use market data. Structural models (Merton, 1974:449) use option pricing methods to compute a probability of default from the level and volatility of market value of assets. Market-based approaches to pricing distress have been embraced by academics and the public. The advocates of structural models believe that this approach yields a highly valid probability of default statistic. Hillegeist, Keating, Cram and Lundstedt (2004:5) find that structural models of default are better at forecasting distress than either of Altman's Z-score and Ohlson's O-score using a large sample of bankruptcies.

The fundamental approach yielding impressive results was first developed by Altman (1968:589) when he introduced the Z-score credit risk model. Altman's (1968:589) Z-score model is based on fundamental information obtained from annual financial statements. The Z-score model attempts to determine and quantify the probability of default based on the Z-score range by classifying companies as failed or non-failed groups. The Z-score model is based on five variables that had the highest predictive power in the multiple discriminant analysis models. The Z-score is still widely used by academics and practitioners.

The fundamental prediction models are often criticised for their lack of theoretical grounding and conceptual basis. According to Agarwal and Taffler (2008:1542), the nature of the accounting statements on which these models are based cast doubt on their validity as:

(i) Accounting statements present past performance of a firm, and may or may not be informative in predicting the future;

(ii) Conservatism and historical cost accounting mean that the true asset values may be very different from the recorded book values;

(iii) Accounting numbers are subject to manipulation by management; and

(iv) Hillegeist *et al.* (2004:5) argue that, since accounting statements are prepared on a going-concern basis; they are of limited utility in predicting bankruptcy.

Manzaneque, Priego and Merino (2016:120) investigated the effect of corporate governance mechanisms on the likelihood of financial distress. The results show that corporate governance mechanisms as board ownership, proportion of independent directors and board size reduce the financial distress likelihood. The research finding of their study makes a connection between the level of independence of board members and the risk of financial distress.

The alternative modelling approach, the structural model, starts with a stylised mathematical representation of how the value of the firm evolves through time. The goal of this type of quantitative risk assessment is to represent the solvency of the issuer in the theoretical economic environment as accurately as possible. Kealhofer and Kurbat (2002:67) once suggested that identifying whether a firm will default prior to actual default is impossible. Therefore, they indicated that the one way to tackle this problem is through the option pricing approach to default risk, sometimes known as the Merton approach (Merton, 1974:449).

Merton (1974:449) pioneered an alternative approach to bankruptcy prediction. He suggested a structural model for default prediction which uses timely information from the equity market. In his approach, it is implied that distress prediction probability could be established using a company's debt ratio together with its asset value volatilities. This approach builds on the idea that an equity holder has an implicit option on the assets of a firm. The usefulness of such an approach depends on how closely its assumptions and structure capture the true nature of the firm dynamics as well as the accuracy with which the model's variables are estimated.

The Merton model relies heavily on economic theories on market efficiency. The model contains embedded assumptions about the comprehensiveness of the information contained in market data when used within the structure of the model. However, knowledge of the market information alone does not inform an investor on a borrower's creditworthiness. The model assumes that the underlying value of each firm follows a geometric Brownian motion and that each firm has issued just one zero-coupon bond.

Merton's (1974:449) model has seen a dramatic evolution from its original presentation through constructive criticism and recommendations from other academics and practitioners. The main focus has been on the relaxation of some of the restrictive assumptions embedded in the original model. Black and Cox (1976:351), Geske (1977:541), Leland (1994:1213), Longstaff and Schwartz (1995:789), Leland and Toft (1996:987), and Collin-Dufresne and Goldstein (2001:1929), are among the academics and practitioners that have improved the original model. A major benchmark in existing literature is the KMV model. The KMV model is based on Merton's (1974:449) bond pricing model, but it was further developed by the KMV Corporation. This corporation was founded in 1989 offering a commercial extension of the Merton model using market-based data. In 2002, it was acquired by Moody's and became Moody's KMV. KMV published a number of papers which reveal some of its methods (Keenan & Sobehart, 1999; Sobehart, Keenan & Stein, 2000; Bohn, 2000). Some of the specifications made by KMV were adopted by academics, such as Vassalou and Xing (2004:831), and Campbell, Hilscher and Szilagyi (2011:14).

Despite the increasing popularity of market-based default metrics, literature evidence suggests that accounting information still plays an important role in predicting distress. Sloan (1996:289) finds that market prices do not accurately reflect the information from company accounts. Hence, accounting data can be used to complement market data. It is from this perspective that this study pursues a hybrid model that considers the fundamental and the market data-based models.

What has drawn the interest of this study in the predictability of financial distress in the South African market using market-based information is the forward-looking nature implied in market prices as opposed to the historic nature of the fundamental data-based information. Moreover, the literature suggests that academics have welcomed the application of market-based information in financial distress prediction models. Hillegeist *et al.* (2004:5) compared the predictive power of the Merton model to the Altman (1968:589) and Ohlson (1980:109) models (Z-score and O-score, respectively), and concluded that the Merton model outperforms these.

The existing South African literature on the subject of financial distress prediction is dominated by studies that consider the merits or shortcomings of different prediction models that are purely based on fundamental data. Therefore, this study will present prediction results that are not only based on fundamental information but also on market-based information.

1.2 PROBLEM STATEMENT

The value derived from predictive models for the investment community is significant, with the amount of global research on this subject matter being testimony to this. The most notable global studies on fundamental models include: Beaver (1966:71); Altman (1968:589); Deakin (1972:167); Altman, Haldeman and Narayanan (1977:29); and Ohlson (1980:109). The researchers who have done prediction studies using market-based data include Black and Scholes (1973:637), Merton (1974:449), Black and Cox (1976:351), Leland (1994:1213), and, recently, Bharath and Shumway (2008:1339), Hillegeist *et al.*, (2004:5), and Vassalou and Xing (2004:831).

The South African investment community, including the equity and debt holders, is in dire need of information relating to their economic and social investments. Notably, South African academics – such as Daya (1977); Strebel and Andrews (1977); De la Rey (1981:11); Clarke, Hamman and Smit (1991:31); Court & Radloff (1993:9); Lukhwareni (2005); Naidoo and Du Toit (2006:33); Van der Colff and Vermaak (2014:243) and Senkoto (2012:1) – may have covered ground in the analysis of prediction and prevention of corporate financial distress. This study could not find research on the prediction forecast using market-data in conjunction with fundamental data. This has presented the opportunity for this study to be the first to present a unique study that incorporates both the fundamental and market data.

The present study understands and applies the concept of fundamental data as pointing to the company specific financial information. These are accounting ratios that calculated from annual financial statements. The investment community and other relevant stakeholders make investment decisions based on the efficacy of these numbers. Indeed, in relying on the fundamental data the investment community sees the future of the company through a rear-view mirror. The future, glimpsed only through a rear-view mirror, is necessarily framed by the past. To this end, the introduction of market-based data in predicting financial distress is eminent. The market-based data brings in the element of independency and a futuristic view about the company performance. The market indicators contain the sentiments of a collective, in the sense of various market participants. It should then follow, that in predicting the future it is pertinent to understand both the past and to have an honest and an impartial view about the future.

It is precisely the two abovementioned compelling perspectives that have persuaded the present study in investigating the efficacy of combining fundamental and market-based data in predicting financial distress. In an attempt of coining this into a statement, this study declares the following problem statement:

The combination of fundamental and market variables in developing a financial distress prediction model yields a better prediction accuracy rate than a distress prediction model that is purely based on the fundamental data.

1.3 PURPOSE STATEMENT

The main purpose of this study is to develop a hybrid financial distress predictive model that incorporates fundamental and market information. There are three models that are developed in the present study.

The first model, the basic model, is based on a systematic loading of three sets of variables: fundamental, market and macroeconomics indicators.

The second model is the Merton model, which is based on the Merton option pricing model. This model technique is chosen based on its simplicity and robustness.

The third model is the Hybrid model, and it is developed by combining independent variables used in the basic model and the distance to default outcome obtained from the Merton model.

1.4 RESEARCH OBJECTIVES

There is evidence that a fair amount of research findings in the South African academic community concentrated on developing fundamental models purely based on fundamental data. This study acknowledges the valuable research work done by South African researchers. However, it aims to extend the academic knowledge base by incorporating the market information in the financial distress prediction research. Therefore, the research objectives for this study are:

- To develop a financial distress prediction model that incorporates three sets of indicators (fundamental, market and macroeconomic data). This model shall be referred to as the basic model.
- To develop a structural financial distress model to calculate distance to default and the probability of distress. This model is referred to as the Merton model.
- To develop a hybrid model incorporating the variables utilised in the basic model and the distance to default score derived from the Merton model.
- To investigate which of the two models is better at differentiating defaulting and non-defaulting firms. In this way, the study assesses the extent to which different failure prediction models may yield significantly different distress prediction results.
- To explore the extent of gains (if any) that can be realised from developing a hybrid model.

1.5 IMPORTANCE AND BENEFITS OF THE PROPOSED STUDY

This study aims to add or expand the existing knowledge base in the South African academic community by comparing the financial distress predictive power of both the basic model (based on the combination of fundamental, market and macroeconomic indicators) and the Merton model (based on market data). Furthermore, the study seeks to introduce the benefits derived from combining the basic and Merton models by developing a hybrid model.

1.6 STUDY OUTLAY

Chapter 1 introduces the background to the study, the problem statement, the study objectives and the academic value-added. Chapters 2 and 3 provide the theoretical framework of the study highlighting, inter alia, the origins, advantages and disadvantages as well as the pioneers of the fundamental and market-based models. Chapter 4 provides the development of the study hypotheses. Once these hypotheses are developed, Chapter 5 provides a detailed strategy as to how they may be tested – a study methodology is discussed. Chapter 6 details the research design and data analysis. While Chapters 7 and 8 present the model empirical results, Chapter 9 ends by presenting the conclusions and recommendations.

1.7 CHAPTER SUMMARY

This chapter sets the scene of the study. It embarks on laying the research background so to fairly introduce the reader to the research topic. Thereafter, the study research problem statement, the purpose of the study and the study objective are clearly presented. It is of no significance spending time on a particular research if it does not intend to add value to the existing academic knowledge base. Therefore, this chapter also lays down its importance and benefits to the academic community.

CHAPTER 2

A LITERATURE REVIEW OF CLASSICAL FINANCIAL DISTRESS MODELS

2.1 INTRODUCTION

This chapter provides a synthetic and evaluative analysis of corporate financial distress and bankruptcy. The incidence of a large company bankruptcy case, like Enron's, has led to a growing interest in corporate bankruptcy prediction models since the 1960s. This is due to financial and social catastrophic ramifications from corporate failure. In certain countries, including South Africa, there is evidence of government intervention in the form of austerity measures or bailout packages to curb job losses among other economic reasons. It is then befitting that mechanisms and systems, such as predictive models, are continuously developed to detect and predict such unfavourable incidences.

This chapter evaluates existing literature and provides a concise synthesis of corporate financial distress and bankruptcy modelling. The review incorporates classical methodologies, contrasting them with contemporary research. The existing research reveals that classical predictive models employed a single set of data (fundamental or market data). However, there has been an emergence of hybrid predictive models seeking to explore the benefits of employing both sets of variables. The hybrid models may have been triggered by lukewarm research results of studies that have attempted to demonstrate the superiority of market-based models over fundamental-based models and vice versa, whereas both methodologies contain useful information on the company's probability of financial distress.

The literature review is covered in Chapters 2 and 3, discussing fundamental and structural models, respectively. Chapter 3 also reviews the contemporary development of a hybrid model.

Chapter 2 is structured as follows: Section 2.1 introduces and sets objectives for the chapter. Section 2.2 reviews the definition of corporate failure – while spending time on the definition of corporate failure might seem mundane, it is interesting to read how researchers have defined it in their studies. To date, no consensus has been reached on this definition. Having dealt with the definition of corporate failure, section 2.3 discusses the classical methodologies of predictive models, looking at their robustness and their continued relevance in contemporary research. Section 2.4 looks at the advancement of financial distress literature within South Africa. Section 2.5 concludes the chapter by joining all the salient highlights of the literature and how these influence the present study.

2.2 THE DYNAMICS IN THE DEFINITION OF FINANCIAL DISTRESS

In South Africa, Chapter 6 of the Companies Act, 2008 (hereafter known as 'the Act') deals with business rescue. Business rescue is largely self-administered by the company under independent supervision within the constraints set out by the Act, and could be subject to court intervention at any time on application by any of the stakeholders.

For business rescue, it is important to understand the meaning of 'financial distress' as the requirements of Chapter 6 of the Act are triggered as soon as a company is in financial distress. When a company is in financial distress and the company failed to adopt a resolution to go into business rescue or provide written notice to shareholders, employees and creditors that it decided not to adopt business rescue, the company is in breach of the Act and the auditors may have to report this as a reportable irregularity.

The above stance stipulates a legalistic and formalised process at a point when the company is in financial distress. The point is that, stakeholders would want to detect, predict and prevent financial distress in advance. The words 'detect' and 'predict' are equivalent to early warning signals so that corrective action is taken where necessary. Therefore, the success of a predictive model should be in the early identification of potential failure or distress and not in declaring distress or failure at a point of no return.

In predictive model development studies, the words 'financial distress', 'financial failure', 'unhealthy or sick' and 'bankrupt' have been used interchangeably with each author attaching his/her meaning or interpretation to the word. Many authors adopted the legalistic definition as it is a legal definition, while some researchers have not. Altman

(1968:589) defines failure in line with the provisions of Chapter X of the National Bankruptcy Act of USA. Yet, Beaver (1966:71) says an enterprise is like a reservoir formed by the cash flow, composed of cash inflows and outflows. An enterprise in financial distress is just like a reservoir whose water is drained.

Recent literature shows a paradigm shift away from the pure legal definition to a more comprehensive definition that also includes the economic and accounting definition.

Most researchers have tended to identify lack of adequate liquidity and tracking net cash flows as the trigger of financial distress. Cao and Chen (2012:70) decided on tracking net cash flows in defining financial distress. Carmichael (1972:94) stipulates four situations that should trigger financial distress, namely:

- Insufficiency of liquidity,
- Insufficiency of equity,
- Default of debt, and
- Insufficiency of liquid capital.

Doumpos and Zopounidis (1999:1138) adopted an accounting definition for financial distress. The authors indicate that a mere inability to repay obligatory payments is not enough, and they also perform an insolvency test which tests whether total liabilities exceed total assets.

Ross, Westerfield and Jaffe (1999:1) summarised previous studies on the definition of 'financial distress' and found a trend of a more comprehensive definition of legal, accounting and economic elements. These include:

- Business failure – that is, a company cannot pay the outstanding debt after liquidation;
- Legal bankruptcy – namely, a company (or its creditors) applies to the court for a declaration of bankruptcy;
- Technical bankruptcy – namely, a company cannot fulfil the contract on schedule to repay principal and interest; and

- Accounting bankruptcy – namely, a company's book net assets are negative.

This distinction and pattern in defining failure among researchers is prevalent. It may then be concluded that there is lack of consensus among academicians on the definition of corporate failure when developing predictive models. This view is also supported by Ohlson (1980:111). Amendola, Restaino & Sensini (2015:41) suggest that there should be a distinction made when defining financial distress, they view bankruptcy, inactivity and liquidation as three different forms of exiting the market.

For purposes of this study, financially distressed companies are those companies that have been delisted or suspended from the Johannesburg Stock Exchange due to financial distress. This study further defines financially depressed companies, as those that show negative movements on profitability year on year as well as signs of technical insolvency. This is a comprehensive definition of financial distress that considers both the economics and the accounting aspects. The intention of this study is to draw a distinction between companies that are already financially distressed and companies that are viewed as financially depressed. This approach is a shift away from the binary classification of companies as failed or not failed.

2.3 CLASSICAL FUNDAMENTAL MODEL

The literature shows that the multiple discriminant analysis model, as originally developed by Altman (1968:589), remains a benchmark for most of the recently developed models. This is despite the introduction of different methodologies, such as logistic analysis, expert systems and contingent claims which are based on market data. Having compared various methodologies, Aziz and Dar (2006:18) concluded that the performance of all these models is comparable, although the use of multiple discriminant analysis and logistic analysis models dominates the research. This finding implies that there is no one methodology that stands apart from others. Having gone through 165 bankruptcy studies, Bellovary, Giacomino and Akers (2007:12) concluded and emphasised that future research should be on refining what is available rather than introducing new models.

The literature provides a clear chronological development of model methodologies from the univariate analysis to the latest structural models.

The path-breaking work was done by Beaver (1966:71) when he pioneered a corporate failure prediction model using fundamental data. He applied the now defunct methodology, a univariate discriminant analysis based on various financial ratios selected by a dichotomous classification test. In response to Beaver, Tamari (1966:15), and Moses and Liao (1987:27) used risk index models to predict failure – these are simple and intuitive point systems based on different ratios.

Altman (1968:589) introduced a statistical multivariate analysis technique – multiple discriminant analysis – to the problem of corporate failure prediction and estimated a Z-score model. Multiple discriminant analysis is a statistical technique used to classify an observation into one of several a priori groups dependent on the observation's individual characteristics. It attempts to derive a linear combination of these characteristics which best discriminates between the groups (Altman 1968:589). Over the years, there have been numerous studies based on Altman's Z-score model. Altman *et al.* (1977:29) adjusted the original Z-score model into a new, better performing Zeta analysis model.

Dimitras, Zanakis and Zopounidis (1996:487) suggest that the use of multiple discriminant analysis has decreased since the 1980s. However, Altman *et al.* (1977:32) say that it remains a generally accepted standard method and it is frequently used as a baseline method for comparative studies. Multiple discriminant analysis has been replaced by less demanding statistical techniques, such as logistic analysis, probit analysis and linear probability modelling. These methods resulted in conditional probability models (Doumpos & Zopoudinis, 1999:1138; Zavgren, 1983:1; Zavgren, 1985:19), consisting of a combination of variables that best distinguish failing from non-failing firms. Ohlson (1980:109) pioneered using logistic analysis in company failure prediction, whereas Zmijewski (1984:59) was the pioneer in applying probit analysis. Until now, logistic analysis has been a very popular method in business failure prediction. The number of studies using probit analysis is much smaller, probably because this technique requires more computations (Dimitras *et al.*, 1996:487; Gloubos & Grammatikos, 1988:37).

In the past decade, Vassalou and Xing (2004:831), Hillegeist *et al.* (2004:5), and Bharath and Shumway (2008:1339) have employed the contingent claims approach to estimate the likelihood of corporate failure. To date, there is no evidence in literature singling out one specific model methodology as the best among predictive accuracy. At worst, Balcaen and Ooghe (2006:65) seem to suggest that all these methods contain certain problems in their features, assumptions and applications to corporate failure prediction studies.

These prediction models, as portrayed in prior research, have been based predominantly on company-specific fundamental data. However, the literature does reveal a propensity by some researchers drifting away from fundamental to market data in predicting bankruptcy. There is also limited evidence of studies that have used macroeconomic data.

The academic value added by the present study is about amassing the South African economic data, Johannesburg Stock Exchange share performances and other relevant market data as well as the company-specific financial performance. This combination is yet to be tested on Johannesburg Stock Exchange listed companies. It is an established fact that the underlying business and economic variables that may cause corporate bankruptcy are both endogenous and exogenous in nature. Surprisingly, the scant attention given in existing literature to macroeconomic variables as potential contributors into bankruptcy is glaring.

2.3.1 Univariate model

This statistical technique was pioneered by Beaver (1966:71) in 1966 and has received mixed reactions due to its inability to simultaneously load multiple independent variables. Altman (1968:589) criticised the use of univariate analysis technique as susceptible to faulty interpretation and potential confusing. Recent research is relatively quiet on this technique with evidence of the application of multiple discriminant analysis, albeit there have been univariate studies since Beaver's – Pinches, Eubank, Mingo and Caruthers (1975:295), and Chen and Shimerda (1981:51). With this background, this study provides a snippet of the univariate analysis with the intention of laying a foundation for fundamental models.

Beaver (1966:71) departs by defining **failure** as a company's inability to pay its financial obligations as they mature. He further adds that a firm is said to have failed operationally when any of the following occur: bankruptcy, bond default, an overdrawn bank account or non-payment of preferred stock dividend. Beaver's definition of failure remains relevant and aligned with contemporary research studies. He used a small sample size of 79 companies classified by industry and asset size. He analysed a sample of bankrupt firms and a matched sample of non-bankrupt firms, and studied the two samples' financial performance indicators up to five years before failure.

Although Beaver's sample size may appear small for one to generalise, Shirata (1998:437) actually suggests that one may not generalise the findings when using a small sample. However, the common limitation in financial distress predictive studies is the availability of information on bankrupt companies – hence; most studies have a small sample. Furthermore, the state of economy over the economic review period of the study may be the determining factor for the number of companies filing for bankruptcy.

Beaver's work was a type of univariate analysis where each measure or ratio was analysed separately and the optimal cut-off point was selected so that the number of accurate classifications was maximised for that particular sample. Beaver tested 14 ratios and found that the cash flow to total debt ratio was the best classifier of corporate bankruptcy. Other important financial measures were the debt to total assets and net income to total assets ratios, and the **no credit interval**. He chose the population of his independent variables based on popularity – that is, the frequent appearance in literature, that the ratios performed well in one of the previous studies, and that the ratio be defined in terms of a **cash-flow** concept. Charitou, Neophytou and Charalambous (2004:283) find that operating cash flow has incremental explanatory power using a recent UK sample.

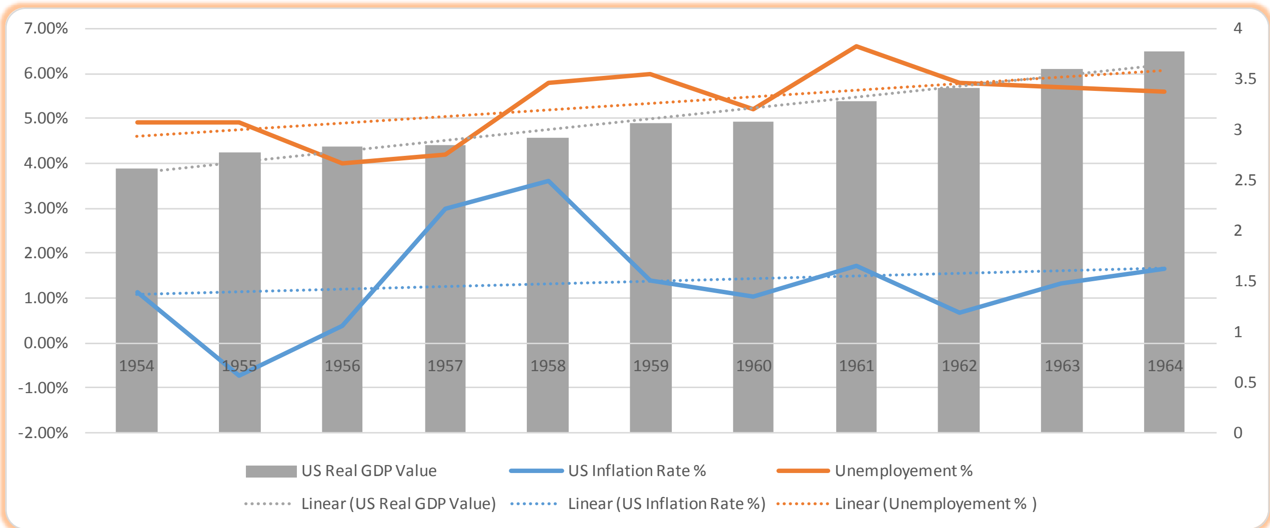
In a multi-ratio analysis, it is desirable that each ratio convey as much additional information as possible – that is, the common elements should be reduced to a minimum. Indeed, Beaver's procedure in selecting independent variables remains relevant in contemporary research.

Five years before failure, an optimal prediction criterion (cut-off value) based on the single accounting ratio misclassified only 22% of the validation. One year prior to failure, the criterion misclassified only 13% of the validation sample. This is impressive given that a random classification would produce a 50% error in the sample.

Beaver (1966:71) conducted his study when economic conditions in the United States of America were stable. The US Bureau records reveal evidence of economic growth and general prosperity with rising wages, where the unemployment rate was as low as an average of 5.4%, and the country recorded an average gross domestic product of $3.11tn over the same period.

The below graph represents the three economic indicators over the period Beaver conducted his financial failure predictive study.

Graph 2-1: US real gross domestic product, inflation rate and unemployment rate (1954-1964)



Source: US Department of Commerce: Bureau of Economic Analysis

Graph 2-1 reflects an overall favourable and stable economy. The real gross domestic product reflects an upward trend over the period, while inflation and unemployment remain steady. Under these economic conditions investor confidence and appetite should be stimulated, with other things being constant. Therefore, the number of companies that have failed during this period should be very low. In instances where companies have failed, it should be because of company-specific operational deficiencies.

2.3.2 Multiple discriminant analysis

With the intention of improving on Beaver's (1966:71) previous work based on the univariate analysis, Altman (1968:589) introduces the multivariate analysis in his predictive study. The analysis is multivariate as a number of variables are combined simultaneously to analyse a firm for its failure potential. A multiple discriminant analysis model consists of a linear combination of variables, which provides the best distinction between failing and non-failing firms (Balcaen & Ooghe, 2006:68).

In his study, Altman (1966:589) defines **failed companies** by adopting a legal definition he based on Chapter X of the National Bankruptcy Act. His approach in identifying failed firms is that companies had to have filed a bankruptcy petition as stipulated in the Act. However, the application of a legal definition hinders the model from identifying financial distress warning signals. Legal processes normally take time to conclude. Therefore, his population of non-failed companies may have been contaminated by companies that are already going through the bankruptcy legal process, but have not yet concluded it.

In line with the previous study, Altman (1966:589) considered a small sample of 66 companies with 33 firms in each group (failed/non-failed). His group of companies was stratified by industry and size, with the asset size range restricted to $1-25m. Altman restricting his study to small and medium-sized companies is likely based on the perception that the number of large companies that would have filed for bankruptcy would have been very small. However, this is perhaps a shortcoming on his study, in that even large companies may contain signs of financial distress – an example of a large company failing is Enron. One of South Africa's biggest banks has recently gone under business rescue.

From the original list of 22 variables from Altman's (1966:589) study, only five variables were found to possess a statistical discriminant power.

The final discriminant function is as follows:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.99X_5$$

Where:

X1 = working capital/total assets;

X2 = retained earnings/total assets;

X3 = earnings before interest and taxes/total assets;

X4 = market value equity/book value of total liabilities;

X5 = sales/total assets; and

Z = overall index.

Any firm with a Z-score below 1.8 is considered a prime candidate for bankruptcy, and the lower the score, the higher the failure probability. This model was over 90% accurate in classifying bankrupt companies correctly, one statement prior to failure, and over 80% accurate in subsequent prediction tests.

In 1977, Altman introduced a revised version of his original model known as the Zeta analysis. He justifies the revision of the original model on the basis of changes in accounting reporting standards since the 1960s. The resulting linear Zeta discriminant model is extremely accurate for up to five years before failure.

The success of multiple discriminant analysis lies on the assumptions that must be complied with for the model to work. Balcaen and Ooghe (2006:67) summarise these assumptions as follows:

- The dichotomy of the data set – that is, groups are discrete, non-overlapping, and identifiable.
- The use of multiple discriminant analysis is based on multivariate normally distributed independent variables, equal variance-covariance matrices across the failing and non-failing group, and specified prior probability of failure and misclassification costs.

What remains highly contentious in the contemporary research regarding the integrity of the multiple discriminant analysis is its statistical assumption that must be complied with for the model to make sense. At the centre of this controversy is the opinion that the process leading to bankruptcy does not follow the assumptions imposed by multiple discriminant analysis. Balcaen and Ooghe (2006:67) capture some of the most highlighted criticism of multiple discriminant analysis in literature as follows:

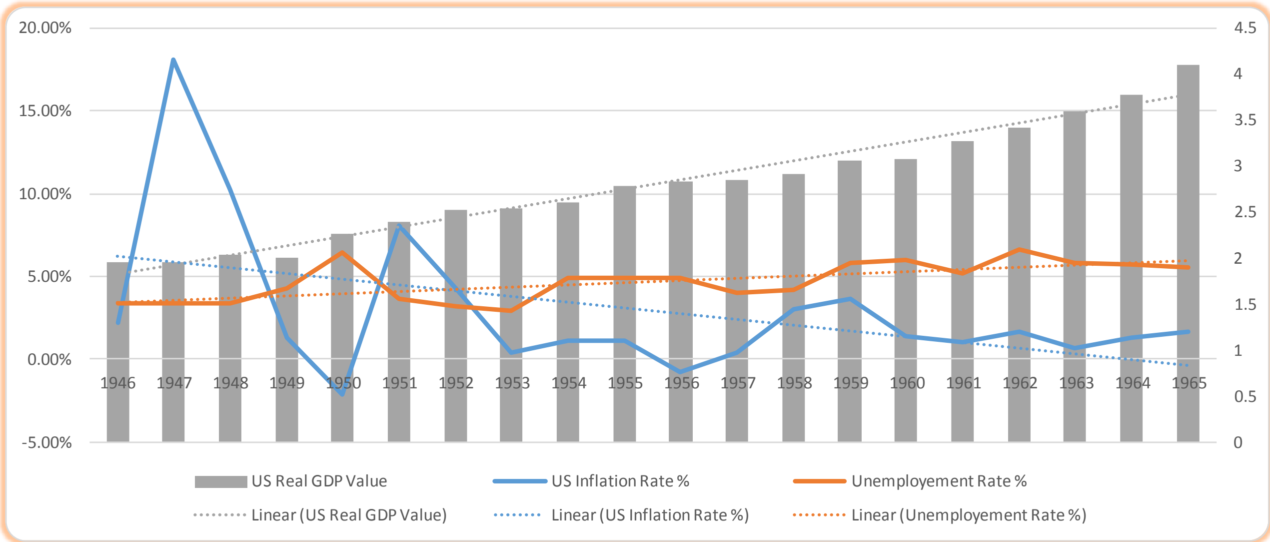
- The multivariate normality is often violated resulting in biased significance tests and error rates.
- The data rarely satisfy the assumption of equal dispersion matrices, which results in biased significance tests.
- Ignoring prior probabilities of failure and the costs of types I and II errors in the definition of the optimal cut-off score of the multiple discriminant analysis model may result in a misleading estimate of model accuracy.
- Severe correlation among the independent variables may cause unstable and difficult-to-explain parameter estimates and misleading model accuracy.

The multiple discriminant analysis methodology remains robust and relevant in contemporary research with most alternative methodologies still being compared to it. However, with Altman's study, the dichotomisation of financial failure into failed/non-failed as well as the selection of non-failed companies to meet the predefined list of failed companies may be flawed and biased. However, he may have had to match the group of companies to meet the statistical requirements of multiple discriminant analysis, especially that variance-covariance matrices across the two groups must be equal to fulfil the requirements of normal distribution.

Given the cited shortcomings identified in the multiple discriminant analysis it is not surprising that market based models seem to perform better. In a recent study, Altman (2016:2) has come back defending the multiple discriminant analysis. He says while there is some evidence that Z-Score models of bankruptcy prediction have been outperformed by competing market-based or hazard models, in other studies, Z-Score models perform very well. In another recent study by Kosmidis & Stavropoulos (2014:66) multiple discriminant analysis is found to have outperformed the logistic and probit regression analysis in terms of correct classification. It is precisely these assertions that compel the present study to investigate both the multiple discriminant analysis and the market based models.

The economic period in which he conducted his study also reflects a healthy state, recording an average gross domestic product of $2.08tn over the same period. The unemployment rate was a low average of 4.7%. Given the favourable economic climate, the author also used a small sample of 33 failed companies (lower than Beaver's). This further supports the impact of the favourable economic climate in companies prospering with limited chances of failure, if at all, attributable to company-specific management acumen.

Graph 2-2: US real gross domestic product, inflation rate and unemployment rate (1946-1965)



Source: US Department of Commerce: Bureau of Economic Analysis

Graph 2-2 reflects a positive and healthy economic state over the 20-year period. The real gross domestic product trend is seen increasing while unemployment remains flat. Interestingly, the country experienced a deflation situation over the 20-year period which should have impacted positively on corporate earnings as input cost reduced over time. This is an opportune economic environment for investors, which should translate to very few companies failing over the same period. This point is also confirmed by the small number of companies considered in his study.

The purpose of including the historical performance of economic parameters in the discussion is merely to provide the economic climate relevant to the time the study is done. This is to further identify the impact, if any, of the economic volatility to company financial distress. The assumption is that if the economy is weak and highly volatile, it is likely to induce negative financial ramifications to certain individual companies and therefore increase the risk of financial distress. Whereas, in a strong and stable economic climate, the general risk of financial distress should be minimum.

2.3.3 Conditional probability models

During the 1980s, there was an emergence of conditional probability models (Doumpos & Zopounidis, 1999:1138; Ohlson, 1980:109; Zavgren, 1983:1; Zavgren 1985:19), introducing logistic analysis and probit analysis. Hand and Henley (1996:533) suggest that logistic analysis is a more appropriate instrument than linear regression since it allows the definition of two distinct classes.

Ohlson (1980:112) says that his chosen econometric methodology alleviates some of the statistical restrictions imposed by multiple discriminant analysis. He highlights these restrictions as follows:

- The variance-covariance matrix of the predictors should be the same for both groups (failed and non-failed firms).
- The requirement of normally distributed predictors.
- The matching principle where failed companies equally match with non-failed companies.

The use of conditional logistic analysis seems to overcome most of the problems highlighted above. The fundamental estimation problem can be reduced to the following statement: given that a firm belongs to some pre-specified population, what is the probability that the firm fails within some pre-specified time period? No assumptions have to be made regarding prior probabilities of bankruptcy and/or the distribution of predictors.

The logistic analysis model combines several firm characteristics or attributes into a multivariate probability score, which indicates the firm's failure probability or vulnerability to failure. It allows for categorical qualitative variables (Keasey & Watson, 1987:340). The logistic function implies that the logistic analysis score P_1 has a value in the [0.1] interval and is increasing in D_i. When the failed status is coded as one (zero), a high (low) logistic analysis score indicates a high failure probability and, hence, poor financial health. The failure probability P_1 follows the logistic distribution.

The major findings in Ohlson's study are recorded as it being possible to identify four basic factors as statistically significant in affecting the probability of failure (within one year).

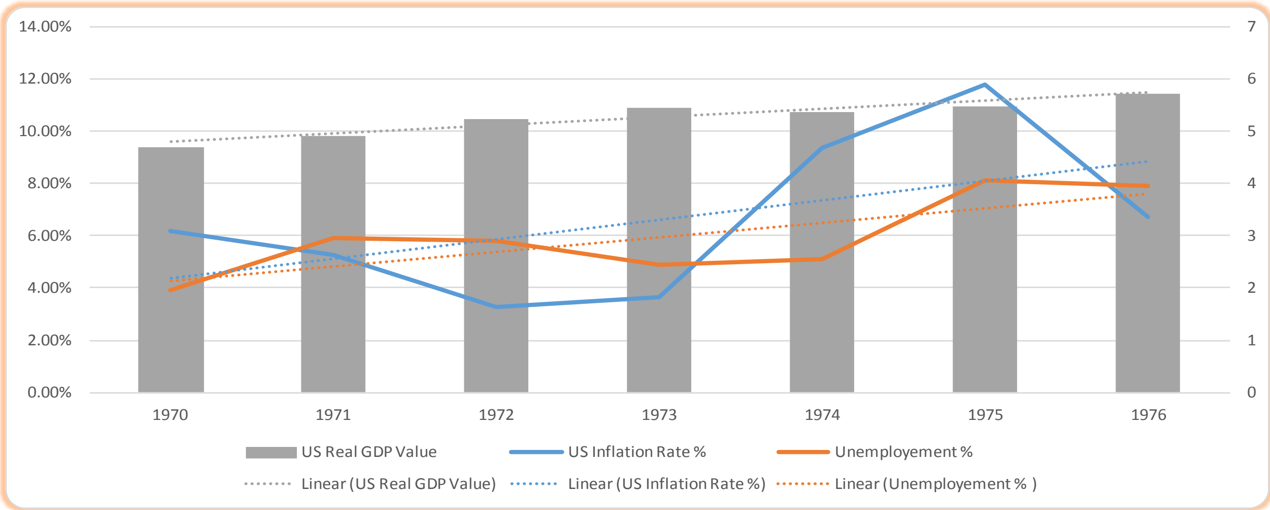
These are:

i. the size of the company;
ii. a measure of the financial structure;
iii. a measure of performance; and
iv. a measure of current liquidity.

Ohlson (1980:130) concludes by saying the predictive power of any model depends on when the information (financial report) is assumed to be available. He further states that, the predictive powers of linear transforms of a vector of ratios seem to be robust across (large sample) estimation procedures. Moreover, the significant improvement probably requires additional predictors.

The US real gross domestic product from 1970 to 1976 was an annual average of $5.27 trillion, with a growth rate of 2.87% over the same period. However, a noticeable deterioration of general consumer price levels soared, which may have had negative implications on corporate earnings as operational costs over the same period. The tough conditions are also reflected in the increasing unemployment level to 7.9% in 1976.

Graph 2-3: US real gross domestic product, inflation rate and unemployment rate (1970-1976)



Source: US Department of Commerce: Bureau of Economic Analysis

Ohlson (1980:109) obtained a sample of 105 failed companies within the shortest period (seven years) compared to Beaver (ten years) and Altman (20 years). This proves the impact of analysing the economic conditions in financial distress studies to obtain a better understanding on certain corporate financial performances.

2.3.4 Artificial intelligence expert systems

The artificial intelligence expert systems may generally be classified in the family of modelling techniques that have gained popularity in predictive studies. Originally aimed at diagnosing infectious diseases and identifying unknown organic molecules, this methodology has been introduced to solve some of the complex financial decisions with great success.

The artificial intelligence expert systems were introduced in financial distress prediction studies in the 1990s (Odom & Sharda, 1990; Tam & Kiang 1992). The level of accuracy and performance of this technique was evaluated against the then popular statistical technique (logistic analysis) and the results indicated that neural networks methods provide superior results to those obtained from the logistic analysis method (Yim & Mitchell, 2005:87). Aydin & Cavdar (2015:3) say neural networks arise as a powerful tool to enhance modeling flexibility and dynamism and to identify the most outstanding properties to predict financial crisis originated in some financial variables such as gold prices, stock exchanges, and exchange rates. To this date, Aydin and Cavdar (2015:11) conclude that neural networks arise as a powerful tool to enhance modelling flexibility and dynamism, and to identify the most outstanding properties to predict financial crisis.

Structurally, this is a computing system that consists of a network of interconnected units called artificial neural networks. They are organised in layers inside the network. The first layer is the input layer, and the last is the output layer. Hidden layers exist between the input and output layers, and there may be several hidden layers for complex applications. Computer programs process the training sample to identify the relationships between input and output data.

In a recent study, Shah (2014:103) separately investigated five techniques for predicting corporate failure: logistic analysis, multiple discriminant analysis, neural networks and two hybrid models. Regarding the hybrid model, Shah first combined logistic analysis and artificial neural networks and coined it Hybrid I. Thereafter, a second hybrid model was constructed combining multiple discriminant analysis and artificial neural networks, coining it Hybrid II. Table 2-1 below depicts the results of his comprehensive study.

Table 2-1 below confirms the general paradigm from existing literature that says hybrid models seem to have a much stronger predictive power over single set techniques. The hybrid model is above the rest at 94%, closely followed by the artificial neural networks at 93.7%. Again, this is the confirmation of the power neural networks have over classical statistical methodologies.

Table 2-1: The accuracy results of five different techniques for predicting financial distress by Shah (2014:123)

Model	Training
Hybrid I - artificial neural networks and logistic analysis	94.00%
Artificial neural networks	93.70%
Logistic analysis	91.90%
Hybrid II - artificial neural networks and multiple discriminant analysis	91.00%
Multiple discriminant analysis	82.80%

Source: Shah (2014:123)

Neural networks appear to be flexible and dynamic when it comes to the rules and restrictions that are often imposed by statistics. When it comes to these rules, multiple discriminant analysis is the most restricted statistical techniques of the above. This may explain the reason why it is the worst performing technique in this particular study. López Iturriaga and Sanz (2015:2858) highlight some of the salient features of expert systems when compared to other empirical approaches to bankruptcy prediction:

(i) They do not make assumptions about the distribution of the data.
(ii) They are the most powerful processors compared to classical econometric methods.
(iii) They perform even better when used in conjunction with linear regression models.
(iv) Artificial neural networks should be viewed as an additional tool to be included in the toolbox of macroeconomic forecasters.
(v) They allow a non-linear set of relations. This allowance is especially important for bankruptcy predictions because the relationship between the likelihood of default and the explanatory variables does not have to be linear. Furthermore, financial data seldom follow the multivariate normal distribution, each of which is a violation of the multiple discriminant analysis assumptions.
(vi) They are powerful and flexible modelling devices that do not make restrictive assumptions on the data-generating process or the statistical law relating variables of interest.

Cleofas-Sánchez, García, Marqués and Sánchez (2016:144) present an alternative technique for financial distress prediction systems which is based on a type of neural network, which is called hybrid associative memory with translation. The experimental results over nine real-life data sets show that the associative memory constitutes an appropriate solution for bankruptcy and credit risk prediction, performing significantly better than the rest of models under class imbalance and data overlapping conditions in terms of the true positive rate and the geometric mean of true positive and true negative rates.

The downside to these expert systems is that it may be difficult to provide proper explanation and logic of the prediction results as the layers in the middle are hidden. Neural network may also suffer with generalisation because of over fitting, and they need a lot of time to train the models and obtain the most adequate configuration. The training of the model may pose practical problems with large volumes of data.

2.4 THE SOUTH AFRICAN PERSPECTIVE

Without an in-depth understanding of the economic climate it may be difficult to accurately predict financial distress. The economic climate may consist of historical, current and forecasted economic indicators reflecting the country’s bill of health. These indicators may be factored in the model as risk elements. This view stems from a hypothesis this study is making that corporate performance is a factor of endogenous and exogenous economic variables. Given this hypothesis, it then follows that the financial distress prediction study has to incorporate internal and external variables. To this end, corporate failure prediction solely relying on financial statement ratios may not be the ultimate solution.

Below is a brief summary of the South African economic bill of health for the past three decades. It is during this period where South African corporate prediction studies were conducted. The objective is to determine whether adequate risk was factored in the models in arriving at prediction results.

When speaking to a group of foreign correspondents, the South African Minister of Trade and Industry, Rob Davies, said: "As a result, the economy in 1994 was characterised by an extended period of negative growth rates, falling per capita incomes, ballooning fiscal deficit, double digit inflation rates, negative rates of fixed investment, rising unemployment, low rates of firm-level R&D, declining gold production coupled with a low gold price, and adversarial labour relations at shop-floor level" (Alexander, 2014).

The minister continued: "At the industrial level concentration was extremely high, with more than 80% of all the Johannesburg Stock Exchange-listed companies owned by just six diversified conglomerates … Exports were highly concentrated around mining and mineral products, mainly exported to Europe and the United States".

Now, reflecting on the above painted economic picture, it appears to have been an economic climate where large and financially sound companies strived while small and medium-sized, financially weak companies perished. It may be concluded that this period was engulfed by a high rate of small business failure, limited global competition, technology advancement, negative investor sentiment and low business confidence. Given this economic climate, simply relying on annual financial statements of a company without factoring the economic outlook could have understated the risk element in the model.

The post-1994 economic period (1994-2013) reflects a step change as the South African economy experienced positive growth in every quarter during this period except for two of the 78 quarters. In both instances where the South African economy experienced negative economic growth, international crises precipitated the contraction. Economic growth suffered in 2012 from social unrest and the Euro crisis, but this accelerated as global demand improved. Now, this economic climate would have required a paradigm shift in risk assessment.

The first comprehensive investigation into corporate failure in South Africa was published by De la Rey (1981:11), who systematically set out to isolate the ratios to be used in his model. In the South African context, as quoted in Court & Radloff (1993:6), De la Rey (1981:11) broadly defines **corporate failure** as a business with a capital structure reflecting negative equity, forced to discontinue operations because it had committed an act of insolvency or was, as a result thereof, put under judicial management. Consequently, the company could not show profit for two out of three years, was unable to pay its preference dividend on time, was unable to declare an ordinary dividend for that year, was unable to honour its loan commitments on time according to a contractual agreement, and reduced the nominal value of its share capital to bring it in line with the assets it represents.

The chosen economic period in De la Rey (1981:11) study is 1972 to 1979. By using multiple discriminant analysis and 25 variables, his model was found to classify companies as healthy or likely to fail with a 98.6% overall prediction accuracy one year prior to failure.

Another great contribution by Court & Radloff (1993:9) was to construct a two-stage model of corporate failure embodying factors which influence the success of a business or organisation. In essence, the success of any business is influenced by two major sets of factors. These factors refer to those that may be controlled by management which are both financial and non-financial. Another set of factors affecting the company are those beyond the control of management, which are the overall economic conditions. The research conducted by Court & Radloff (1993:9) aimed to combine the two major set of factors in a simple, yet comprehensive, model. Therefore, a two-stage model was developed.

Court & Radloff (1993:9) also set to evaluate the two most common methodologies: multiple discriminant analysis and logistic analysis. The author found that logistic analysis achieved superior results when predicting failure for all of the five years prior to failure. Alternatively, a Z-test indicated that there was insufficient evidence to suggest that either technique was superior to the other. The overall conclusion is that logistic analysis cannot be regarded as a superior statistical technique to multiple discriminant analysis when failure prediction is in question. Nevertheless, it appears to be a more robust technique under certain circumstances.

On analysing the non-financial variables where Court & Radloff (1993:9) used three groups of non-financial variables which relate to the delay in publishing the annual report, director resignations and appointments and director shareholdings were investigated. The model containing these variables gave comparable results (95-92%) to the failure prediction model containing only financial ratios.

Naidoo and Du Toit (2006:33) introduced a different angle in the area of corporate distress prediction research. The authors move away from a traditional dichotomous methodology by introducing a two-stage approach to identifying (first stage) and analysing (second stage) the States of Health in a company. They split the first stage into three states, classifying a company as healthy, intermittent or distressed. Models were developed for the current year (Yn), one (Yn-1), two (Yn-2) and three years (Yn-3) forward using a test sample of 20 companies and their predictive accuracy determined by using a holdout sample of 22 companies and all their data points or years of information. The statistical methods employed included a naïve model using the simple shareholder value added ratio, chi-square automatic interaction detector and multiple discriminant analysis.

In the second stage of their study, Naidoo and Du Toit (2006:33) introduce a unique analysis factor compared to previous research work. They develop a financial risk analysis model (FRAM) using ratios in the categories of growth, performance analysis, investment analysis and financial status to provide underlying information or clues (independent of the first stage model) to enable the stakeholder to establish a more meaningful picture of the company. This would pave the way for the appropriate strategy and course of action to be followed, to take the company further – be it taking the company out of a distressed state (D) or improving its healthy status (H).

The main objectives of the study of Naidoo and Du Toit (2006:33) are highlighted as:

(i) First stage – to derive statistical models to predict the states of health in each company, to test the predictive ability of the models, and to test the best two models against a notable South African model, namely the De la Rey (1981:11).
(ii) Second stage – to provide a more intensive analysis of a company.

While their models produced good results, Naidoo and Du Toit (2006:51) believe prediction models should be used as a prognosis, giving management direction in improving company performance. This is because prediction models are not 100% accurate all of the time and their results should not be isolated.

2.5 THE EVOLUTION OF CLASSICAL FINANCIAL DISTRESS MODELS

Thus far, Chapter 2 provided a detailed literature on the evolution and development of financial distress prediction studies. Since the 1930's, literature development reflects a paradigm shift from relying purely on financial ratio comparison, between failed and successful companies, to the introduction of sophisticated statistical techniques during the sixties. This era ushered in the utility of the univariate and multivariate statistical techniques in predicting financial distress.

Section 2.3.1 provides a detailed account regarding the development of the univariate analysis as a statistical technique in predicting financial distress. Beaver (1966:71) was the first to develop a financial distress prediction model by applying univariate analysis. Beaver's work entailed that each measure or ratio was analysed separately and the optimal cut-off point was selected so that the number of accurate classifications was maximised for that particular sample. However, this statistical technique has received mixed reactions due to its inability to simultaneously load multiple independent variables. Altman (1968:589) criticised the use of the univariate analysis technique as susceptible to faulty interpretation and potential confusing.

In 1968, barely two years after the introduction of univariate analysis in this context, another sophisticated statistical technique was introduced by Altman (1968:589). Pointing to the shortcomings of the univariate analysis, Altman (1968:589) introduced multiple discriminant analysis in predicting financial distress. Again, the detail about the origins of this statistical technique and its subsequent development is presented in Section 2.3.2. The multivariate analysis carries an advantage to its predecessor technique in that a number of variables are combined simultaneously to analyse a firm for its failure potential. A multiple discriminant analysis model consists of a linear combination of variables, which provides the best distinction between failing and non-failing firms (Balcaen & Ooghe, 2006:68).

With a view of continuous improvement, the utility of multiple discriminant analysis in predicting financial distress attracted a number of other researchers in the subject matter introducing alternative solutions. What is clearly evident from existing literature is that multiple discriminant analysis may contain statistical restrictions that could be eliminated. These include, amongst others: the need for the same grouping of the variance-covariance matrix of predictors; the requirement of normally distributed predictors; and the matching principle where failed companies equally match with non-failed companies.

In a further study Ohlson (1980:112) introduces logistic analysis as an alternative solution. He is of the opinion that his chosen econometric methodology alleviates some of the statistical restrictions imposed by multiple discriminant analysis. The logistic analysis model combines several firm characteristics or attributes into a multivariate probability score, which indicates the firm's failure probability or vulnerability to failure. It allows for categorical qualitative variables (Keasey & Watson, 1987:340). As example, the logistic function implies that the logistic analysis score P_1 has a value in the [0.1] interval and is increasing in D_i, which represents the response variables. When the failed status is coded as one (zero), a high (low) logistic analysis score indicates a high failure probability and, hence, poor financial health. The failure probability P_1 would then follow the logistic distribution.

In the 1990s artificial intelligence systems were used for distress prediction. These systems, sometimes called expert systems, were largely known for their capacity to perform operations analogous to learning and decision making in humans. Originally aimed at diagnosing infectious diseases and identifying unknown organic molecules, this methodology has been introduced to solve some of the complex financial decisions with great success (Odom & Sharda, 1990; Tam & Kiang 1992).

Contemporary research proves the popularity and successful use, albeit cited limitations, of the multiple discriminant analysis, logistic analysis and artificial intelligence systems as financial distress prediction techniques. Again, the extant literature reveals a common golden thread between these three techniques as they were introduced over time. That common thread is the absolute reliance on fundamental data, or company specific accounting ratios calculated from annual financial statements. The missing link, according to Merton (1974:449), is the incorporation of the market perspective in the study of financial distress prediction. The market based data carry an independent market sentiment on a company's future performance. It is this independence of market sentiment that could lead to further improvement of prediction models. .

In response to financial distress prediction models based only on fundamental data, Merton (1974:449) identifies the need to include market based variables in calculating the distance to default. This shift away from fundamental models seems to have drawn remarkable interest within the academic sphere with many researchers subsequently making contributions that enhance some of the underlying theoretical assumptions of the so called Merton model. His approach finds its logical sense from the Black and Scholes (1973:637) option pricing framework. Merton (1974:449) developed a model for assessing a firm's credit risk by characterising the firm's equity as a call option on its assets. Alternatively, the debt holders of the firm could be viewed as holding a short put position on the firm's assets. Merton's approach is referred to as the 'structural approach' because it relies entirely on the capital structure of the firm for modelling credit risk.

As part of the literature review, the existing theoretical framework on the Merton model and other structural models is covered in detail in Chapter 3. The theoretical narrative on financial distress prediction models has evolved to a stage where less of new prediction methodologies are introduced but more hybrid models are developed. In the recent past, hybrid models comprising market-based and fundamental models made noticeable inroads in predicting corporate distress and bankruptcies. This proves that if one forecast is superior to another, one should not neglect the other altogether. It may be possible to combine the two forecast models to form an even better one. In Chapter 3, the present study also covers the theoretical framework on hybrid models.

2.6 CHAPTER SUMMARY

This chapter deals with the theoretical background and development of financial distress prediction studies. It highlights certain pioneers with remarkable milestones in the study and paves the way for further research development.

The literature seems to suggest that the efficacy of a predictive model is dependent on the research methodology adopted in the selection of variables relevant to financial distress. The literature reveals a diverse approach in the definition and understanding of corporate failure. Some authors have followed a legalistic definition identifying failed companies as companies that have filed for bankruptcy. This approach may pose a narrow view in defining financial distress, in that, companies that have not yet filed for bankruptcy but are experiencing financial depression would be classified as healthy. If this happens, the likelihood of sample noise in the population arises as this may lead to a list of healthy companies that is actually contaminated with companies that are in the process of filing for bankruptcy or are depressed. However, there is a different approach where authors have a set criterion in identifying failed companies. This criterion is often based on the financial performance of the company over a period of one, three or five years.

While the literature on failure prediction models using fundamental data appears rich, what comes out vividly across the literature (both domestic and foreign) is that each researcher appears to be benchmarking their study with Beaver’s (1966:71) or Altman’s (1968:589). Furthermore, regarding statistical methodologies, researchers appear to be benchmarking them with either multiple discriminant analysis or logistic analysis. This propensity leaves an impression that the multiple discriminant analysis and logistic analysis statistical methodologies remain relevant and reliable techniques. The drawback of these statistical methodologies appears to be the statistical assumptions imposed on them. Failure to meet the statistical assumptions imposed and applicable to a particular methodology may render that method weak, therefore undermining its integrity.

The methodology that has come out strong in performance against the two popular methods in bankruptcy prediction is the family of expert systems. The major advantage expert systems have managed to score compared to multiple discriminant analysis and logistic analysis is flexibility and dynamism when it comes to statistical rules and assumptions. Even though expert systems also attract a level of criticism in that the process of training the model may be tedious, their performance is impressive.

The selection of independent variables across literature seems to have found common ground. This view stems from the observation that literature suggests that variables are selected based on their popularity but most importantly their successful use in previous studies. Concerning testing for collinearity and trickling down to the most powerful explanatory variables, the statistical methodology that is commonly used is the stepwise discriminant analysis. However, the literature also reflects the use of correlation matrix, factor analysis and back-propagation algorithm when using Neural network. The independent variables that are commonly used in predictive studies have concentrated on the liquidity, leverage, activity and profitability ratios to assess a company's performance and its future vision of triumph.

What is also evident from literature is the significant role economic conditions played at the time the study was conducted. There is a view that companies tend to have a higher propensity to fail in times of economic recession than in times of economic prosperity. Therefore, a comparison of predictive percentages of studies conducted in different economies without a view on the circumstances at the time may be flawed.

Yet another observation is the outright classification of companies into failed and non-failed. This dichotomous approach tends to imply that failure hits companies suddenly. The present study is of the objective that a multi-stage approach provides valuable input to investors, stakeholders or management to put strategies in place aimed at salvaging or turning around the company before filing for bankruptcy.

CHAPTER 3

A LITERATURE REVIEW OF THE MERTON AND OTHER HYBRID MODELS TO PREDICT FINANCIAL DISTRESS

3.1 INTRODUCTION

The purpose of this chapter is to discuss the literature on the Merton and Hybrid models. It begins by briefly highlighting the theoretical background and provides the construction methodology. The chapter is structured as follows: Section 3.1 introduces and set objectives for the chapter. Section 3.2 lays the background and the statistical framework of the Merton model. Section 3.3 discusses the Merton model assumptions. Section 3.4 is about the construction of the Merton model. Section 3.5 highlights the global review of structural models with reference to the Merton model. Section 3.6 embarks on the background and development of the Hybrid model. Section 3.7 concludes the chapter by providing a summary of both models.

3.2 BACKGROUND

This chapter covers the theoretical background of the Merton model. In response to managing credit risk, Merton (1974:449) introduced a technique that could be used to determine the distance to default and the probability of default. He introduced a technique that used market variables and not fundamental data.

The Basel Committee on Bank Supervision, which establishes capital standards for international banks, advocated for the inclusion of market-based data or market discipline in addition to minimum capital requirements and supervisory review as the three key pillars of comprehensive capital-adequacy regulations (Basel Committee on Banking Supervision, 2006:1). The appetite in the use of market information arises from financial markets' ability to interpret public information quickly. With the availability of various corporate debt products and credit derivatives in the market allowing borrowing options to corporate, banks and other financial institutions have had to invest sizeable resources in assessing their credit risk exposures. The popular methodology or mechanism adopted by these financiers in predicting credit default is the use of structural or market-based models originally proposed by Merton (1974:449).

The collapse of a large bank is likely to have serious repercussions for the domestic economy and possibly the global economy. The case of African Bank in South Africa is a recent credit event that demanded a swift intervention from the central bank and other government agencies to minimise the financial catastrophe. It is for this reason that the robust and timely evaluation of the future health of corporations is significant. This may be the underlying reason for academics and practitioners continuously developing corporate default models in an attempt to better forecast the probability of failure.

This alternative to fundamental models seems to have drawn remarkable interest within the academic sphere with many researchers subsequently contributing to the original paper of 1974. The contributions enhance some of the underlying theoretical assumptions which Merton (1974:449) makes. Indeed, some researchers are making fundamental points, suggesting that the theoretical assumptions supporting his study actually weaken it practically. This chapter reviews the Merton model and other market-based alternative model subsequent to that of Merton – the Merton model and the hazard model. The latter models are major contributions and improvements on the original Merton model. Thereafter, it presents a review from various authors who have reflected on predicting financial distress using market data.

Merton (1974:449) opens by defining the value of a particular issue of corporate debt as depending on three items:

(i) the required rate of return on riskless debt;
(ii) the various provisions and restrictions contained in the indenture; and
(iii) the probability that the firm will be unable to satisfy some of the covenants contained in the indenture.

The probability of default modelling entails a theoretical framework that describes the causality between the attributes of the borrowing entity and its potential bankruptcy. The approach which has gained prominence in credit risk literature is the contingent claims approach, which was proposed by Merton in his seminal paper on the valuation of corporate debt (1974:449). His approach finds its logical sense from the Black and Scholes option pricing framework (1973:637). Merton (1974:449) developed a model for assessing a firm's credit risk by characterising the firm's equity as a call option on its assets. Alternatively, the debt holders of the firm could be viewed as holding a short put position on the firm's assets. Merton's approach is referred to as the 'structural approach' because it relies entirely on the capital structure of the firm for modelling credit risk.

The Merton model generates the probability of default for each firm in the sample at any given point in time. To calculate the distance to default, the model subtracts the face value of the firm's existing debt from an estimate of the firm's future market value, and then divides this difference by an estimate of the volatility of firm. The resulting distance to default is then substituted into a cumulative density function to calculate the probability that the value of the firm will be less than the face value of debt at the forecasting horizon. The market value of the firm is the sum of the market values of the firm's debt and the value of its equity. If both these quantities were readily observable, calculating default probabilities would be simple. While equity values are readily available, reliable data on the market value of firm debt are generally unavailable.

Although Merton presented a robust alternative to fundamental models of predicting the state of a company's financial distress, the essence of his model is its parsimonious specification to derive major insight on the determinants of credit spreads.

3.3 MERTON MODEL KEY ASSUMPTIONS

(i) There are no transactions costs, taxes, or problems with indivisibilities of assets.

(ii) There are sufficient investors with comparable wealth levels – such that each investor believes that he/she can buy and sell as much of an asset as he/she wants at the market price.

(iii) There is an exchange market for borrowing and lending at the same rate of interest.

(iv) Short sales of all assets, with full use of the proceeds, are allowed.

(v) Trading in assets occurs continuously in time.

(vi) The Modigliani-Miller (1958:261) theorem that the value of the firm is invariant to its capital structure obtains.

(vii) The term structure is flat and known with certainty – that is, the price of a riskless discount bond that promises a payment of $1 at time *t* in the future is P(*t*) = exp[-r^{t}], where r is the (instantaneous) riskless rate of interest, the same for all time.

(viii) The dynamics for the value of the firm, V, can be described by a diffusion type stochastic process through time.

Having provided the assumptions of his model, Merton (1974:449) clarifies that many of the above assumptions are not necessary for the model to obtain but are chosen for expositional convenience. In particular, the perfect market (i-iv) can be substantially weakened. The fifth assumption requires that the market for these securities be open for trading most of the time. The sixth assumption is proved as part of the analysis, and the seventh is chosen to clearly distinguish risk structure from term structure effects on pricing. The eighth requires that price movements be continuous and that the returns on the security be serially independent, which is consistent with the efficient markets hypothesis.

3.3.1 THE CONSTRUCTION OF THE MERTON MODEL

The Merton model makes two particularly important assumptions. Firstly, it takes an overly simple debt structure, and assumes that the total value *V* of a firm's assets follows a geometric Brownian motion under the physical measure:

$$dV = \mu V dt + \sigma \mathrm{v} V dW \qquad (3.1)$$

where *V* is the total value of the firm, μ is the expected continuously compounded return on *V*, σV is the volatility of firm value, and *dW* is a standard Weiner process.

Secondly, it assumes that debt consists of a single outstanding bond with face value and maturity. If the total value of the assets at maturity is greater than the debt, the latter is paid in full and the remainder is distributed among shareholders. However, if the total value of the assets is less than the debt, then default is deemed to occur. The bondholders exercise a debt covenant giving them the right to liquidate the firm and receive the liquidation value (equal to the total firm value since there are no bankruptcy costs) in lieu of the debt. Shareholders receive nothing in this case but, by the principle of limited liability, are not required to inject any additional funds to pay off the debt.

Taking from the above observations, shareholders have a cash flow at a particular time where the total value of the assets is greater than the debt. Symbolically, the Merton model stipulates that the equity value of a firm satisfies:

$$E = VN(d_1) - e^{-rT}FN(d_2) \qquad (3.2)$$

where *E* is the market value of the firm's equity, *F* is the face value of the firm's debt, *r* is the instantaneous risk-free rate, *N*(·) is the cumulative standard normal distribution function, *d*1 is given by:

$$d_1 = \frac{(In(V/F) + (r + 0.5\sigma^2 v)T}{\sigma v \sqrt{T}} \qquad (3.3)$$

and d_2 is just $d_2 = d_1 - \sigma v \sqrt{T}$. While this is a fairly complicated equation, most financial economists are familiar with this formula as the Black-Scholes-Merton option valuation equation.

This model makes use of two important equations. The first is the Black-Scholes-Merton equation (3.2), expressing the value of a firm's equity as a function of the value of the firm. The second equation relates the volatility of the firm's value to the volatility of its equity. Under Merton's assumptions, the value of equity is a function of the value of the firm and time, so it follows directly from Ito's lemma that:

$$\sigma E = \left(\frac{V}{E}\right) \frac{\partial E}{\partial E} \sigma v \qquad (3.4)$$

In the Black-Scholes-Merton model, it can be shown that $\frac{\partial E}{\partial E}$ = *N* (d_1), so that under the Merton model's assumptions, the volatilities of the firm and its equity are related by:

$$\sigma E = \left(\frac{V}{E}\right) N(d_1) \sigma v \qquad (3.5)$$

where d_1 is defined in equation (3.3).

The Merton model uses these two non-linear equations – (3.2) and (3.5) – to translate the value and volatility of a firm's equity into an implied probability of default. In most applications, the Black-Scholes-Merton model describes the unobserved value of an option as a function of four variables that are easily observed (strike price, time-to-maturity, underlying asset price, and the risk-free rate) and one variable that can be estimated (volatility). However, in the Merton model, the value of the option is observed as the total value of the firm's equity, while the value of the underlying asset (the value of the firm) is not directly observable. Thus, while *V* must be inferred, *E* is easy to observe in the marketplace by multiplying the firm's shares outstanding by its current share price. Similarly, in the Merton model, the volatility of equity, *σE*, can be estimated but the volatility of the underlying firm, *σV*, must be inferred.

The first step in implementing the Merton model is to estimate *σE* from either historical share returns data or from option implied volatility data. The second step is to choose a forecasting horizon and a measure of the face value of the firm's debt. For example, it is common to use historical returns data to estimate *σE*, assume a forecasting horizon of one year (*T* = 1), and take the book value of the firm's total liabilities to be the face value of the firm's debt. The third step is to collect values of the risk-free rate and the market equity of the firm. After performing these three steps, the values for each of the variables in equations (3.2) and (3.5) are obtained, except for *V* and *σV*, the total value of the firm and the volatility of firm value, respectively.

The fourth, and perhaps most significant step in implementing the model is to simultaneously solve equations (3.2) and (3.5) numerically for values of *V* and *σV*. Once this numerical solution is obtained, the distance to default can be calculated as:

$$DD = \frac{In(\frac{V}{F}) + (\mu - 0.5\sigma_v^2)T}{\sigma v\sqrt{T}} \qquad (3.6)$$

where μ is an estimate of the expected annual return of the firm's assets. The corresponding implied probability of default, sometimes called the expected default frequency, is:

$$PD = N\left(-\left(\frac{In\left(\frac{V}{F}\right)+\left(\mu-0.5\sigma_v^2\right)T}{\sigma v\sqrt{T}}\right)\right) = N(-DD) \tag{3.7}$$

If the assumptions of the Merton model hold, the Merton model should give accurate default forecasts. In fact, if the Merton model holds completely, the implied probability of default defined above should be a sufficient statistic for default forecasts.

The most critical inputs to the model are the market value of equity, the face value of debt, and the volatility of equity. As the market value of equity declines, the probability of default increases. This is both a strength and weakness of the model. For the model to work well, both the Merton model assumptions must be met and markets must be efficient and well informed.

In its promotional material, Moody's rating agency use the Enron case as an example of how their method is superior to that of traditional agency ratings. When Enron's share price began to fall, their distance to default immediately decreased. The ratings agencies took several days to downgrade Enron's debt. Using equity values to infer default probabilities allows the Moody's structural model to reflect information faster than traditional agency ratings. However, when Enron's share price was unsustainably high, the expected default frequency for Enron was significantly lower than the probability of default assigned to Enron by standard ratings. If markets are not perfectly efficient, then conditioning on information not captured by Moody's distress prediction methodology makes sense.

3.4 A GLOBAL REVIEW OF STRUCTURAL MODELS

Global literature contains academic reaction to Merton's original model. The analysis is a mixture of shortcomings and improvements on the original model, with contributions being made by Wei and Guo (1997:8); Hillegeist *et al.* (2004:5); Duffie, Saita and Wang (2007:659); Bharath and Shumway (2008:1339); Campbell *et al.* (2011:14); Sun, Munves and Hamilton (2012:1); and Afik, Arad and Galil (2016:43).

Wei and Guo (1997:8), Longstaff and Schwartz (1995:789) test the models of Merton (1974:449) and find the Merton model to be empirically superior. Hillegeist *et al.* (2004:5) compared the predictive power of the Merton model to Altman's (1968:589) and Ohlson's (1980:109) models (Z-score and O-score) and concluded that the Merton model outperforms these. They further found that the Merton model has more explanatory power than Altman's or Ohlson's models. These authors acknowledge the fact that there may be other variables on the market important enough to influence the probability to bankruptcy.

Duffie *et al.* (2007:659) compared they research that of Merton (1974:449). The main distinctions between the two modelling approaches are the nature of the event that triggers default. The Merton models apply a solvency test, regarding whether the distance to default falls below some barrier which is, in some cases, determined endogenously. Whereas, the Duffie *et al.* (2007:635) model assumes that, at each small time period, default occurs (or not) at random, with a probability that depends on the current distance to default and other explanatory variables. In an attempt to improve on the Merton model, Duffie *et al.* (2007:635) showed that macroeconomic variables (such as interest rate, historical share return and historical market return) have default prediction ability even after controlling Merton model's distance to default.

In 2008, Bharath and Shumway (2008:1339) examined the accuracy and the contribution of the Merton distance to default model. Using hazard models, they managed to develop a naïve yet robust alternative that outperforms Merton model. They found that the Merton distance to default model does not appear to produce a sufficient measurement for default. Whereas the naïve probability model they developed captures both the functional form and the same basic inputs of the Merton distance to default probability, performing surprisingly well. Bharath and Shumway (2008:1339) acknowledge that the Merton distance to default probability is a useful variable for forecasting default, but it is not a sufficient statistic for default. The usefulness of the Merton distance to default probability is due to the functional form suggested by the Merton model. In conclusion, their results indicate that structural models like the Merton model provide useful guidance for building default forecasting models.

Campbell *et al.* (2011:15) presented a model of financial distress that predicts corporate failure using accounting and market-based variables. They defined distressed firms as those that have recently suffered losses; have high leverage, low and volatile recent returns; have levels of market-to-book; and have low share prices. Developing what they termed "best model", Campbell *et al.* (2011:14) claim that it outperforms leading alternatives, such as the model proposed by Shumway (2001:1) and distance to default, an approach popular in industry and used by Vassalou and Xing (2004), and Hillegeist *et al.* (2004:5).

A notable and distinguishing factor of Campbell *et al.* (2011:14) in comparison to the comparative studies highlighted above is that these authors considered seven prediction horizons, ranging from predicting failure over the next few months to predicting it in three years. Another factor is that distance to default is one single measure and it performs quite well, whereas these authors used eight variables which should give their study some leverage over comparative studies.

Afik *et al.* (2016:43) examine the sensitivity of Merton model default predictability to its parameter specifications. They also explore several alternatives to apply the Merton model in default prediction. They conclude by suggesting that equity historical return and historical volatility produce under-biased estimates for assets expected return and assets volatility, especially for defaulting firms.

Several alternatives to apply the Merton model in default prediction are explored, and Afik *et al.* (2016:43) decided to compare the area under the curve of receiver operating characteristic curves and use the DeLong, DeLong and Clarke-Pearson (1988:1) nonparametric test to measure the statistical differences between the receiver operating characteristic curves. Afik *et al.* (2016:43) further examined how the key inputs of defaulting and non-defaulting firms evolve over time prior to default.

The expected default frequency metrics are industry-leading probability of default estimates publicly for traded companies. These credit measures were first produced by a company called KMV Corporation in the early 1990s. A recent study by Sun *et al.* (2012:1) researchers employed by Moody's reflects the latest adjustments or improvements they have made since the original acquisition of KMV Corporation.

Sun *et al.* (2012:1) improved the original Merton model to develop what they called expected default frequency. The basic assumption of expected default frequency is that there is a causal, economically motivated reason why firms default. According to these authors, default is highly likely to occur when the market value of a firm's assets is insufficient to cover its liabilities at a future date that is, when it is insolvent. This balance sheet approach to measuring risk means that the expected default frequency model shares common ground with fundamental models. However, the differentiator of expected default frequency over the fundamental approach is that they utilise market information, so they provide both timely warning of changes in credit risk and an up-to-date view of a firm's value.

Although the foundations of Sun *et al.* (2012:1) expected default frequency model are built on the Merton basic structural modeling framework, it is a significant extension and improvement. The public expected default frequency introduces more realistic features into the theoretical model itself, which provides a better approximation of real-world firm capital structures. It supplements the theoretical assumptions with practical extensions that better reflect real-world aspects of credit risk, and uses estimation procedures that produce significantly improved estimates of credit risk over the basic structural model implementation. A summary of the enhancements over the basic model is provided in the table below.

Table 3-1 below is a demonstration that Sun *et al.* (2012:10) have improved greatly on the original structural models. Their focus was on both the theoretical and empirical level. It is highlighted earlier in the study that the Merton model has a number of theoretical assumptions, with some researchers indicating that the same assumptions weaken his model structure.

Table 3-1: The comparison of the Merton model and the model developed by Moody's

Basic structural model		Public expected default frequency model
Two classes of liabilities: short-term liabilities and common stock	Theoretical modifications	Five classes of liabilities: short- and long-term liabilities, common stock, preferred stock, and convertible stock
No cash payouts		Cash payouts: coupons and dividends (common and preferred)
Default occurs only at the horizon date		Default can occur any time
Default point is total debt	**Empirical advances**	Default point is empirically determined
Estimation method of asset values and asset volatilities is not specified		Proprietary numerical routine to estimate asset value and asset volatility
Gaussian relationship between Probability of Default and Distance to Default		Distance to default-to-Expected Default Frequency mapping empirically determined from calibration to historical data

Source: Sun *et al.* (2012:10)

The literature on structural models is mainly found in developed economies. In this study, the intention is to fill this lacuna by employing this methodology within the scope of Johannesburg Stock Exchange listed companies.

3.5 HYBRID MODELS

The fundamental models are built by searching through a large number of the fundamental data with the ratio weightings estimated on a sample of failed and non-failed firms, whereas the market-based approach relies on asset and equity prices, and applicable volatilities as dictated by the market. One of the prominent shortcomings of fundamental models appear to be their inability to project the future as they are based on financial statements prepared on historical data. The emergence of the market-based approach in predicting bankruptcy provides an appealing alternative, in that, the market prices tend to reflect the company's future sentiments.

The development of a predictive model based on fundamental or market data tends to assume that all relevant failure or success indicators are reflected in the annual financial records for fundamental models, and on market data for market-based models. This assumption undermines the fact that corporate performance is influenced by both endogenous and exogenous factors. Maltz, Shenhar and Reilly (2003:187) say the use of financial measures as sole indicators of organisational performance is limited. It may be for this reason that the literature shows some growth on hybrid models.

In a recent paper, Agarwal and Taffler (2008:1541) compared market- and accounting-based bankruptcy prediction models, and found that classical models based on financial ratios are not inferior to structural option-based models for credit risk assessment purposes. They conclude that, “in terms of predictive accuracy, there is little difference between the market-based and accounting models”. This finding contrast with a previous finding by Hillegeist *et al.* (2004:26) who suggest that the Black-Scholes-Merton option-pricing model provides significantly more information on the probability of bankruptcy than Altman's Z-score or Ohlson’s O-score do.

This section commences by highlighting the shortcomings of relying on one set of data, be it fundamental or market-based. This is done to lay a foundation or justification for hybrid model development. The chapter then reviews current literature on hybrid models and their benefits.

3.5.1 Reliance on one set of variables

The success of fundamental models is based on the reliability and accuracy of annual financial statements. The problem is that financial statement users usually cannot assess the presence of garbage by just reading the statements. The statements may look fine, but in reality could be riddled with inaccuracies. While a combination of stringent internal controls and the use of external auditors generate a high degree of reliance and accuracy, there is evidence of notorious audit failures involving large corporations. Argenti (1976:1) says financial ratios may send signals of financial depression in the company. However, one may not be in a position to predict failure with certainty on these ratios alone. An interesting point made by Johnson (1970:1167) is that financial ratios do not contain information on the intervening economic conditions, and that the riskiness of a given value for a ratio changes with the business cycle.

Structural models based on market data carry an independent market sentiment on a company's future performance. The independence of this data brings a level of comfort in developing a predictive model. However, research has proven that this type of model is not without shortcomings. This model is based on the theory of an efficient market and its practical implementation may be very cumbersome. Saunders and Allen (2002:58) suggest that the underlying theoretical base of this model requires the assumption of normality of share returns. It also does not distinguish between different types of debt and assumes that the firm only has a single zero coupon loan. In addition, it requires the estimation of asset value and volatility, which are unobservable and need to be approximated introducing potentially large errors.

Therefore, it is not surprising that the empirical evidence on the performance of market-based models is mixed. Kealhofer and Kubart (2002:67) find that such models outperform credit ratings. Furthermore, Hillegeist *et al.* (2004:5) compared the predictive power of the Merton model to Altman's (1968:589) and Ohlson's (1980:109) models (Z-score and O-score, respectively) and concluded that the Merton model outperforms them. They further found that the Merton model has relatively more explanatory power than either of Altman's or Ohlson's models.

On the contrary, Campbell *et al.* (2011:15) combined the Merton model probability of default with other variables relevant to default prediction. However, they found that Merton model probabilities contribute very little to the predictive power. The major shortcoming with the Merton model – other than its complex nature in application – is the number of assumptions applicable to make it work.

Taking in cognisance what comes out of the literature, it appears that both the fundamental and market-based model possess unique advantages and disadvantages. To this end, it should then follow that the development of a model that contains elements from both model types should yield even better results. Having said that, the challenging questions are how to combine the two types of variables and how much weight to assign to each in developing a hybrid model?

In his paper, Löffler (2007:38) challenged himself on the question of combining two models into one and concluded that; "When it comes to default prediction, the answer I derive from an empirical study is very simple: Put equal weight on both measures and you can hope to get the best results". In a different research, Sloan (1996:289) finds that market prices do not accurately reflect the information from company accounts. Hence, accounting data can be used to complement market data. In line with these arguments, the latest hybrid models dismantle the strict separation of accounting and market data while incorporating the informational benefit of both.

In the recent past, hybrid models comprising market-based and fundamental models made noticeable inroads in predicting corporate bankruptcies. This proves that if one forecast is superior to another, one should not neglect the other altogether. It may be possible to combine the two forecasts to form an even better one. However, the selection or the optimal loading of the right combinations of independent variables from each model remain a challenge. These hybrid models are highly, statistically technical and this study does not intend to interrogate the technical derivation of a formula, but accepts formulae as previously researched and found acceptable.

3.5.2 The development of hybrid models

The word hybrid generally refers to a combination of two different elements. In predictive studies, hybrid models are threefold:

(i) a model that combines financial with non-financial independent variables into one model;
(ii) a model that combines two or three different independent variables into one model; and
(iii) a model that brings together two different methodologies into one model.

In the first instance, a hybrid model is developed by combining quantitative and qualitative variables. For example, the analysis of fundamental data may be interpreted or analysed together with a company's ability and means to be proactive and to take action in response to strategic business issues (Van der Colff & Vermaak, 2015:243). The second hybrid model highlighted above refers to models that have combined fundamental data and market ratios, and in some instances macroeconomic variables (Tinoco & Wilson 2013:394). In the third type of hybrid, these models are a mixture of two different methodologies like artificial neural networks combines with logistic analysis (Shah, 2014:103). He also developed a hybrid model that combined artificial neural networks and multiple discriminant analysis. With the introduction of structural models in predictive studies coupled with the prosperity of the hybrid model, the literature reveals a combination of a Z-score multiple discriminant analysis models with option contingent claims models. This is a combination of accounting and market data to assess the risk of a firm going bankrupt.

Löffler (2007:38) combines the agency ratings and market-based measures of default risk and concludes that combining the two improves the prediction of defaults over the use of a single measure. When challenged by weight loading of the two elements in his model, he concludes that a simple equal-weight combination of ratings and market-based measures is hard to beat out of sample. The results suggest that both ratings and market-based measures provide genuine information of their own.

Das, Hanouna and Sarin (2009:719) say models of financial distress rely primarily on accounting- and market-based information. The authors provide evidence on the relative performance of these two classes of models. Using a sample of 2 860 quarterly credit default swap spreads they find that a model of distress using accounting metrics performs comparably to market-based structural models of default. Moreover, a model using both sources of information performs better than either of the two models. Overall, their results suggest that both sources of information (accounting- and market-based) are complementary in pricing distress.

Tinoco and Wilson (2013:394) use a sample of 23 218 company-year observations of listed companies from 1980 to 2011 – the paper empirically investigates the utility of combining accounting-based, market-based and macroeconomic data to explain corporate credit risk. The purpose of their paper was to produce models with predictive accuracy, practical value and macro-dependent dynamics relevant for stress testing. The results show the utility of combining accounting-based, market-based and macroeconomic data in financial distress prediction models for listed companies.

Tsai (2014:58) says bankruptcy prediction and credit scoring are two important problems facing financial decision support. As many related studies develop financial distress models by machine learning techniques, more advanced machine learning techniques, such as classifier ensembles and hybrid classifiers, have not been fully assessed. In his paper, he develops a novel hybrid financial distress model based on a combination of the clustering technique and classifier ensembles. He concludes that combining self-organizing maps with classifier ensembles by the weighted voting approach can provide the best prediction result and the lowest type I and II errors.

Doumpos, Niklis, Zopounidis and Andriosopoulos (2015:606) conduct a multi-criteria classification approach that combines accounting data with a structural default prediction model to obtain improved prediction results. Having achieved impressive results, they recommend that empirical results be extended in various directions. Additional predictor attributes could be considered, focusing on macroeconomic factors, which could be imperative over the business cycle and during economic turmoil, providing a better description of cross-country differences.

3.5.3 Combining the basic model with the Merton model

Hybrid models also have their own challenges that need to be considered when they are developed. The one challenge is the issue of weights to be assigned in each element. For instance, in a case where a hybrid model is loaded with accounting and market data, a decision needs to be made as to how much weight is loaded on either the accounting or market data. Li and Miu (2010:819) point out that in determining the weights to be assigned to the various default prediction techniques; these studies either employ the straightforward logistic analysis or some subjective combination rules.

The determination of the optimal combination or loading of data into the hybrid model appears to be a challenge. This means accounting and market independent variables are selected as inputs in the model. The combination is well presented by Li and Miu

(2010:820) as they captured information for both accounting ratio-based Z-score and market-based distance to default by conducting a regression in which both the Z-score and distance to default are used as explanatory variables.

In their research work, they concluded that the distance to default variable derived from the market-based model is statistically significant in explaining the observed default events, particularly in firms with relatively poor credit quality (high credit risk). Conversely, the Z-score obtained with the accounting ratio-based approach is statistically significant in predicting bankruptcies of firms of relatively good credit quality (low credit risk).

Li and Miu (2010:821) initially applied the conventional logistic analysis model to establish the hybrid bankruptcy prediction model with constant loadings. They later modified their model by applying dynamic loadings. They found that in-sample and out-of-sample bankruptcy prediction tests demonstrated the superior performance of utilising dynamic loadings rather than constant loadings derived by the conventional logistic analysis model. They concluded their study by providing theoretical and empirical underpinnings of a dynamic hybrid model, which is more able to explain and predict the default events of companies of diverse credit qualities than conventional logistic analysis model.

3.6 CHAPTER SUMMARY

This chapter discusses the Merton and Hybrid models. The former is a structural model whose objective is to assess corporate credit risk by predicting its probability of default. The latter is merely a combination of the fundamental and market based models. The interest of credit risk assessment emanates from the Basel I and Basel II accords that are intended to protect and regulate the banking sector. Credit risk is understood as the risk that any borrower will breach the debt covenant at a particular time for some reason. In line with the Basel II guidelines, academicians and research practitioners have shown immense interest in numerous recent attempts to develop models that could predict the probability of default in the future. These models and their risk predictions are based on economic theories of corporate finance and are referred to as structural models.

As discussed in detail section 3.3 and 3.4 above the downfall to the Merton model is its complex nature and the various assumptions that must stand for the model to work. Campbell *et al.* (2011:14) successfully reconstructed the Merton model with the intention of simplifying it. These authors introduced an alternative using the hazard model. They found that the Merton model could be simplified without compromising the results.

The emergence of a hybrid model was an attempt to encapsulate the strengths that exist in both model types with a view of an even better predictive power. A hybrid model is a model loaded with accounting and market data to assess the risk of a firm going bankrupt. This study reviews the work done by Li and Miu (2010:819) in more detail. These authors start by presenting the fundamental model based on Altman, then move on to the simplified version of Merton's distance to default before the development of the hybrid model. The conclusion of their paper confirms the view that there is a benefit to using both model qualities in a hybrid model for better results.

This chapter is structured to distinguish existing international research material with that which has been conducted in South Africa. This study finds that as much as there is research work on financial distress prediction, it is largely based on fundamental models and not so much on the market-based or the hybrid models. It is this contribution that the present study wants to make.

CHAPTER 4

HYPOTHESES DEVELOPMENT

4.1 INTRODUCTION

The previous chapters lay out the body of literature in predicting the probability of financial distress. Some of the salient features include the broad definition of financial distress, the significance of classical model types in modern literature, and various predicting variables. The valuable information gathered in the previous chapters provides reasonable ground for the development of testable hypotheses.

The goal of this chapter is to formulate testable hypotheses based on the theoretical and empirical issues discussed in the preceding chapters. The rest of the chapter is organised as follows: Section 4.2 discusses the construction of the hypotheses. Section 4.3 discusses the hypotheses' testing strategy, and section 4.4 provides the summary of the chapter.

4.2 CONSTRUCTING HYPOTHESES

The important consideration in the formulation of a research problem in quantitative research is the construction of a hypothesis. Hypotheses bring clarity, specificity and focus to a research problem. The number of hypotheses constructed is mainly dictated by the context of the research study (Kumar, 2011:82). The author further says that hypotheses primarily arise from a set of hunches that are tested through a study and, most importantly, they tell the researcher what specific information to collect, thereby providing greater focus.

The formulation of hypotheses may indicate that the researcher does not know for certain about a phenomenon or a situation, the prevalence of a condition in a population or the outcome of a programme, but has a hunch to form the basis of certain assumptions. Therefore, these hypotheses need to be tested separately, by collecting information that will enable the researcher to conclude if the hunch was correct. The verification process can have one of three outcomes:

(i) it may prove to be right;
(ii) it may prove to be partially right; or
(iii) it may prove to be wrong.

Without proper verification, the researcher may not conclude anything on the validity of the hypotheses (Kumar, 2011:82). According to Grinnell (1988:200), a hypothesis is written is such a way that it can be proven or disproven by valid and reliable data.

4.2.1 Hypothesis one

Having defined the concept of financial distress in Chapter 2, paragraph 2.2, it may then be inferred that the event of financial distress is preceded by a state of financial depression. In the state of financial depression, if timely identified and heeded to, the financial performance of the company may still be turned around and distress avoided. Therefore, the state of financial depression may be viewed as providing early warning signs of financial distress.

Generally, financial distress prediction is about predicting the financial state of a particular company by analysing and converting financial or market data into valuable business information. This information may become vital for managerial decision-making, investment decision-making for investors, credit decision-making for creditors and customer credit rating by banks.

Companies may be classified as experiencing financial distress when they are experiencing financial difficulties that are likely to result in Johannesburg Stock Exchange delisting or suspension. The related reasons include, but are not limited to, the inability to pay debts or preferred dividend, unsustainable bank overdraft, an application by creditors for a liquidation process, or when the company is officially going through a statutory bankruptcy proceeding. The above cited financial conditions aimed at identifying the possibility of financial distress are based on the theoretical framework of cash flow or liquid assets model.

The present study advocates for the identification of a financial state that may exist before the company enters the financial distress state. This suggestion is premised on the basis that once a company enters distress, recovery is almost impossible. Therefore, the identification and accentuation of another financial state that precedes distress is important. At this stage, the company may still be salvaged and made profitable or solvent. With the appropriate and timely action plan from management, an opportunity exists for a company to turnaround and avoid financial distress.

While literature has mainly adopted a binary approach – in that, companies are split into failed and non-failed – the present study adopts a multinomial approach in testing for financial distress. The binary approach of classifying companies as failed or non-failed as done in most studies may appear to ignore that company performance indicators may at a certain point contain early warning signs of financial distress. With timely corrective interventions, a company with these warning signs may still be saved and turned to a financial healthy state.

In view of the above, the present study intends to prove that, when evaluating the credit risk of a company, the company may be found to be in one of three financial states:

(i) Distressed;
(ii) Depressed; or
(iii) Healthy.

Based on the above, the outcome of a financial distress should be determined using a multinomial specification that distinguishes between distress, depression and healthy. Therefore, the hypothesis can be stated as follows:

$H_{1\,=}$ The financial distress model using a multinomial specification is able to distinguish between the three financial states of a company: distressed, depressed and healthy.

4.2.2 Hypothesis two

The study investigates empirically the advantage of combining three sets of variables – fundamental, market and macroeconomic – to determine financial distress. The first model, the basic model, uses a combination of fundamental, market and macroeconomic indicators.

In the first model this study draws financial ratios from different accounting groups including: liquidity, profitability, solvency, and efficiency. These accounting groups seek to communicate different facets of a company's finances and operations. The analysis of financial ratios is intended to provide endogenous factors influencing the financial performance of a company. Therefore, to also control exogenous factors, the present study incorporates the market and macroeconomic indicators.

The literature evidence indicates that certain researchers have chosen to use fundamental data only, or just market data when determining financial distress. However, this direction may induce opportunity cost, in that, when using just the fundamental data, the researcher may be forgoing certain valuable information contained in the market data. Conversely, using just market data, the researcher may be forgoing certain valuable information contained in the fundamental data. Therefore, the present study intends to improve the prediction results by using both set of variables.

Based on the above background, the hypothesis can be stated as follows:

$H_{2\,=}$ The prediction accuracy of a financial distress model is enhanced when combining fundamental, market and macroeconomic variables.

4.2.3 Hypothesis three

After the extensive review of literature, there is a strong persuasion to infer that researchers remain indifferent on the issue of model type. The industry is flooded with different models that are purported to be the best in financial distress prediction. It is clear that some are more popular than others, with multiple discriminant analysis, logistic analysis, artificial intelligence expert systems, and the Merton model dominating literature. The previous chapter details the background of these models in terms of their success and popularity.

The distinguishing factors between various models are the statistical strength and integrity of the model. This means that the more demanding the model is statistically, the more manipulation is likely to happen on data in the interest of meeting statistical requirements. Furthermore, the integrity of input data becomes very important. The debate on the choice of model becomes very intricate and technical, and eventually lies with the researcher concerned as to what model to use.

Generally speaking, fundamental data may be perceived less independent than market data. This generalisation stems from the fact that fundamental data are based on financial statements prepared by management, albeit the involvement of independent auditors. Conversely, market data largely reflect market sentiment, carrying a level of independence.

The literature review also reveals that there is little research on financial default assessment using the Merton model done in South Africa. The present study has the opportunity to test Johannesburg Stock Exchange listed companies using this model technique. Equally, the study develops a basic model using one of the popular classic statistical techniques. The results of these models will be compared for accuracy in predicting failure.

This background leads to the next hypothesis that needs to be tested. The results of the two models are expected to be relatively similar. This study develops the basic model using logistic analysis and the Merton model. This presents the opportunity to test the accuracy level of the two methodologies. Based on the above background, the hypothesis can be stated as follows:

H_3 = The Merton model produces prediction accuracy results that are within 5% of the accuracy results of the basic model.

4.2.4 Hypothesis four

The fourth hypothesis seeks to test the prediction accuracy rate when combining the basic model and the Merton model. This option may be seen as a deviation from the norm of choosing either the fundamental or the only market variables when constructing a model. It is conceded in the present study that both variables, fundamental and market, possess vital information of the company. Therefore, using both in developing a model should yield results that are better than those obtained when using just one set of variables.

With this background the hypothesis can be stated as:

H_4 = Although the prediction ability of a financial distress model based on the logistic analysis approach is very close to the Merton-based approach, combining the variables from these two models give better prediction results.

4.3 HYPOTHESES TESTING

According to Kumar (2011:83), to test a hypothesis, the researcher needs to go through three phases:

(i) constructing a hypothesis;
(ii) gathering appropriate evidence; and
(iii) analysing evidence to draw conclusions as to its validity.

When concluding about a hypothesis, conventionally, the researcher specifically makes a statement on the correctness of a hypothesis in the form of the hypothesis is true or the hypothesis is false. Therefore, it is imperative that hypotheses are formulated in a manner that is clear, precise and testable.

In concluding on the validity of the hypotheses, the way evidence is collected is important, and it is therefore essential that the study’s design, sample data, collection method, data analysis and conclusion are appropriate and free from bias.

The hypotheses that have been developed in the present study will be categorised into research hypotheses and alternate hypotheses. The formulation of an alternate hypothesis is a convention in scientific research. Its main function is to explicitly specify the relationship that will be considered as true in case the research hypothesis proves to be wrong. In a way, an alternative hypothesis is the opposite of the research hypothesis. Conventionally, a null hypothesis, or hypothesis of no difference, is formulated as an alternate hypothesis.

4.3.1 Stating the hypotheses

The four hypotheses that have been developed above need to be defined into two categories:

- The research hypothesis, denoted H_1, is the hypothesis being tested and
- The null hypothesis denoted $H_{0.}$

The different possibilities represented by the two hypotheses should be mutually exclusive and collectively exhaustive.

The first hypothesis developed is stated as:

H_1: The financial distress model using a multinomial specification is able to distinguish between the three financial states of a company: distressed, depressed and healthy.

$H_{0:}$ The financial distress model using a multinomial specification is not able to distinguish between the three financial states of a company: distressed, depressed and healthy.

The second hypothesis developed is stated as:

H_1: The prediction accuracy of a financial distress model is enhanced when combining fundamental, market and macroeconomic variables.

H_0: The prediction accuracy of a financial distress model is not enhanced when combining fundamental, market and macroeconomic variables.

The third hypothesis developed is stated as:

H_1: The Merton model produces prediction accuracy results that are within 5% of the accuracy results of the basic model.

H_0: The Merton model produces prediction accuracy results that are more than 5% of the accuracy results of the basic model.

The fourth hypothesis developed is stated as:

H_1: Although the prediction ability of a financial distress model based on the logistic analysis approach is very close to the Merton-based approach, combining the variables from these two models give better prediction results.

H_0: Although the prediction ability of a financial distress model based on the logistic analysis approach is very close to the Merton-based approach, combining the variables from these two models do not give better prediction results.

4.3.2 Formulation of an analysis plan

The next two chapters (Chapters 5 and 6) detail the study research methodology and data analysis, respectively. The analysis plan describes how to use sample data to accept or reject the hypothesis. It details the data sampling process, and the number and type of models that are developed. The first model that is developed, the basic model, is based on logistic analysis. The model accuracy rate is measured using the prediction results, reflecting the percentage prediction accuracy per financial state.

Once again, a detailed calculation and analysis is performed on the Merton model. The key input variables and proxies are: equity and equity volatility values as directly obtained from the INET BFA database, the treasury bill is used as a proxy for the risk-free interest, and the total debt is obtained from the published financial statements downloaded from the INET BFA database.

Substituting these variables into the Merton formula, the outcome is the distance to default percentage. The distance to default figure, which is calculated for all companies, is used as a score indicator and this list of scores is then categorised into distressed, depressed and healthy using predetermined cut-off points. Once categorised, the list is compared to the original list indicating different financial states. The purpose of this comparison is to calculate the correct prediction percentage.

With the basic and Merton models completed and their percentage prediction accuracies measured, a hybrid model is then developed using logistic analysis as the statistical technique. The list of variables used in the hybrid model will be a combination of all variables used in the basic and the distance to default factor calculated in the Merton model. Like the basic model, the prediction accuracy of the hybrid model is measured using the prediction results that indicates the percentage correctly predicted per financial state.

4.4 CHAPTER SUMMARY

This chapter has formulated four hypotheses based on the study research objective and the existing body of literature. The four hypotheses that have been developed are intended to evaluate the benefits derived from categorising the model outcome into three financial states; using a combination of independent variables; to also evaluate the performance or the prediction accuracy the Merton model over the basic model; lastly, the benefits derived from using a hybrid model.

In testing the above hypotheses the study relies on the prediction results. Therefore, in testing H_1, the basic model outcome is expected to predict the three states. However, if the basic model only predicts two states – distressed and healthy – then the research hypothesis shall be rejected and the null hypotheses accepted.

With H_2, the basic model outcome that contains the fundamental data will be compared with the model outcome that contains a combination of three sets of variables. The research hypothesis will therefore be accepted in the event that the model outcome that contains a combination of variables is better than the model outcome that only has the fundamental variables. However, should the results not improve or be lower, than the null hypothesis will be accepted.

Regarding H_3, the overall percentage prediction results of the basic model one year before failure will be compared with the overall percentage results of the Merton model. If the two results are within the 5% range difference, the research hypothesis will be accepted. However, if one result is more than 5% of the other, the null hypothesis will be accepted. A similar approach is adopted in testing H_4 where the accuracy results of the hybrid model are compared with those of the basic and the Merton models.

CHAPTER 5

RESEARCH METHODOLOGY

5.1 INTRODUCTION

Chapter 5 details the research methodology expected to enable this study to reach its research objectives and to prove or disprove the developed hypothesis. The study of financial distress prediction appears to be underpinned by three fundamental decision pillars:

(i) Definition of financial distress.
(ii) Selection of the appropriate ratios.
(iii) Choosing the most appropriate model type.

These pillars demand that a researcher be thorough in developing the research strategy. The body of literature and research paradigms need to be clearly understood, available techniques and methodologies also need to be understood to enable a researcher in choosing the most appropriate route, and reliable and reputable database sources need to be identified upfront.

Therefore, the objective of this chapter is to:

(i) recommend the most appropriate definition of financial distress;
(ii) identify the techniques used in selecting ratios;
(iii) identify and choose the right model type; and
(iv) define the dependent variables and independent variables to be used in the study.

5.2 RESEARCH PARADIGM

In describing the research methodology it is important to briefly highlight again the definition of financial distress as found in literature but more importantly as defined in this study. The definition financial distress is dealt with at length in Chapter 2, section 2.2 of the literature review with adequate referencing.

5.2.1 Defining financial distress

The literature and the criteria adopted by various researchers helped identify companies experiencing financial distress. Many researchers use a binary approach in their studies with companies being classified as failed or non-failed. This narrow definition of financial distress refutes the fact that financial distress is preceded by financial warning signs. For that matter, the state of financial distress should not surprise management running the company's day-to-day operations.

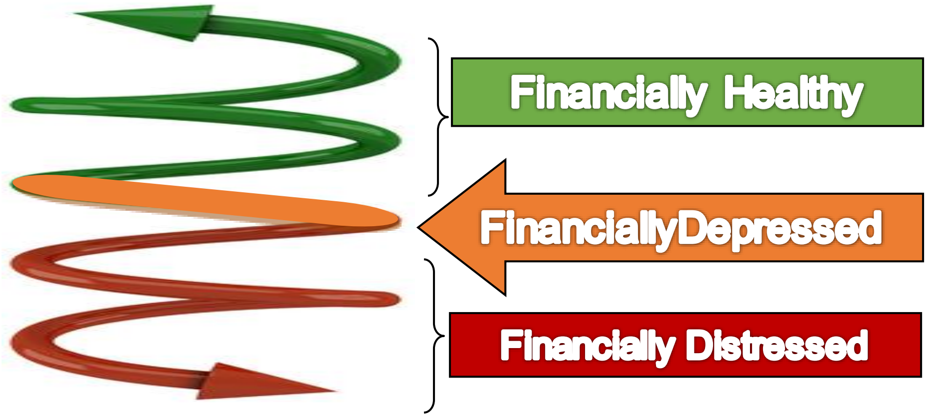
In many developed and developing countries, like South Africa, there is a legal process governing companies that have been declared insolvent or in the state of financial distress. As in other legal proceedings, this process is likely to take a long time before the attorneys or business rescuers officially declare the company bankrupt. The challenge often presented by this process is that it has far reaching effects on creditors, financial institutions, shareholders, employees and restructuring specialists.

This study pins the financial state of a company on a spiral chart. Figure 5.1 below attempts to convey a message that the financial state of a company is in a constant state of flux influenced by prevailing economic variables (internal or external). The chart contains three zones:

- green zone;
- orange zone; and
- red zone.

The companies in the red zone are companies that are identified as distressed. The companies in the green zone are companies that are still listed and assumed to be in a healthy financial condition. The most important state is the orange state – in this state, the financial results are sending warning signals to management for immediate intervention. Failure to react promptly may lead to the red zone.

Figure 5-1: A spiral curve reflecting the three financial states



Source: own research

In an attempt to determine the financial health of Johannesburg Stock Exchange listed companies, the present study considers three possible financial states.

5.2.2 Selection of the appropriate ratios

Literature reveals a myriad of ratios available for researchers to use when determining companies' financial distress. Yet with all the available ratios previously used in literature Liang, Tsai & Wu (2015:289) contend that there remains no consensus upon specific financial ratios as input features for model development. Using all available ratios may inadvertently lead to incorrect research conclusions, and it may just be impractical and time consuming without valuable benefits. However, nowadays ratios are used as a standard tool for the analysis of financial statements. The main reasons for using ratio analysis are for financial institutions in credit decision-making, investment decision-making and management of company performance, liquidity, financing risk.

In financial distress prediction literature, the initial population of ratios are selected based on their successful performance in previous studies. The ratio selection is also often based on popularity. Once the ratios are selected they are categorised into solvency, profitability, operational capabilities, business development capacity, structural soundness, and capital expansion capacity. Some ratios contain similar elements and thus introduce problems of spuriousness into data analyses. Therefore, these ratios are tested for collinearity with significantly correlated ratios eliminated. The use of linier discriminant analysis to select ratios, as found in older studies, is not found is later studies.

Bellovary *et al.* (2007:7) reviewed 165 financial distress prediction studies. After scanning 752 different ratios in different studies, they found that the number of ratios considered in any one study ranged from one to 57. The most common ratio in multiple studies is the ratio of net income to total assets, included in 54 studies. The second most common ratio is the ratio of current assets to current liabilities found in 51 studies. Another set of commonly used variables are the five variables included in Altman's (1968:589) original multivariate model.

Zhou, Lu & Fujita (2015:52) share an interesting sentiment in their study, they say experts in finance and accounting select ratios for corporate financial distress prediction according to their professional understanding of the characteristics of the ratios, while researchers in data mining often believe that data alone can tell everything and they use various mining techniques to search the ratio subset without considering the financial and accounting meanings of the features. This extract is understood as suggesting that, it does not really matter categorising or analysing the ratios according to their accounting groups. A mere analysis and understanding the behaviour of certain ratios over time should suffice in selecting appropriate ratios for financial distress prediction.

In line with previous studies, this study targets a final sample of ratios to be a maximum of ten carefully selected ratios. This study adopts a staggered strategy in scanning the literature and finally selecting appropriate ratios. The first step is to scan the literature for commonly used ratios. The main aim in this step is to target a maximum of 40 ratios. The list of ratios consists of fundamental ratios (30), market ratios (five) and macroeconomic ratios (five). The fundamental ratios are understood to be referring to the accounting ratios calculated from published annual financial statements. These ratios are further split into profitability, solvency and liquidity.

In the second step, the selected 40 ratios are analysed. The emphasis is on their successful performance in previous studies. This is to ensure that the final sample consists of market leading ratios that are often used in contemporary studies. The second stage aims at curtailing the list from 40 to a desirable population of 17 ratios. The last stage in this process is to test the 17 ratios coming from the second stage for collinearity. Testing for collinearity is only done at this stage as the 17 ratios are considered popular based on the extant research. Furthermore, the collinearity test would not be desirable with 40 ratios. Once this statistical test is conducted, the final population used to develop the models is 10 ratios, consisting of fundamental ratios (five), market based (three) and macroeconomic variables (two), a number in line with previous studies.

5.2.3 Choosing the most appropriate model type

The existing literature has not been able to identify the most appropriate model to predict financial distress. Many models have been introduced to the academic community, with each presenting its own advantages and disadvantages. Balcaen and Ooghe (2006:63) studied 35 years of information on business failure studies – they found all classical model types to contain problems. Bellovary *et al.* (2007:12) raised the question: “Why do we continue to develop new and different models for bankruptcy predicting?” They believe that the focus of future financial failure research should be on the perfection of existing bankruptcy prediction models as opposed to the development of new models.

Having thoroughly studied the existing literature, there is a clear trend across literature in using multiple discriminant analysis, logistic analysis or neural networks. While this trend does not necessary indicate that these techniques are the best, it does provide a level of comfort in them producing reliable results. Since 1968, the primary methods used for model development have been multiple discriminant analysis, logistic analysis, and neural networks. These techniques are still used today, with an example being Grünberg and Lukason (2014:93), who applied logistic analysis and neural networks in a recent study.

Logistic analysis began to appear in the late 1970s, but did not overtake multiple discriminant analysis in popularity until the late 1980s. One of the reasons researchers may have shifted away from multiple discriminant analysis to logistic analysis, is that logistic analysis is said to be less demanding than multiple discriminant analysis in terms of statistical assumptions that must be satisfied for the model to work. The logistic analysis model is not based on the assumptions that independent variables should follow normal distribution and equal covariance. However, it still requires that the independent variables should not contain collinearity problems.

In the late 1980s, neural networks began to appear and became the primary method used in studies in the 1990s. Neural networks analyse inputs to find patterns and develop a model capable of a decision-making process. Several sample cases are run during the training mode, during which the network learns the decision-making process. The testing mode is used to validate the neural networks model using hold-out sample data.

With this background, the present study adopts the multinomial logistic analysis as used by Ohlson (1980:112), to develop the first model, the basic model. The multinomial logistic analysis is based on the classic logistic analysis with the extension that it allows for more than two possible outcomes or dependent variables.

The popularity and dominance of multiple discriminant analysis in the extant literature is undisputed. Newer models have been introduced with very little improvement to classical methodologies. The present study chooses logistic analysis – yet another relevant classic model. The econometric methodology of logistic analysis was chosen to avoid well-known problems associated with multiple discriminant analysis. Some of the problems with multiple discriminant analysis, as advocated by Ohlson (1980:112), are:

(i) “There are certain statistical requirements imposed on the distributional properties of the predictors. For example, the variance-covariance matrices of the predictors should be the same for both groups (failed and non-failed firms). Moreover, a requirement of normally distributed predictors mitigates against the use of dummy independent variables.

(ii) The output of the application of a multiple discriminant analysis model is a score with little intuitive interpretation, since it is an ordinal ranking. For decision problems, such as a misclassification structure is an inadequate description of the payoff partition, the score is not directly relevant.' However, if prior probabilities of the two groups are specified, it is possible to derive posterior probabilities of failure. But, this Bayesian revision process will be invalid or lead to poor approximations unless the assumptions of normality are satisfied.

(iii) There are also certain problems related to the “matching” procedures which have typically been used in multiple discriminant analysis. Failed and non-failed firms are matched according to criteria such as size and industry, and these tend to be arbitrary. It is by no means obvious what is really gained or lost by different matching procedures, including no matching at all. At the very least, it would be more fruitful to include variables as predictors rather than to use them for matching purposes”.

The use of conditional logistic analysis avoids all of the problems regarding multiple discriminant analysis. The fundamental estimation problem can be reduced by the following statement: given that a firm belongs to some pre-specified population: What is the probability that the firm fails within a pre-specified time period? No assumptions have to be made regarding prior probabilities of bankruptcy and/or the distribution of predictors. These are the major advantages. The statistical significance of the different predictors is obtained from asymptotic (large sample) theory. To be sure, as is the case in any parametric analysis, a model must be specified, so there is always room for misspecification of the basic probability model.

The model type used in the second model is the Merton distance to default technique. Again, the literature seems to be dominated by this technique when it comes to structural models (Afik *et al.,* 2016:43; Bharath & Shumway, 2008:1339; Campbell *et al.,* 2011:14; Duffie *et al.*, 2007:659; Sun *et al.*, 2012:1). Developing a structural model based on option pricing in line with Merton’s original model may add academic value for Johannesburg Stock Exchange listed companies.

Individual researchers often have different views. When developing models for predicting financial distress, some may argue that applying just one set of variables (fundamental data) yields sufficient predictive power. However, recent research indicates that hybrid models are even more relevant and yield significantly better results than the single variable discriminant model. The third model represents a combination of the basic and Merton models, and is called the hybrid model.

5.3 PREDICTIVE MODELS IN SOUTH AFRICA

The objective of this section is to briefly present the research strategy implemented in recent similar studies in South Africa so as to establish guiding principles and enable study comparability. The first research strategy to be analysed is by Senkoto (2012:1), whose study is based on structural modelling in calculating probability of default. It is the best comparison as it is the only available study recently done that could be found that has applied capital structural technique using Johannesburg Stock Exchange listed companies. The present study applies a similar technique in developing its second model.

Another relevant research strategy that is analysed is from the study by Van der Colff and Vermaak (2014:243), who developed a hybrid model combining financial and non-financial variables. Their study shares similar characteristics with the first model to be developed in the present study. Van der Colff and Vermaak (2014:243) based their scenario 1 and 3 financial failure models on De la Rey (1981:11) K-Score model. In their study, scenario 1 uses a model based on financial variables only and scenario 3 uses a model based on a combination of financial and non-financial variables.

5.3.1 Research strategy in developing a fundamental model

In the Van der Colff and Vermaak (2014:243) study, the INET BFA database is used to identify the sample for an 11-year observation period from January 2000 to December 2010. The standardised financial statements are used to calculate the financial variables, and the director’s reports are used to obtain the non-financial variables. Ninety-five companies are identified as suitable subjects for the present study. These are extracted from 416 companies and other trade securities listed on the Johannesburg Stock

Exchange Main Board, the Alternative Exchange, the Development Capital Market, and the Venture Capital Market on 6 April 2010.

A phased approach is applied to eliminate traded securities and companies that are not regarded as suitable subjects for the study. Firstly, all listed traded securities – such as, debt instruments, preference shares and other trade instruments – and suspended shares are eliminated. Secondly, all mining and mining-related companies, financial companies, financial service providers (banks, long- and short-term insurance companies), and property companies are excluded from the sample. The reason for this criterion is due to the differences in accounting systems and financial reporting formats, which may differ from those in the sample sectors. Thirdly, any companies not primarily listed on the Johannesburg Stock Exchange are eliminated. Fourthly, only companies listed for longer than 11 years or listed prior to 2010 are retained. Lastly, all companies which changed their financial year-end within the 11-year observation period are eliminated. The final sample is limited to industrial sector companies, services sector companies, and wholesale and retail sector companies.

When selecting the independent variables in developing their first model Van der Colff and Vermaak (2014:243) adopt the same independent variables used in De la Rey's (1981:11) K-Score model. In terms of the statistical choice, Van der Colff and Vermaak (2014:243) were limited by the fact that their second model was a qualitative analysis that could not just produce a yes or no answer. Consequently, they had to use Cramer's V statistic as it is applied to accommodate multiple variables, irrespective of whether they can be quantified. It is a chi-square-based measure of nominal association resulting in a value between zero and one (inclusive, regardless of table size).

5.3.2 Research strategy in developing the Merton model

Senkoto (2012:1) started with a sample of 100 Johannesburg Stock Exchange listed non-financial companies. He justifies this sample size based on previous studies where 100 companies were used quoting the study of Bandyopadhyay (2006:255) which uses a sample of 104 companies, and Nguyen (2007:1), and Gaffeo and Santoro (2009:435) who use a sample of 100 companies. Senkoto's study covers the period from January 1997 to

December 2010, which was chosen as he needed to cover different economic cycles. By applying the 14-year economic period, his final sample size was reduced to 80 companies as this meant companies needed to be listed for at least the full period. Concerning industry distribution, his sample is skewed towards mining houses, but this was not viewed as detrimental to the study.

Senkoto (2012:1) sourced his data from the Share Magic database owned by Profile Data, and the trading data for each company from the INET BFA database. The daily average yield of government bond is sourced from Global Insights. The output of his model is a large panel data. The large dimension data set is then further analysed using factor analysis to extract common factors that drive company financial default in South Africa.

5.3.3 Comments based on the two research strategies

The intention is not to critically evaluate the two strategies, but to identify the positives as guiding principles for the present study. The first model to be developed by the present study is based on a fundamental model technique sharing similar characteristics with the model developed by Van der Colff and Vermaak (2014:251). The second model to be developed in the present study applies the structural modelling techniques as applied by Senkoto (2012:1). The two studies are recent and provide a level of confidence in their adopted research strategies.

Regarding sample size, the present study aims to follow a similar strategy as that adopted by Van der Colff and Vermaak (2014:251), in that, a full list of Johannesburg Stock Exchange listed companies is considered as the original sample and then a predetermined criterion is applied to clean up the sample to the qualifying companies. The targeted database source is also similar to the sources used in the above two studies, but the present study further obtains data from the South African Reserve Bank. These sources are considered reliable and reputable. The present study has undergone a thorough process in identifying and selecting independent variables. A stepwise statistical technique is used to trim the pool of ratios to explanatory variables that will be used in the model.

In terms of the statistical procedure, the present study applies logistic analysis to develop the first model and the structural technique based on the Merton approach to develop the second model.

5.4 VARIABLE DEFINITION

It is important to clearly identify and select independent variables and dependent variables when conducting financial distress prediction studies. This section discusses some of the commonly used predictors found in literature. They represent seven domains of ratios: solvency, profitability, capital structure, liquidity, efficiency, market data and macroeconomics data. Once data are collected and cleansed, they are statistically tested using some of the renowned tests in regression analysis. The significance of data preparation and testing is to maintain the reliability and the integrity of the model by ensuring that all relevant statistical requirements are adhered to.

The first statistical test that is conducted in preparing the data is checking and dealing with outliers, missing data and data transformation. These statistical tests are explained in detailed in chapter 7. Failure to cleanse the data by conducting this test may lead to incorrect conclusions. The second statistical test that is conducted is the normality test and the third is variable collinearity. Testing variables for collinearity is aimed at identifying the level of correlation between the variables, but most importantly the significance level of that correlation.

5.4.1 Independent variables

Taking from the study of Killough and Koh (1986:25) that states that it is not necessary but rather desirable to have a huge number of ratios to predict business failure is a set of dominant ratios derived from a larger set of correlated ratios. Bellovary *et al.* (2007:7) conclude that there has been some fluctuation in the range of the ratios used in studies over the last 40 years, although the average has remained fairly constant, around eight to ten ratios.

The independent variables that are used in this study consists of fundamental ratios (five), market based (three) and macroeconomic variables (two), a number in line with previous studies. These independent variables are carefully selected as the process is detailed in section 5.2.2 above.

The three sections below provide a brief explanation of some of the variables that the study uses in predicting the probability of financial distress. Section 5.4.1 (a) discusses the fundamental ratios, section 5.4.1 (b) discusses market indicators, and section 5.4.1 (c) discusses the macroeconomic indicators.

5.4.1 (a): Defining the most used fundamental ratios in literature

1. **Working capital/total assets**

This ratio measures the liquid assets in relation to the size of the company. The difference between current assets and current liabilities represents working capital. The current assets of a firm include cash on hand, accounts receivable, and inventories, with the latter two being considered current if cash conversion is expected within an operating cycle of a business. Current liabilities consist of the firm's financial obligations short-term debt and accounts payable, which will be met during the operating cycle. A positive working capital indicates a firm's ability to pay its bills. A business entity with a negative working capital will struggle to meet its obligations.

2. **Retained earnings/total assets**

This ratio measures profitability that reflects the company's age and earning power. It represents a measure of cumulative profitability reflecting the firm's age and its earning power. A history of profitable operations and reduced debt is signified by firms that retain earnings or reinvest operational profits. Low retained earnings may indicate a poor business year or reduced longevity for the firm. A measure of an organisation's operating efficiency separated from any leverage effects is a true depiction of asset production.

3. Earnings before interest and tax/total assets

This ratio measures operating efficiency apart from tax and leveraging factors (interest), it recognises operating earnings as important for long-term viability. It also estimates cash supply available for allocation to creditors, government, and shareholders.

4. Market value of equity/book value of liabilities

This ratio measures the ratio of equity compared to total debts or liabilities. Altman (1968:589) defines the market value of equity, or market capitalisation, as a summation of preferred and common stock or market value of equity/book value of total debt. The stock market, the primary estimator of a firm's worth, suggests that price changes may foreshadow pending problems if a firm's liabilities exceed its assets. Altman believes this ratio is a more effective financial distress predictor than net worth/total debt (book values).

5. Sales/total assets

This ratio measures the revenue generating power of the company assets (assets turnover). It signifies a standard turnover measure that varies in different industries. Yet, the ratio is an indicator of a firm's efficient use of assets to create sales (Chuvakhin & Gertmenian, 2003:1). Altman (2000:22) defined this as "…one measure of management's capacity in dealing with competitive conditions".

5.4.1 (b): Defining the most used market variables in literature

The study includes four market variables in the model to test whether they increase the predictive power of an accounting and macroeconomic based model. The rationale behind the inclusion of market variables in the models is that they tend to contain a broad mix of public independent sentiment concerning the future cash flows that can be expected from a company. It is also assumed that market prices will complement the financial statement and macroeconomic information by enhancing the predictive power of the general model, and not compete or be mutually exclusive alternatives that should be used in isolation.

1. Price to earnings ratio

The P/E ratio is the ratio of market price per share to earnings per share. The P/E ratio is a valuation ratio of a company's current price per share compared to its earnings per share.

2. Price to sales ratio

The P/S ratio compares the price of a share to the revenue per share. This ratio is usually used for the valuation of shares. It considers a company's past performance for valuation of its shares.

3. Share price

A share price indicates the market price per share of the target company. It also helps to ascertain the changes of value of the company in the economy. Therefore, it is assumed that a share price contains relevant information on the probability of financial distress even if it is not a direct measure of that probability. The advantage to including a share price is that it reflects a mixture of financial statement data as well as the public sentiment on the future cash flows of the company. In this light, it should enhance the accuracy of financial distress prediction. Christidis and Gregory (2010:1) successfully used share price as a variable in enhancing the predictive accuracy of their model.

To the extent that market prices reflect investor's expectations of future cash flows or earnings, and that the company's earnings are affected by its financial position, it is expected that there be a close relationship between price levels/movements and the probability of financial distress. Therefore, it is assumed that a high level of the share price will decrease the probability of financial distress, with the opposite also being true.

4. Market size of the company

The fourth market variable incorporated to the model represents the size of the company measured by its market capitalisation relative to the total size of the relevant index. The market value is calculated as the share price multiplied by the number of ordinary shares in issue. This is an important predictor when it is considered for option pricing because, in the event that a share price is in distress, debt holders will find themselves at an even higher risk. The persistent distress of the share price stemming from the negative market perception of the company's financial performance may progress to a level where the company is unable to meet its financial obligations. Agarwal and Taffler (2008:1541) states that, the probability of bankruptcy is the probability that the call option will expire worthless, which means the value of the assets becomes less than the face value of the liabilities at the end of the holding period.

Therefore, it is predicted that a high value of the market size variable should entail a low probability of failure/financial distress. Conversely, a relatively small-sized company should have a higher probability of financial distress. That is, a negative sign of the market size variables estimate is therefore expected, suggesting that a high value of this variable should have a negative impact on the firm's probability of financial distress or failure.

5. **Market capitalisation to total debt**

The final market variable that was used in the final model is the ratio market capitalisation to total debt. Total debt is measured as the total sum of current and long-term liabilities. The higher the value of this financial ratio, the less likely it is for a company to be in a distressed financial position. Thus, it is posited that a high value of this variable should entail a low probability of failure/financial distress. Conversely, a low value should involve a higher probability of financial distress.

5.4.1 (c): Defining the most used macroeconomic variables in literature

1. **Consumer price index**

The consumer price index is a current social and economic indicator constructed to measure changes over time in the prices of consumer goods and services that households acquire, use, or pay for. The South African consumer price index has two equally important objectives:

- To measure inflation in the economy so that macroeconomic policy is based on comprehensive and up-to-date price information, and to provide a deflator of consumer expenditure in the expenditure national accounts.
- To measure changes in the cost of living of South African households to ensure equity in the measures taken to adjust wages, grants, service agreements and contracts (Statistics South Africa, 2013:2).

The body of literature contains limited information on the relationship between consumer price index and financial distress. However, consumer price index as a measure of inflation is a major determinant of interest rates for the South African Reserve Bank. Rising prices erode the purchasing power and, if wages remain constant making the living standards of fixed-income earners miserable, it complicates the task of corporate planning and blurs the vision of politicians and economists as they try to resolve the economy.

The South African Reserve Bank increasingly regard the inflation rate as the main target of policies and, due to the importance of the repo rate to economic trends, the consumer price index serves as an early warning indicator of changes in central bank policy directions. High inflation may result to a generally weak macroeconomic environment, which in turn increases the number of banking crises. Banking crises and increasing lending rates have a direct impact on companies deciding on their capital structure. Therefore, a high value of this variable should positively impact on the firm's probability of financial distress of failure.

2. Treasury bill rate

Treasury bills are short-term debt instruments denominated in South African Rand, which are sold at a discount to par and carry no coupon. They are issued to the market at different maturities from one day to 12 months. Treasury bills are used by government as short-term funding instruments and as tools to manage government’s liquidity.

According to the Treasure bill memorandum of 2008, “The South African Reserve Bank, as established by Section 223 of the Constitution of the Republic of South Africa, Act No. 108 of 1996 as amended, acts as an issuing agent of the National Treasury and is authorised to receive and deal with applications for the issuing of Treasury Bills”. Treasury bills are typically considered as the least risky investment available. They are much more liquid although the yield rate is normally lower than on longer-term securities.

The present study uses the annualised level of the 91 days discount rate to test another measure intended to capture the state of the macroeconomic environment that could potentially affect the probability of financial distress of companies. This indicator is a proxy for risk-free interest rates, which, similar to the consumer price index variable, is very likely to affect companies according to their capital structure. Lower interest rates tend to stimulate investment expenditure, while higher interest rates may result in financial distress.

3. Gross domestic product

South African Reserve Bank uses data, such as the real gross domestic product and other related economic indicators, to adjust its monetary policy. Invariably, the economic policy adjustments correlate positively with the decision-making process of the investment community. This means, a policy adjustment that is received negatively by the investment community is likely to result in a situation where investors are only willing to buy a given share for less, leading to a decline in the stock market. Similarly, positive policy adjustments are likely to persuade investors to pay more for any given share.

A declining stock market has a negative effect on company market capitalisation, making it difficult for companies to raise funds on the market. The declining value of a share price exposes the company to a risk that the value of equity may become less than the value of debt. Consequently, the reducing value of company assets against its debt slides the company into insolvency and thereafter financial distress. Therefore, it is assumed in the present study that the negative impact of gross domestic product is likely to cause financial distress.

4. Unemployment rate

The last major factor influencing the economy and likely to cause financial distress is the labour market. The unemployment rate as the key economic indicator used to measure the potential wellbeing of the economy is closely tracked by the investment community. Unemployment is a matter of potential serious concern because of its effects on economic welfare, production, erosion of human capital, social exclusion, crime, and social instability.

Unemployment is likely to be higher when the private sector experiences negative shocks, like depressed commodity and oil prices. Often, and where possible, when these shocks occur, the government employs debt-financed fiscal stimulus plans to cushion the social impact. Where this is not possible or where the fiscal stimulus is insufficient, the unemployment rate increases. Labour force as a factor of production when it reduces the general production, output follows suite only when labour is not substituted with machinery. A negative multiplier effect may be experienced downstream as the unemployed community will no longer have disposable income to support local business. Therefore, it is assumed in the present study that high levels of unemployment will result in financial distress.

5.4.2 Dependant variables

In defining the dependant variables this study intends to predict the financial distress of Johannesburg Stock Exchange listed companies into three possible outcomes. The first outcome is about the prediction of distressed companies; the second outcome is the prediction of depressed companies and lastly the prediction of healthy companies. This study has deliberately adopted a multinomial model outcome instead of a commonly used binary outcome of failed or not failed.

The multinomial financial distress outcome is preferred on the basis that decision makers would want to know well in advance should the company enter financial distress. The decision makers will receive an early but noisy warning signal that a company is facing financial distress. Andrade and Kaplan (1998:1443) talk about companies that may be experiencing financial distress without being in economic distress and how these are likely targets for takeovers, or likely to weather through a liquidity crisis on their own.

There are two distinct principles adopted in the present study that do not follow the norm. Firstly, the application of a three-level approach in defining dependent variables as opposed to the usual dichotomous approached of failed/non-failed. Secondly, defying the commonly used one-on-one matching principle where one failed company is matched or paired with a similar non-failed company and opting for an unmatched population.

5.5 CHAPTER SUMMARY

This chapter develops the research methodology of the present study. It focuses on the research paradigm shift, the extant research in South Africa and also explains the study independent and dependant variables. The financial health of a company contains a broad range of definitions that reflect two dimensions. On one side, there is a legalistic definition where financial distress is recognised only when a company has engaged a legal process like administration or receivership. On the other side, the extant literature reveals a more economic definition based on operational efficiencies, capital structure, liquidity, profitability or market capitalisation. The present study views a company's financial health on a spiral curve and in a constant state of flux where a company is healthy, depressed or distressed, depending on the prevailing economic variables.

The study adopts a proven research methodology in selecting relevant variables to be used in the models. The literature evidence confirms a large number of available fundamental data, at the same time acknowledging that not all of them are relevant predictors of financial distress. The present study is in line with previous studies in selecting a total of 40 ratios as the initial population. Also, the statistical methodology adopted in the testing of collinearity has been successfully used before in similar studies.

Literature evidence suggests that researchers should stop developing new models that only produce negligible differences from classical methodologies, but rather concentrate on improving the accuracy of these classical models. The present study adopts a classical statistical methodology (logistic analysis) in developing its predictive model. However, in doing so, the literary contribution is on the combination of ratios that are used in the models, that is, accounting, market and macroeconomics. Furthermore, the development of a hybrid model combining the basic and Merton models.

The chapter concludes by providing definitions and contextualising some of the ratios used in the model. With the research methodology clearly discussed, the next step is to provide the research design and data analysis.

CHAPTER 6

RESEARCH DESIGN AND DATA ANALYSIS

6.1 INTRODUCTION

The primary goal of this chapter is to specify the sampling process, data collection and the data analysis strategy. The chapter starts by detailing the data sampling procedure and the data collection method. The study uses secondary data obtained from the INET BFA database. The chapter also provides templates that are used in the study to organise raw data. The first template is for sampled companies and the second template is for selected independent variables. Once the sampling and collection procedures are discussed, the chapter discusses the relevant statistical tests used to refine raw data. The chapter further details the statistical techniques applicable in developing the three models.

In summary, the chapter is laid out as follows: section 6.2 details the sampling and data collection procedures, section 6.3 is about data analysis, section 6.4 discusses the model techniques, section 6.5 contains the measurement estimation and surrogates used in the study, and section 6.6 summarises the chapter.

6.2 SAMPLING AND DATA COLLECTION

The sample consists of Johannesburg Stock Exchange listed firms that were listed from 31 December 2005 to 31 December 2014. The INET BFA (a South African supplier of quality financial data) is used to source the published statement of comprehensive income, the statement of financial position and the financial ratios for sampled firms. The macroeconomic indicators are extracted from the South African Reserve Bank website.

6.2.1 Sampling of companies

A stratified random sampling technique is adopted in selecting companies. There are two groups of companies that are selected at the initial stage, a group of Johannesburg Stock Exchange listed companies and a group of delisted companies. The next process is to clean up the data by applying an elimination process on the population to derive the final list of companies that are used in the models. The following companies, as per the following factors, were eliminated:

- Firms that changed their financial year-end in the ten-year period under review and therefore do not have 12 annual financial periods.
- Firms that change their main line of business. This is aimed at allowing ease of comparison and elimination of the effects of confounding factors such as mergers, acquisitions and restructurings.
- Firms that did not report consecutively on their financial position on an annual basis during all financial periods under review.
- Financial firms such as banks and insurance companies. These companies are highly regulated which, at times, may limit their involvement in taking up more debt.
- Among the group of delisted companies, only companies that were delisted due financial distress are selected. This is to avoid selecting companies that were delisted voluntarily and for other business reasons.

The above elimination process should then result into a category of listed and delisted companies. With the selection of delisted companies which are categorised as financially distressed, the next process is to then categorise the group of listed companies into healthy and depressed category. In defining 'financially depressed' companies this study looks at the recent five year span of the year on year movement on company profitability and solvency position. There are two parameters that are considered in identifying depressed companies: year-on-year movement in earnings before interest and tax, plus income from associated companies; and current assets over current liabilities. The companies that show positive movement year on year on both or one of the parameters for the period under review are categorised as healthy. Equally, the companies showing negative movements are categorised as depressed.

6.2.2 Sampling of independent variables

According to Saunders, Lewis and Thornhill (2009:212), the need for sampling arises when it would be impracticable to collect data from the entire population. A non-probability sampling technique is adopted in the selection of independent variables as the samples are gathered in a process that does not give the entire population equal chances of being selected. To this end, sampling of independent variables in the present study is based on relevance and successful use in previous studies as well as popularity. Therefore, the onset is to carefully select 40 ratios based on their successful use in previous similar studies. The sample is a combination of fundamental, market and macroeconomic variables.

Pilinkus and Boguslauskas (2009:26) investigated the relevance of macroeconomic factors in influencing the movement of equity prices and the most relevant indicators that best explain this relationship. Their findings contain two significant points that have a positive impact on the present study. Firstly, they confirm that macroeconomic variables are relevant indicators of movements in equity markets. Secondly, their paper identifies the following variables as relevant indicators in explaining the positive relationship between macroeconomics and equity prices: gross domestic product, inflation, interest rates, money supply, exchange rate, and unemployment rate. The sample of macroeconomic indicators therefore includes the following: gross domestic product, consumer price index, prime lending rate, 90 day South African Treasury bill and unemployment rate.

The five selected market ratios are commonly used by investors, fund managers, and ratings agencies. The objective is to derive the most powerful combination of financial ratios. The initial population, which forms a range of potential independent variables was selected and tested based on extant empirical studies. The variables cover seven domains: solvency, profitability, capital structure, liquidity, efficiency, market, and macroeconomics.

6.3 DATA ANALYSIS

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

6.3.1 Data analysis plan

Once all the archival data are collected from the already mentioned reliable and reputable sources, the next task is to prepare it for analysis. The statistical package, SPSS, will be used for all statistical analysis in the process of model building.

6.3.2 Statistical analysis

The analysis is based on a panel data set consisting of firm-year observations involving Johannesburg Stock Exchange listed companies from 2005 to 2014. The sample covers different business sectors and all company sizes: small, medium and large.

- Testing for outliers, missing data and data transformation

  The influence of outliers can be severe in regression analysis and can lead to incorrect inferences. Therefore, this test is conducted to mitigate that risk in trimming all variables that are identified as outliers. An outlier is an observation that appears to deviate markedly from other observations in the sample. Outliers are inherently experienced in studies of financial distress as the sampled population would consist of companies from different economic sectors and of different sizes economically and financially.

- Normality test

  A normality test is conducted on the selected data before running the correlation matrix. The statistical procedures applied in this instance are the Kolmogorov-Smirnov and the Shapiro-Wilk tests. This statistical procedure works on the basis that the null-hypothesis of the population is normally distributed. Thus, if the p-value is less than the alpha level of 0.05, then the null hypothesis is rejected and there is evidence that the data tested are not from a normally distributed population. In other words, the data are not normal. On the contrary, if the p-value is greater than the alpha level of 0.05, then the null hypothesis that the data came from a normally distributed population cannot be rejected.

- Multicollinearity test

  Multicollinearity is present when there is linear dependency among two or more independent variables in a multivariate model. This problem arises because some of them may be measuring the same concept. Consequently, when a given independent variable is a linear or a quasi-linear combination of other independent variables, the affected estimates are unstable and the standard errors inflated. Multicollinearity may be tested using Pearson correlation test or the Spearman Rho test. The Pearson correlation test works better with normally distributed data, therefore this study uses the Spearman Rho test since the data is not normally distributed.

6.4 MODEL SPECIFICATION TECHNIQUES

6.4.1 Basic model

The outcome variable in logistic analysis is either binary or multinomial, and the purpose of the analysis is to assess the effects of multiple explanatory variables, which can be numeric and/or categorical on the outcome variable. To conduct a logistic analysis, the following need to be specified:

(i) An outcome variable with two or more possible categorical outcomes (1=success; 0=failure).
(ii) A way to estimate the probability (P) of the outcome variable.
(iii) A way of linking the outcome variable to the explanatory variables.
(iv) A way of estimating the coefficients of the regression equation, as well as their confidence intervals.
(v) A way to test the goodness of fit of the regression model.

The probability of the outcome is measured by the odds of occurrence of an event. If (P) is the probability of an event, then (1-P) is the probability of it not occurring.

Odds of success = P / 1-P (6.1)

The joint effect of all explanatory variables put together on the odds is:

Odds = P / 1-P = $e^{\alpha + \beta 1X1 + \beta 2X2 + \ldots + \beta pXp}$ (6.2)

Taking the logarithms of both sides,

Log{P/1-P} = $\log^{\alpha+\beta 1X1+\beta 2X2+\ldots+\beta pXp}$ (6.3)

Logit P = $\alpha + \beta_1X_1 + \beta_2X_2 + \ldots + \beta_pX_p$ (6.4)

The coefficients β_1, β_2, β_p are such that the sums of the squared distance between the observed and predicted values (regression line) are smallest.

Logit P = $\alpha + \beta_1X_1 + \beta_2X_2 + \ldots + \beta_pX_p$

α represents the overall risk;

β_1 represents the fraction by which the distress risk is altered by a unit change in X_1;

β_2 is the fraction by which the distress risk is altered by a unit change in X_2, and so on. The odds themselves are changed by $e^{\boldsymbol{\beta}}$.

If $\beta = 1.6$, the odds are $e^{1.6} = 4.95$

In applying the logistic analysis as discussed above, the present study defines three possible outcomes: healthy = 2, depressed = 1 and distressed = 0. Therefore, the slight change from the above is that the present study uses the multinomial logistic analysis and not binomial analysis.

6.4.2 The Merton model

The literature review reveals certain improvements on the original Merton model by researchers like the Moody's rating agency as authored by Sun *et al.* (2012:10), and

Bharath and Shumway (2008:1339). The latter dissected the original model to simplify it without compromising quality. These authors introduce a naïve alternative to the original model with the intention of achieving the following objectives:

(i) To have a reasonable chance of performing as well as the Merton model;
(ii) To approximate the functional form of the original model probability; and
(iii) To be simple and avoid solving any equations or estimating any difficult quantities in its construction.

The power behind a default prediction model lies not with its complexity, but with the output accuracy of the model. Therefore, introducing a new model that produces similar results as the existing models may not be as valuable.

The Merton model makes two particularly important assumptions. Firstly, it takes an overly simple debt structure, and assumes that the total value of a firm's assets follows a geometric Brownian motion under the physical measure:

$$dV = \mu V dt + \sigma v V dW \tag{6.5}$$

where *V* is the total value of the firm, *μ* is the expected continuously compounded return on *V*, *σV* is the volatility of firm value, and *dW* is a standard Weiner process.

The second assumption built into his model is that it assumes that debt consists of a single outstanding bond with face value and maturity. At maturity, if the total value of the assets is greater than the debt, the latter is paid in full and the remainder is distributed among the shareholders. However, if the total value of the assets is less than the debt, then default is deemed to occur. The bondholders exercise a debt covenant, allowing them to liquidate the firm and receive the liquidation value (equal to the total firm value since there are no bankruptcy costs) in lieu of the debt. Shareholders receive nothing in this case, but by the principle of limited liability are not required to inject any additional funds to pay off the debt.

From the above observations, shareholders have a cash flow at a particular time where the total value of the assets is greater than the debt. Symbolically, the Merton model stipulates that the equity value of a firm satisfies:

$$E = VN(d_1) - e^{-rT}FN(d_2) \qquad (6.6)$$

where *E* is the market value of the firm's equity, *F* is the face value of the firm's debt, *r* is the instantaneous risk-free rate, *N*(·) is the cumulative standard normal distribution function, *d*1 is given by:

$$d_1 = \frac{(In(V/F)+(r+0.5\sigma^2 v)T}{\sigma v\sqrt{T}} \qquad (6.7)$$

and d_2 is just $d_2 = d_1 - \sigma v\sqrt{T}$. While this is a fairly complicated equation, most financial economists are familiar with this formula as the Black-Scholes-Merton option valuation equation.

This model makes use of two important equations. The first is the Black-Scholes-Merton equation (6.6), expressing the value of a firm's equity as a function of the value of the firm. The second relates the volatility of the firm's value to the volatility of its equity. Under Merton's assumptions, the value of equity is a function of the value of the firm and time, so it follows directly from Ito's lemma that:

$$\sigma E = \left(\frac{V}{E}\right)\frac{\partial E}{\partial E}\sigma v \qquad (6.8)$$

In the Black-Scholes-Merton model, it can be shown that $\frac{\partial E}{\partial E}$ = *N* (d_1), so that under the Merton model's assumptions, the volatilities of the firm and its equity are related by:

$$\sigma E = \left(\frac{V}{E}\right)N(d_1)\sigma v \qquad (6.9)$$

where d_1 is defined in equation (6.7).

The Merton model uses these two non-linear equations – (6.6) and (6.9) – to translate the value and volatility of a firm's equity into an implied probability of default. In most applications, the Black-Scholes-Merton model describes the unobserved value of an option as a function of four variables that are easily observed (strike price, time-to-maturity, underlying asset price, and risk-free rate) and one variable that can be estimated (volatility).

However, in the Merton model, the value of the option is observed as the total value of the firm's equity, while the value of the underlying asset (the value of the firm) is not directly observable. Thus, while *V* must be inferred, *E* is easy to observe in the marketplace by multiplying the firm's shares outstanding by its current stock price. Similarly, in the Merton model, the volatility of equity, *σE*, can be estimated but the volatility of the underlying firm, *σV*, must be inferred. In this study, the equity volatilities, prices and market capitalisation are obtained from the INET BFA database.

The first step in implementing the Merton model is to obtain *σE,* which is sourced from the INET BFA database in the present study. The second step is to choose a forecasting horizon and a measure of the face value of the firm's debt. For example, it is common to assume a forecasting horizon of one year (*T* = 1), and take the book value of the firm's total liabilities to be the face value of the firm's debt. The third step is to collect values of the risk-free rate and the market equity of the firm. For the risk-free rate, the present study uses a proxy of the 90-day Treasury bill rate. After performing these three steps, there are values for each of the variables in equations (6.6) and (6.9) except for *V* and *σV*, the total value of the firm and the volatility of firm value, respectively.

The fourth, and perhaps most significant step in implementing the model, is to simultaneously solve equations (6.6) and (6.9) numerically for values of *V* and *σV*. Once this numerical solution is obtained, the distance to default can be calculated as:

$$DD = \frac{In(\frac{V}{F})+\left(\mu-0.5\sigma_v^2\right)T}{\sigma v\sqrt{T}} \qquad (6.10)$$

where μ is an estimate of the expected annual return of the firm's assets. The corresponding implied probability of default, sometimes called the expected default frequency (EDF), is:

$$PD = N\left(-\left(\frac{In\left(\frac{V}{F}\right)+\left(\mu-0.5\sigma_v^2\right)T}{\sigma v\sqrt{T}}\right)\right) = N(-DD) \qquad (6.11)$$

If the assumptions of the Merton model hold, the Merton model should give accurate default forecasts. If the Merton model holds completely, the implied probability of default defined above should be a sufficient statistic for default forecasts.

The most critical inputs to the model are the market value of equity, the face value of debt, and the volatility of equity. As the market value of equity declines, the probability of default increases. This is both a strength and weakness of the model. For the model to work well, both the Merton model assumptions must be met and markets must be efficient and well informed.

6.4.3 The hybrid model

The hybrid model is a model that is a combination of two distinct models. In developing the hybrid model in this study, the basic model is combined with the Merton model. In achieving this combination, the distance to default factor that is derived from the Merton model is added to the list of independent variables utilised when developing the basic model. When these variables are combined, a logistic analysis is conducted to determine the financial distress prediction accuracy.

In the existing literature, hybrid models frequently take on the functional form of discrete hazard models using logistic analysis functions. This methodology was pioneered by Shumway (2001:101) in predicting bankruptcy. The discrete hazard models use time-varying variables to estimate a firm's bankruptcy risk at each point in time.

As mentioned in the previous section, the probability that a firm will eventually go bankrupt in t+1 depends on turnaround strategies implemented by management until t.

Campbell *et al.* (2011:14) used the discrete probability of failure at time t as specified below. A similar logistic analysis equation is applied in the present study.

$$P_{i,t}\,(Y_{i,t+1} = 1|Y_{i,t+1}=0) = \frac{1}{1+\exp\,(-\alpha_t - \beta X_{i,t})} \qquad (6.12)$$

Therefore, using the logistic analysis statistical technique as constructed in section 6.4.1 above, there are eleven independent variables that are used to predict the financial state of companies. The first ten independent variables are intended to provide financial distress information based on accounting information whereas the eleventh variable is the distance to default variable derived from the Merton model and it seeks to represent information coming from the market. The fundamental variables are drawn from the basic model 3 which incorporated ten independent variables. The market based variable is drawn from the Merton model.

6.5 MEASUREMENT ESTIMATION AND SURROGATING

There are five primary inputs to the distance to default calculation that need to be estimated. The estimation of these variables means building certain assumptions to support the model. The estimation input variables are the following:

- Asset values (V_0);
- Asset volatility (σ_A);
- Debt levels (D);
- Risk-free rate (μ);
- Time (T)

The most critical inputs of the model are the market value of assets and its volatilities. For this study's purposes, the share price and its recorded beta values are used as proxies of the asset values and volatilities. The next input is the face value of debt, which will be observed from the annual financial statements.

As quoted in Strydom and Charteris (2013:2815), Firer says parameters like beta, the risk-free rate and the return on the market are theoretical constructs that are not easily observable in the market, and consequently proxies are used for these variables in practice. Correia and Ulius (2004:31) further say that the difficulty in selecting these surrogates has hampered the implementation of the model.

a) Estimation of asset values (A_0)

The asset values are readily available for listed companies and are easy to observe in the market place by multiplying the firm’s shares outstanding by its current share price. Using share prices to estimate asset values is the best option as it reflects the market's collective opinion of the prospect of its business. A_0 is estimated by computing the mean value of equity over a year. Therefore, the market value of equity is used as the proxy for the value of a company’s assets.

b) Estimation of asset volatility (σ_A)

The study uses the volatility of equity value (σ_E) as a proxy of the volatility of asset value (σ_A). The standard deviation (σ_E) of equity values are estimated using daily data observed during the year.

c) Debt Levels (D)

The level of debt will mark the default point, a point at which, if the firm’s asset values drop below it, a default is predicted. The default point should consist of all current liabilities and half of the long-term liabilities.

d) Risk-free rate (μ)

In their study, Strydom and Charteris (2013:2815) concluded that the appropriate risk-free rate of return should represent the pure interest rate and a premium for expected inflation. The most preferred proxies for the risk-free rate asset in South

Africa are T-Bill and T-Bond rates. To this end, the present study applies this variable as surrogates for risk-free rate.

e) Time (T)

The general complexity of predictive studies is always around predicting future values. This model attempts to predict (A_1), a value representing assets at time (T). For practicality purposes, this model assumes (T) to be one year. Therefore, the model will estimate (A_1) in a year's time after considering the estimated return and risk-free rate.

6.6 CHAPTER SUMMARY

This chapter develops the research design and data analysis of the present study. It explains the sampling and data collection methodologies. This chapter also describes the data analysis plan but more importantly the model specification techniques. Lastly, it highlights and describes the measurement estimation and surrogating. The sampling methodology adopted by the present study is akin to previous research work of a similar nature. In related studies, the integrity and reliability of data sources is of paramount significance. Similarly, this study sources its data from sources that have been used in similar and other research. The availability of such sources assists in ensuring that data is available timely.

The technical side of the research that includes the model specifications as well as measurement estimates is thoroughly checked and aligned with extant research. In terms of the statistical technique, the present study uses the logistic analysis, a classical theoretical framework that has been found to remain robust in the contemporary research. Regarding testing for collinearity, the study also adopts a tried and tested technique, the stepwise logistic analysis statistical methodology.

Three models specification techniques are developed in this chapter. The basic model is a combination of three variables (accounting, market and macroeconomics data), which are tested using logistic analysis. The Merton model, based on distance to default, is chosen based on its simplicity and robustness. The outcomes of the two models are combined using the using logistic analysis function to develop a hybrid model.

CHAPTER 7

THE FIRST TIER TO DETERMINE FINANCIAL DISTRESS

7.1 INTRODUCTION

Thus far, the study has developed a solid theoretical framework based on the extant literature in alignment with the identified research objectives. Furthermore, testable hypotheses and the research strategy have also been developed. It was critical to identify precise statistical techniques and mechanisms that would allow for the development of financial distress models.

Chapter 7's objective is to present the profile analysis that seeks to expound on the selected companies and variables. The chapter further provides a thorough analysis of various statistical output reports regarding the final sample of independent variables.

Section 7.2 of this chapter deals with the strategy adopted in selecting companies and independent variables. Section 7.3 is the trend analysis reflecting the movement of ratios over a five-year period and also the relationship between financial states. Section 7.4 discusses relevant statistical tests conducted in the present study. Section 7.5 provides a brief analysis of the chosen statistical technique applied in the present study. Section 7.6 is about the development of the basic model. Lastly, the chapter is summarised in the chapter summary in Section 7.7.

7.2 SELECTION OF COMPANIES AND INDEPENDENT VARIABLES

The study presents its empirical results based on 100 selected companies. Of these companies, 92 are listed on the Johannesburg Stock Exchange while the other eight are companies that have been delisted due to financial distress. Therefore, in line with the research methodology, the list of delisted companies is treated in this study as the list of financially distressed companies. The study recognises three financial states: distressed, depressed and healthy. Hence, a criterion is set to identify any company that may be in financial depression among the 92 companies that are still listed. Companies that are classified as depressed may be companies that have not been delisted but are already showing signs of financial pressure. The rationale in identifying these companies is to create awareness for management to take corrective actions while there is still time. Therefore, financial depression may be viewed as a warning signal.

Two parameters are considered in identifying depressed companies: year-on-year movement in earnings before interest and tax, plus income from associated companies; and working capital. After applying the criterion, 14 companies are identified as depressed. Table 7-1 outlines the final population of companies according to their financial states.

Table 7-1: The percentage composition of selected companies according to their financial state

Financial state	Number of companies	Percentage composition
Healthy	78	78%
Depressed	14	14%
Distressed	8	8%
Total	100	100%

Source: own research

The approach adopted in the present study regarding the percentage composition of companies is in line with existing literature, for instance Ohlson (1980:109), whose study consisted of 5% failed companies. It is also in line with more contemporary studies, like Åstebro and Winter (2012:1) who had a 12% representation of failed companies, and Tinoco and Wilson (2013:394) who had a 12.6% representation of failed companies. Therefore, at 8% of distressed companies, the present study is in line with extant research.

7.2.1 Selected companies according to their economic sectors

The list of companies comes from various economic sectors, but the dominance of industrial companies cannot be ignored. This industrial sector represents 37% of the total population. This is followed by the retail sector constituting 19% of the population. The other economic sectors represented include: chemicals at 6%, food and beverages at

10%, healthcare sector at 3%, media at 3%, personal and households at 3%, technology at 9%, travel and leisure at 9%, and telecoms at 2%.

Table 7-2: Companies according to their Johannesburg Stock Exchange industry classification

Economic sector	All firms	Percentage	Distressed	Depressed	Healthy
Chemicals	6	6%		2	4
Food and beverages	10	10%		2	8
Healthcare	3	3%			3
Industrials	37	37%	4	2	31
Media	3	3%		1	2
Personal and household	3	3%			3
Retail	19	19%	1	3	15
Technology	9	9%	2		7
Telecoms	2	2%		1	1
Travel and leisure	8	8%	1	3	4
Total	100	100%	8	14	78

Source: own research

7.2.2 Selected independent variables

The screening and selection of the final set of independent variables that is used in the model followed a thorough scrutiny of existing research. Other researchers opted for criteria that looked at simplicity and relevancy to the local environment in choosing their financial ratios (Low, Fauzias & Yatim, 2001; Mohamed, Ang & Sanda, 2001). The process used in the present study culminated in a list of 17 variables based on their successful utilisation in previous studies. Of this, nine variables represent the fundamental data group, three represent the market indicators, and five represent the macroeconomic indicators. This list is further processed to condense it to a desirable level, which literature suggests as a combination of about five fundamental data, one or two market variables, and one macroeconomic variable. This observation relates to studies that have developed hybrid financial distress models.

In further processing the list, the study uses the forward stepwise method in and the test for variable correlation. The correlation test applied is Spearman's Rho test. While

Pearson's procedure is considered robust, it is not recommended for the nature of the present study's data. Instead, the Spearman procedure is adopted as it is viewed as appropriate for the composition of data. The correlation matrix table represented below is constructed using the Spearman procedure.

Table 7-3 below is based on a ten-year average for the nine financial ratios for the 100 sampled companies from 2005 to 2014.

Table 7-3: Correlation matrix for nine fundamental variables extracted from the literature as the most popular ratios used in similar studies

Variables	WCTA	EBITTA	CACL	CATA	TD/TE	TDTA	METD	TOTA	TD/CF
WCTA **Sig, (2 tailed)**	1 0								
EBITTA **Sig, (2 tailed)**	0.208 0.036	1 0							
CACL **Sig, (2 tailed)**	0.924 < 0.0001	0.266 0.007	1 0						
CATA **Sig, (2 tailed)**	0.460 < 0.0001	-0.023 0.819	0.235 0.018	1 0					
TD/TE **Sig, (2 tailed)**	-0.405 < 0.0001	-0.052 0.605	-0.474 < 0.0001	-0.039 0.695	1 0				
TDTA **Sig, (2 tailed)**	-0.578 < 0.0001	-0.207 0.037	-0.644 < 0.0001	0.129 0.197	0.827 < 0.0001	1 0			
METD **Sig, (2 tailed)**	0.270 0.006	0.596 < 0.0001	0.388 < 0.0001	-0.159 0.110	-0.349 0.000	-0.524 < 0.0001	1 0		
TOTA **Sig, (2 tailed)**	0.050 0.617	0.184 0.064	-0.056 0.579	0.372 0.000	0.185 0.062	0.139 0.162	0.052 0.601	1 0	
TD/CF **Sig, (2 tailed)**	0.025 0.806	0.000 0.999	-0.017 0.868	0.186 0.062	0.275 0.005	0.206 0.038	-0.006 0.951	0.166 0.095	1 0

Source: own research

WCTA – working capital over total assets, **EBITTA** – earnings before interest and tax over total assets, **CACL** – current assets over current liabilities, **CATA** – current assets over total assets, **TD/TE** – total debt over total equity, **TDTA** – total debt over total assets, **METD** – market capitalisation over total debt, **TOTA** – turnover over total assets, **TD/CF** – total debt over total assets.

The above correlation matrix shows that the fundamental data selected in the first round based on literature requires no elimination of further variables. The selected nine individual ratios appear to possess statistical power to predict financial distress. The only ratios reflecting correlation closer to 1, indicating a strong positive relationship, are current assets over current liabilities and working capital over total assets. This relationship is also significant with p-values below 0.01. This is an encouraging yet undesirable outcome as the number of variables is too high compared to the expected five variables.

Therefore, to further reduce the number of variables, two prominent studies are used as guides. These two studies are based on prominence and originality rather than on recency. Altman (1968:589) is used as an international indication, while De La Rey (1981:1) is used as a South African indication. The tables below reflect the fundamental ratios used by Altman and De la Rey, respectively. From these fundamental ratios a list of the present study's ratios is compiled and reflected.

Table 7-4: Fundamental variables selected by De la Rey (1981)

De la Rey model
Total outside financing/total assets
Income before interest and tax/average total assets
Total current assets and listed investments/total current liabilities
Income after tax/average total assets
Net cash flow/average total assets
Stock/inflation adjusted total assets

Source: De la Rey (1981:1)

Table 7-5: Fundamental variables selected by Altman (1968)

Altman model
Working capital/total assets
Retained earnings/total assets
Earnings before interest and taxes/total assets
Market value of equity/book value of total debt
Sales/total assets

Source: Altman (1968:589)

Table 7-6: Fundamental variables selected in the present study

Present study	Used by
Working capital/total assets	Altman
Earnings before interest and taxes/total assets	Both
Total debt/total assets	De la Rey
Market value of equity/book value of total debt	Altman
Turnover/total assets	Altman

Source: own research

Therefore, the final list of fundamental data used in the present study is a combination of Altman and De la Rey. It must be noted that this list of selected fundamental variables continue to dominate in contemporary research studies. Furthermore, the ratios in the final list are all included in the original selection.

Table 7-7 below is based on ten-year average market ratios for the 100 sampled companies from 2005 to 2014 based on the correlation levels among the market indicators.

Table 7-7: Correlation matrix for selected market indicators

Variables	P/E	P/S	P/CF
P/E **Sig, (2 tailed)**	1 0	0.459 < 0.0001	0.684 < 0.0001
P/S **Sig, (2 tailed)**	0.459 < 0.0001	1 0	0.527 < 0.0001
P/CF **Sig, (2 tailed)**	0.684 < 0.0001	0.527 < 0.0001	1 0

Source: own research

P/E – price per earnings, **P/S** – price per share, **P/CF** – price per cash flow

Table 7-7 reflects the collinearity outcome of the selected market indicators. The intention is to identify any indicators that appear to communicate a similar message and the significance of that relationship. As reflected, all these indicators have prediction power and therefore may all be used in the model.

Lastly, the test is conducted on macroeconomics indicators. The results of the test are in Table 7-8 below based on ten=year average macroeconomic indicators from 2005 to 2014.

Table 7-8: Correlation matrix for selected macroeconomic indicators

Variables	CPI	TBR	GDP	UR	PLR
CPI **Sig, (2 tailed)**	1 0	0.998 < 0.0001	-1.000 < 0.0001	0.378 < 0.0001	0.998 < 0.0001
TBR **Sig, (2 tailed)**	0.998 < 0.0001	1 0	-0.999 < 0.0001	0.381 < 0.0001	1.000 < 0.0001
gross domestic product **Sig, (2 tailed)**	-1.000 < 0.0001	-0.999 < 0.0001	1 0	-0.379 < 0.0001	-0.998 < 0.0001
UR **Sig, (2 tailed)**	0.378 < 0.0001	0.381 < 0.0001	-0.379 < 0.0001	1 0	0.382 < 0.0001
PLR **Sig, (2 tailed)**	0.998 < 0.0001	1.000 < 0.0001	-0.998 < 0.0001	0.382 < 0.0001	1 0

Source: own research

CPI - consumer price index, **TBR** – 90 day South African Treasury bill, **GDP** – gross domestic product, **PLR** – prime lending rate, **UR** – unemployment rate

There appears to be various indicators correlated within the macroeconomic indicators. When there are two correlated variables, a decision to eliminate one of the two variables becomes important. The consumer price index is positively correlated to the 90 day South African Treasury bill and prime lending rate with correlation closer to 1. However, it is negatively correlated to the gross domestic product at -1. The gross domestic product is positively correlated to 90 day South African Treasury bill and prime lending rate. With these combinations, the variables that are eliminated from the analysis are consumer price index, 90 day South African Treasury bill and prime lending rate – these reflect a high correlation which is significant according to the p-values.

7.3 TREND ANALYSIS BETWEEN FINANCIAL STATES

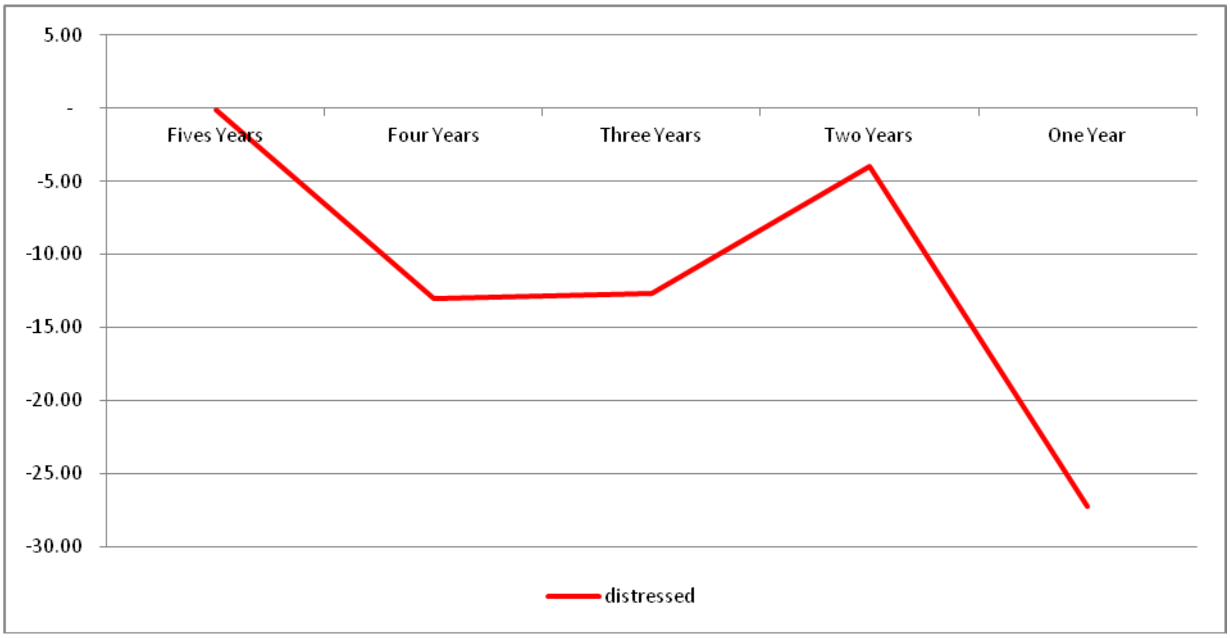
This section seeks to provide a deeper understanding of the relationship between selected variables and the company financial state. There are two graphs presented for each variable. The first graph represents the distressed companies and the second graph shows the trend for the depressed and healthy companies. The first section covers the fundamental data, followed by the market and macroeconomic indicators.

7.3.1 Fundamental data trend analysis

The objective is to monitor the trend of the indication for a particular financial state. For example, what direction does the indicator take as the company approaches distress? Also, are depressed companies really in danger? Are they following the same trajectory as the distressed companies or do they tend to follow the trajectory of the healthy companies?

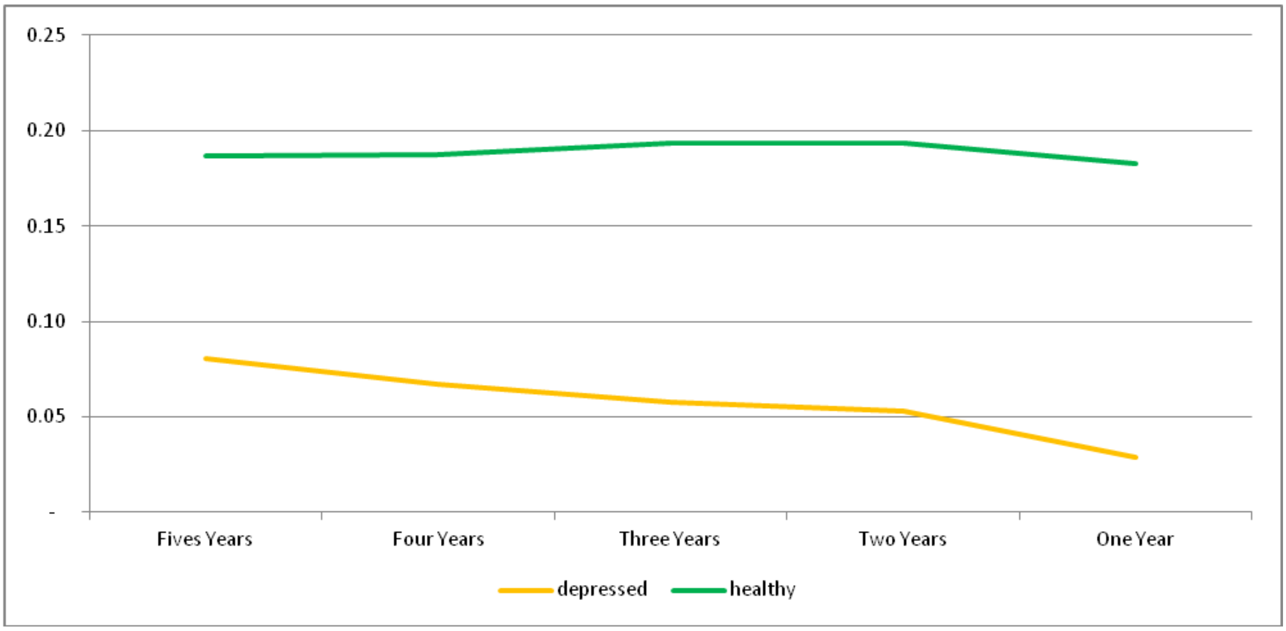
Please note that the x-axis of each graph below represents the recent five years of financial performance. This is deliberately not presented as 2014-2010 as the distressed companies failed in different periods. However, with regard to healthy and depressed companies, year one to five represent 2014-2010.

Graph 7-1a: Working capital to total assets for distressed companies over the five years prior to distress, using the average for all companies defined as distressed



Source: own research

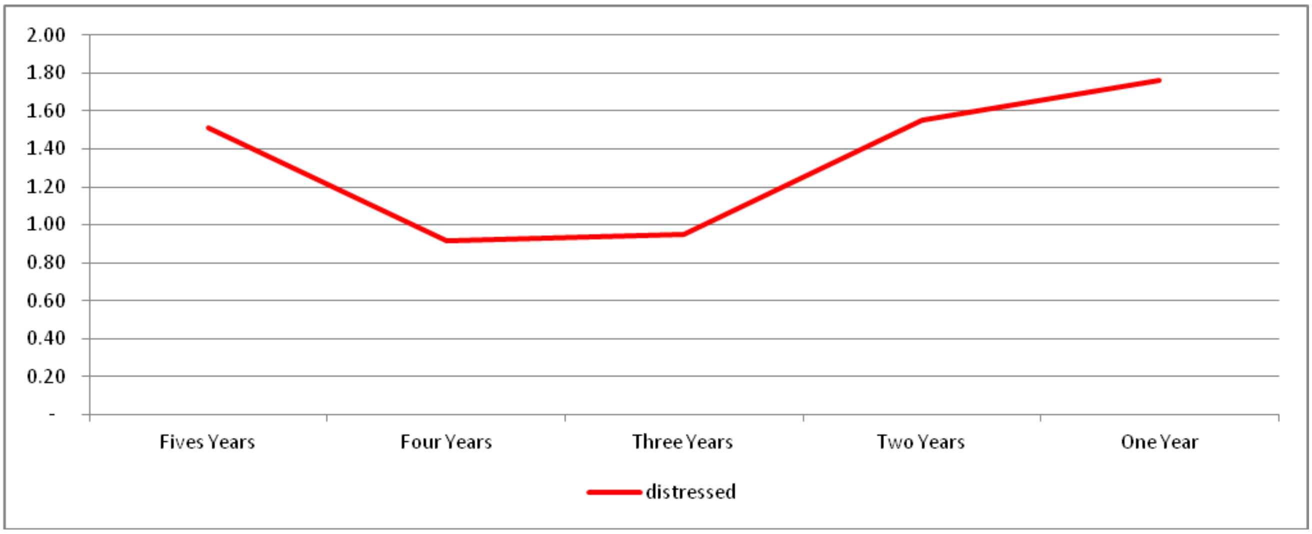
Graph 7-1b: Working capital over total assets for depressed and healthy companies over the five years, using the average for all companies defined as depressed and healthy



Source: own research

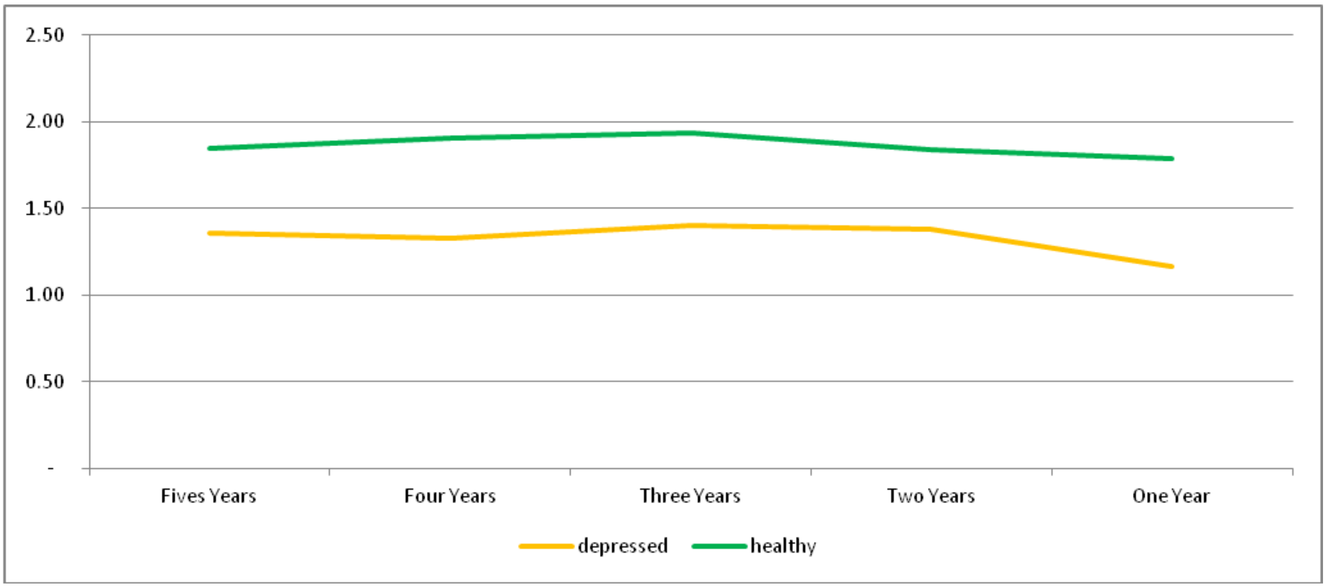
Graphs 7-1a and 1b clearly depict the differences between trend lines. Firstly, the glaring trend is the instability in working capital management. The first graph representing distressed companies appears to be unstable compared with the depressed and healthy companies. Secondly, distressed companies are showing signs of technical insolvency. Lastly, the working capital over total assets ratio decreases significantly one year before failure for distressed companies.

Graph 7-2a: Current assets over current liabilities for distressed companies over the five years prior to distress, using the average for all companies defined as distressed



Source: own research

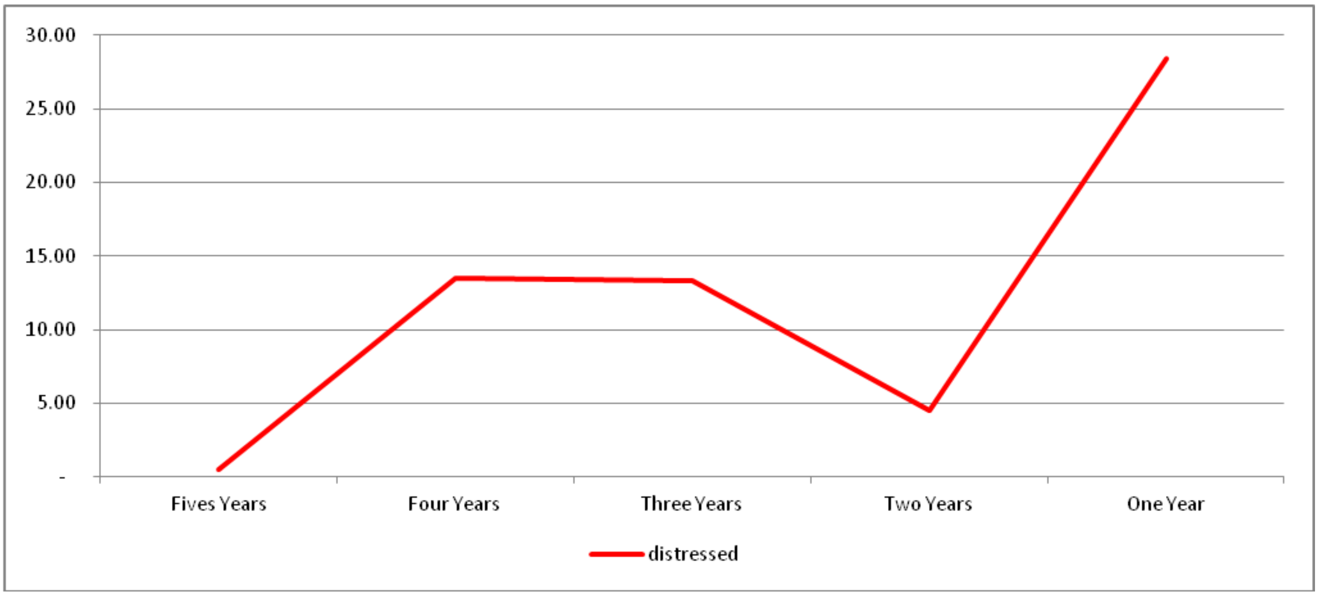
Graph 7-2b: Current assets over current liabilities for depressed and healthy companies over the five years, using the average for all companies defined as depressed and healthy



Source: own research

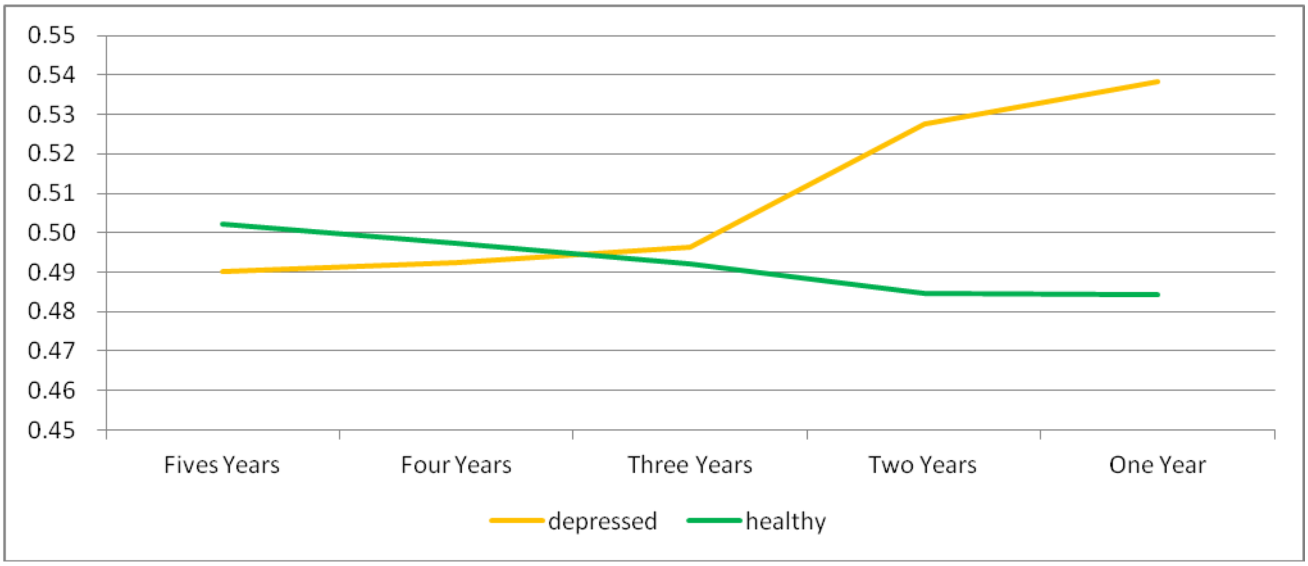
Again, a similar trend is evident in the above graphs in terms of trend volatility. The bottom trend appears very stable while the above one fluctuates year-on-year. This is a liquidity ratio and these fluctuations may be evidence of financial pressure in financing short-term obligations.

Graph 7-3a: Total debt over total assets for distressed companies over the five years prior to distress, using the average for all companies defined as distressed



Source: own research

Graph 7-3b: Total debt over total assets for depressed and healthy companies over the five years, using the average for all companies defined as depressed and healthy

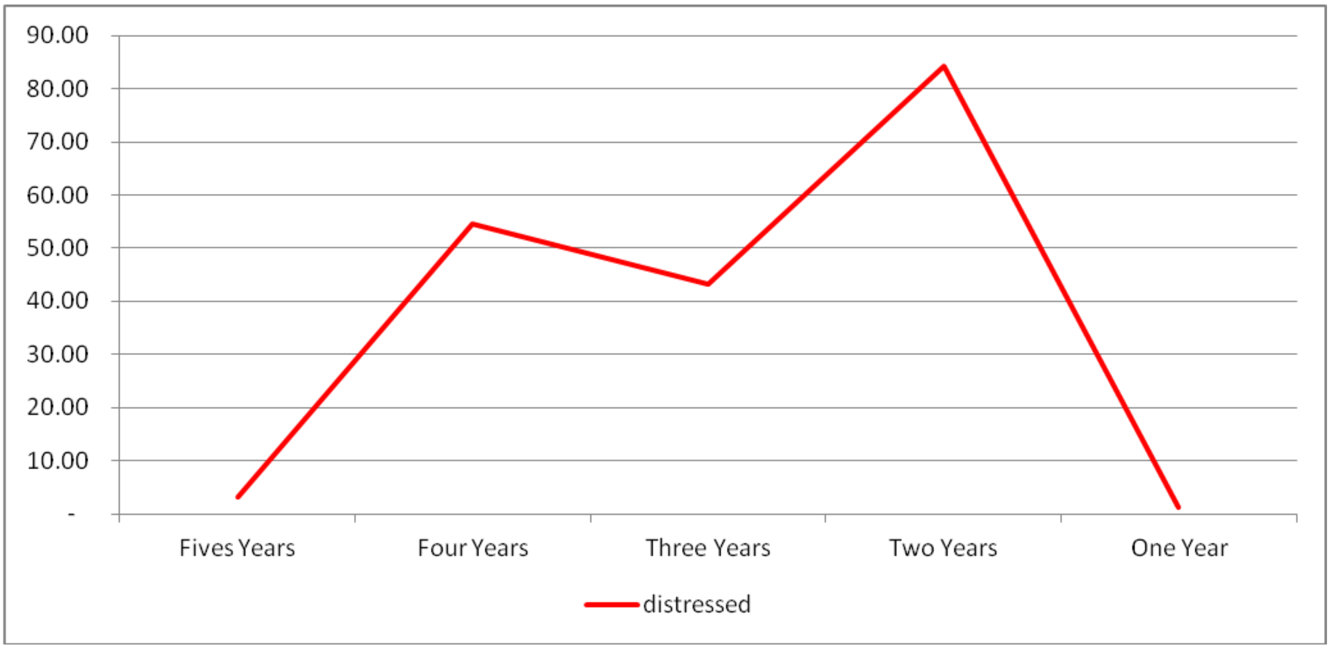


Source: own research

The total debt to total assets ratio as depicted in Graphs 7-3a and 3b above is a solvency ratio. It indicates how geared the company is. The higher the gearing ratio, the higher the probability of financial distress. While it is possible for certain companies to reflect a higher gearing ratio while financially healthy, it remains a high risk environment to operate under. The challenge for most companies is the ability to pick the optimal debt level point.

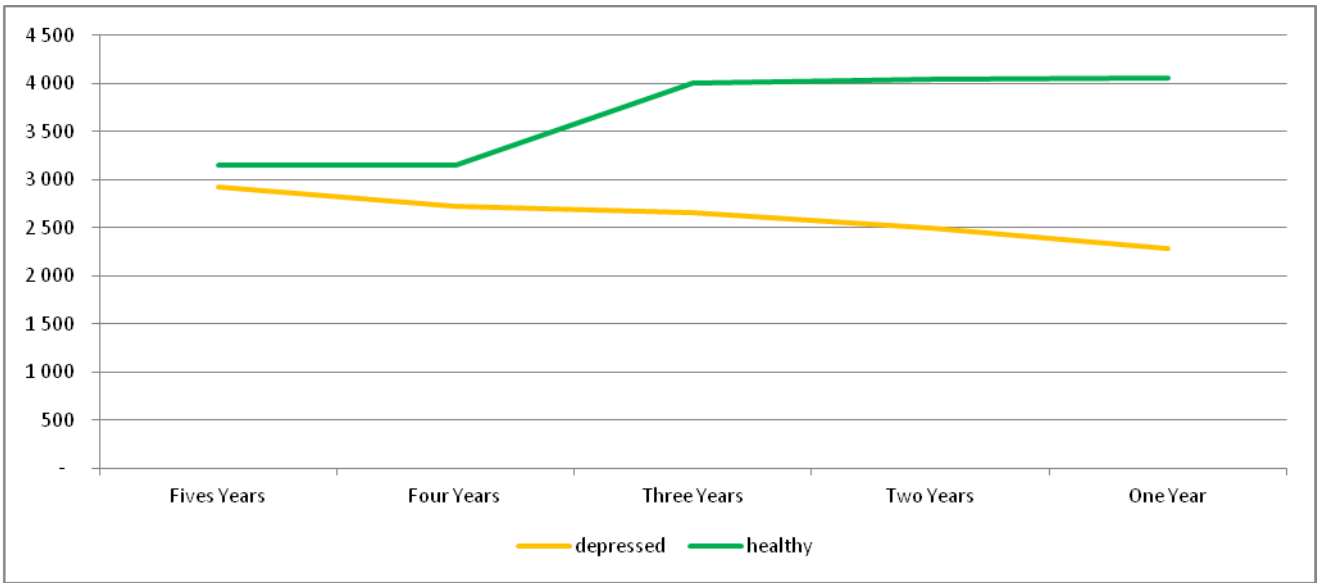
However, for the present study, a higher ratio is construed as an indication of distress. The debt levels of financially healthy companies are on average below 50% for the full five years. Also, a flat trend may also reflect stability and stringent investment policy within these companies. The same may be inferred with financially depressed companies, albeit the fact that their debt level hovers around an average of 53% of its total assets.

Graph 7-4a: Market capitalisation over total debt for distressed companies over the five years prior to distress, using the average for all companies defined as distressed



Source: own research

Graph 7-4b: Market capitalisation over total debt for depressed and healthy companies over the five years, using the average for all companies defined as depressed and healthy



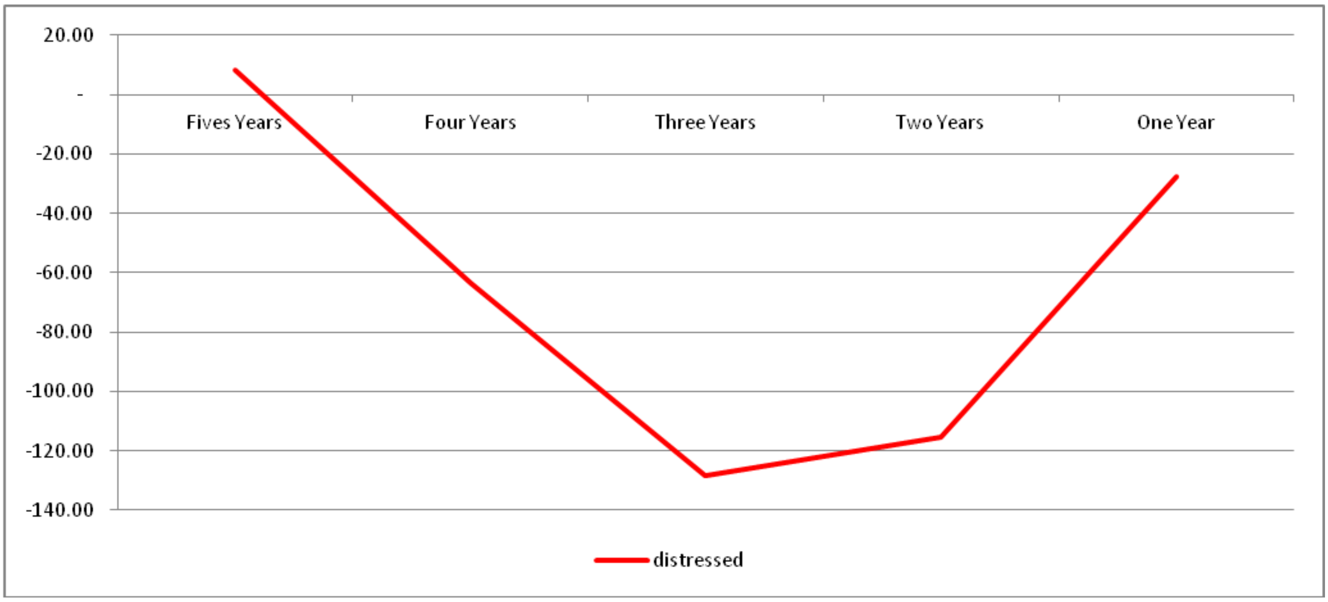
Source: own research

Market capitalisation divided by a company's total debt is an indication of the investor's view of the company's debt level as depicted in the market value of the company. The investor view may also be a good indication of the company repayment capability. If investors are not confident that the company operations or future returns are positive enough to meet financial obligations, the share price will depict this sentiment.

Evidence of the above is obvious when comparing the three financial states. The financially healthy state has a much stronger market capitalisation to total debt ratios than the other two financial states. The financially depressed state, for the first time using this ratio, appears to have moved slightly away from the healthy companies. The numbers reflect a worsening situation as they start healthy in fifth year and deteriorate towards the first year. This could be a sign of the investor confidence level dropping as these companies may be experiencing negative signs of year-on-year profitability.

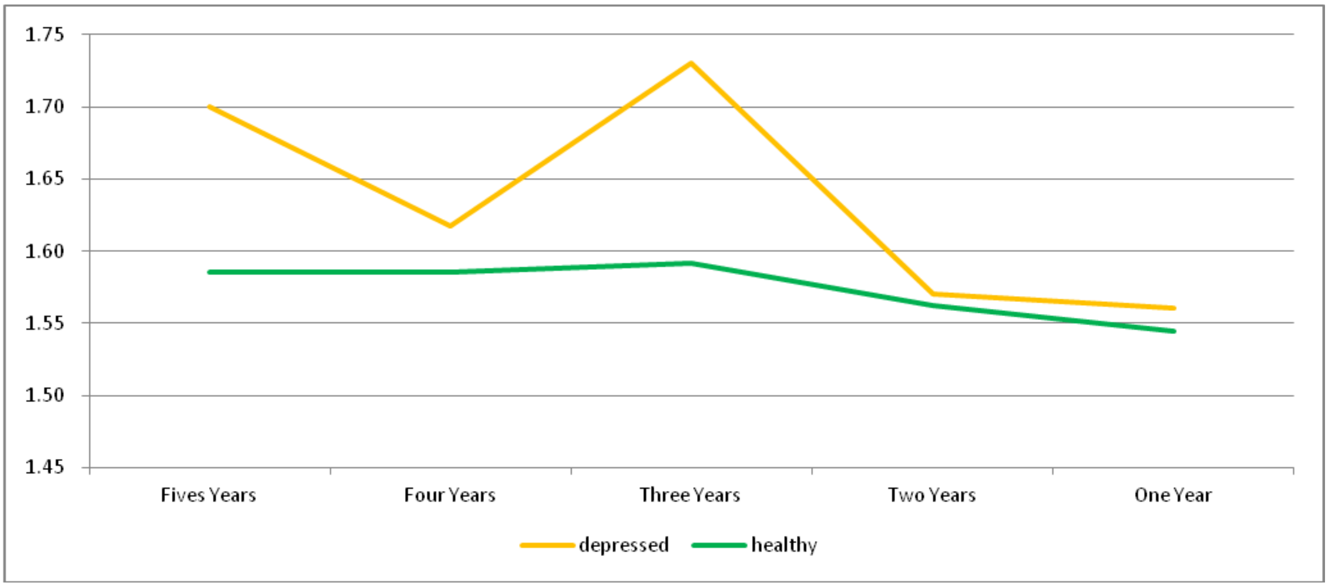
The financially distressed companies reflect an almost incompatible trend with the other financial states. The numbers are so low and they worsen before failure. The learning point from this graph is that financial distress is not an incident, but is rather a process that may take over five years. It is very important that investors and potential investors study the historical financial performance of companies before committing to any kind of investment.

Graph 7-5a: Turnover over total assets for distressed companies over the five years prior to distress, using the average for all companies defined as distressed



Source: own research

Graph 7-5b: Turnover over total assets for depressed and healthy companies over the five years, using the average for all companies defined as depressed and healthy



Source: own research

Graphs 7-5a and 5b relate to the operational efficiencies of companies. One of the distressed companies, as extracted from the database, strangely reported negative ratios over the period. The purpose of this ratio is to reflect the level at which companies sweat their assets to generate revenues. The higher the ratio, the lesser companies are to sweat their assets. The sweating of assets points to the optimal utility of assets to generate maximum revenues. This is well expounded by the figures of different financial states. Financially distressed companies reflect weak ratios compared to the other two financial states, while the difference between healthy and depressed is marginal on average.

7.3.2 Market trend analysis

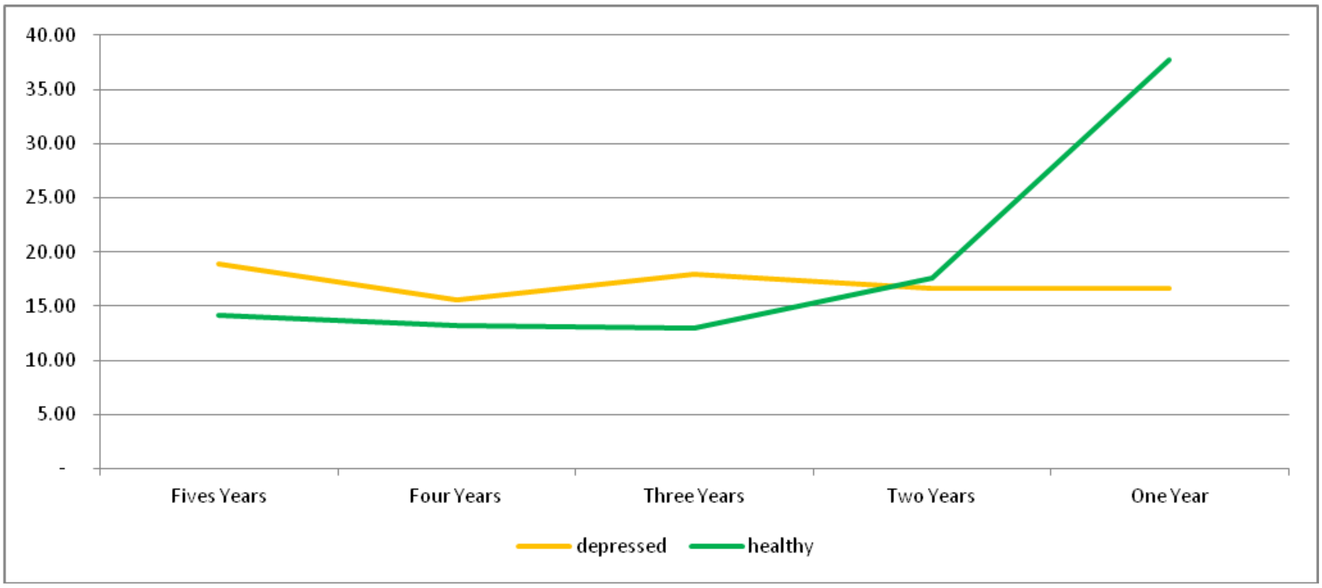
In addition to the fundamental data that has been discussed above, the study incorporates the market indicators. Once again, the study closely analyses the trend relationship these indicators have on different financial states. When discussing the impact of the fundamental data on each financial state, the gap between the distressed state and the other two financial states was obvious. The deterioration of the ratios as the companies neared failure was also noticeable.

Below is the analysis of the market indicators so as to observe their impact as companies near failure.

Graph 7-6a: Price per earnings for distressed companies over the five years prior to distress, using the average for all companies defined as distressed

Source: own research

Graph 7-6b: Price per earnings for depressed and healthy companies over the five years, using the average for all companies defined as depressed and healthy



Source: own research

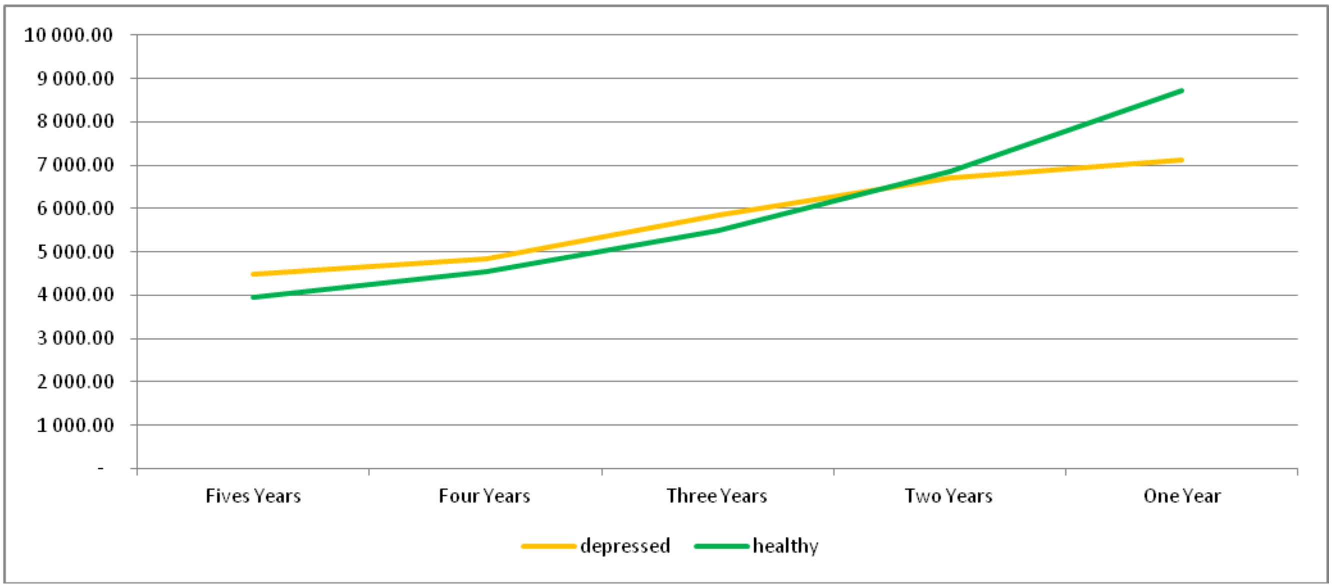
The price per earnings ratio is a market prospect ratio that calculates the market value of a share relative to its earnings, by comparing the market price per share by the earnings per share. In other words, the price earnings ratio shows what the market is willing to pay for a share based on its current earnings. Investors often use this ratio to evaluate what a share's fair market value should be by predicting future earnings per share. Companies with higher future earnings are expected to issue higher dividends or have appreciating shares in the future.

Graphs 7-6a and b prove this. The comparison of distressed companies to the two financial states provides a clear visual of the investor confidence based on the company's earnings capacity. As expected, with the distressed state, the indicator actually deteriorates as companies approach failure.

Graph 7-7a: Price per share for distressed companies over the five years prior to distress, using the average for all companies defined as distressed

Source: own research

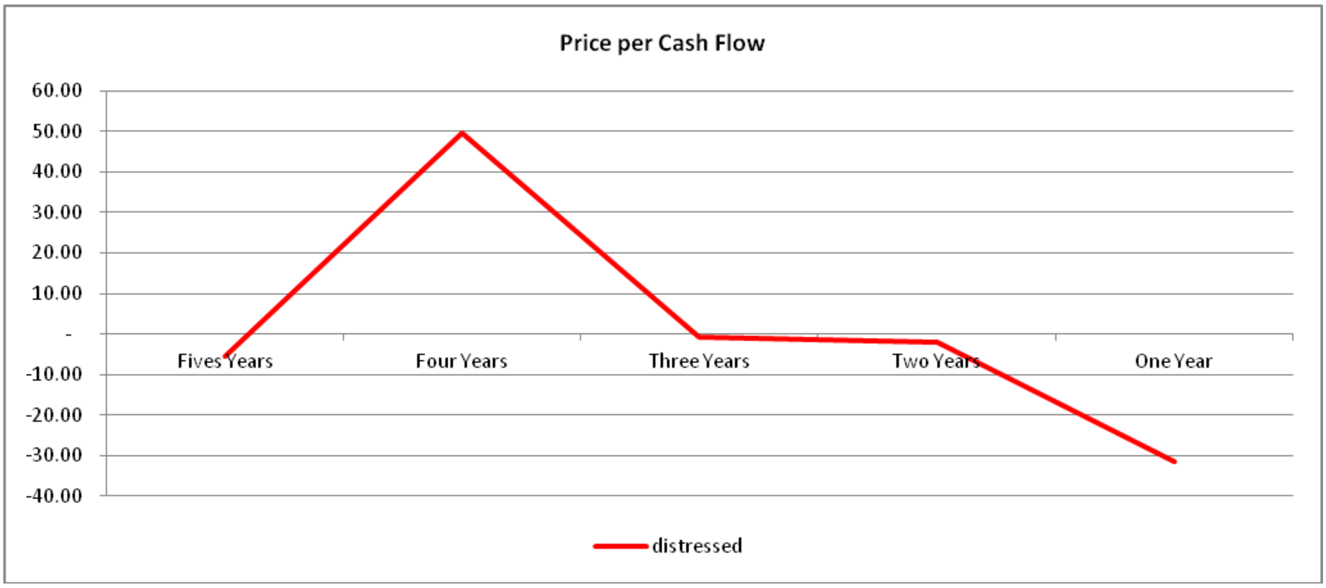
Graph 7-7b: Price per share for depressed and healthy companies over the five years, using the average for all companies defined as depressed and healthy



Source: own research

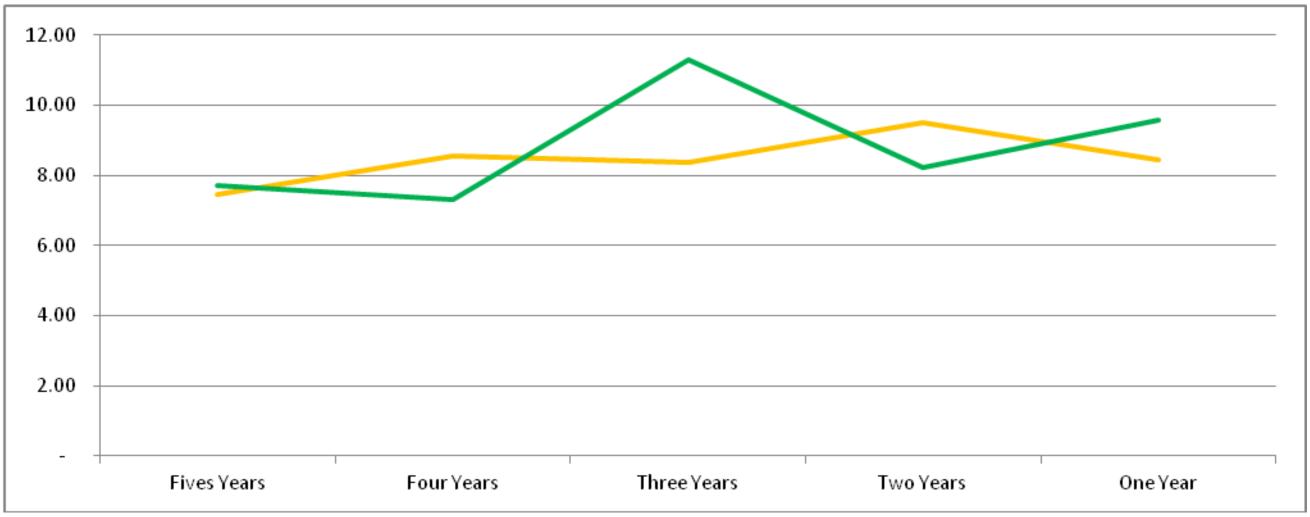
While some analysts say past performance of the price of shares must not be relied upon as a guide to their future performance, historical movements remain a core aspect of the analysis to make investment decisions. There is a gradual drop in the share prices of distressed companies, although it is not the same for the other two financial states showing an improvement within the five-year horizon.

Graph 7-8a: Price per cash flow for distressed companies over the five years prior to distress, using the average for all companies defined as distressed



Source: own research

Graph 7-8b: Price per cash flow for depressed and healthy companies over the five years, using the average for all companies defined as depressed and healthy



Source: own research

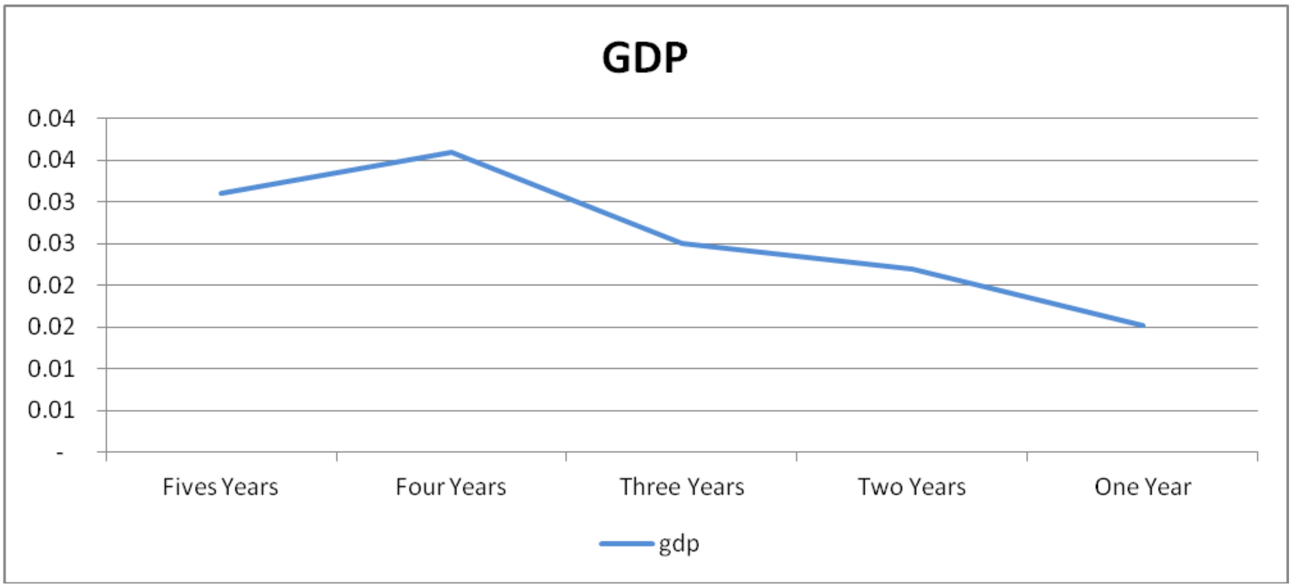
The price-to-cash-flow ratio considers a company's operating cash flow, which adds non-cash earnings such as depreciation and amortisation to net income. It is especially useful for valuing shares that have positive cash flow but are not profitable because of large non-cash items. The ratio removes the effect of non-cash items and gives realistic and reliable results without any deliberate or intentional manipulation.

Again a glaring difference between the distressed state and the other two states, over and above that, another glaring downward trend in the case of distressed companies over the five-year period.

7.3.3 Macroeconomic indicator trend analysis

It is a generally accepted truth that many companies are, in one way or the other, affected by macroeconomic dynamics. Therefore a movement, upward or downward, of especially gross domestic product and unemployment rate is highly likely to somewhat affect the companies. It is for this reason, in studying financial distress, these indicators are considered to assess or verify the impact caused by their volatility.

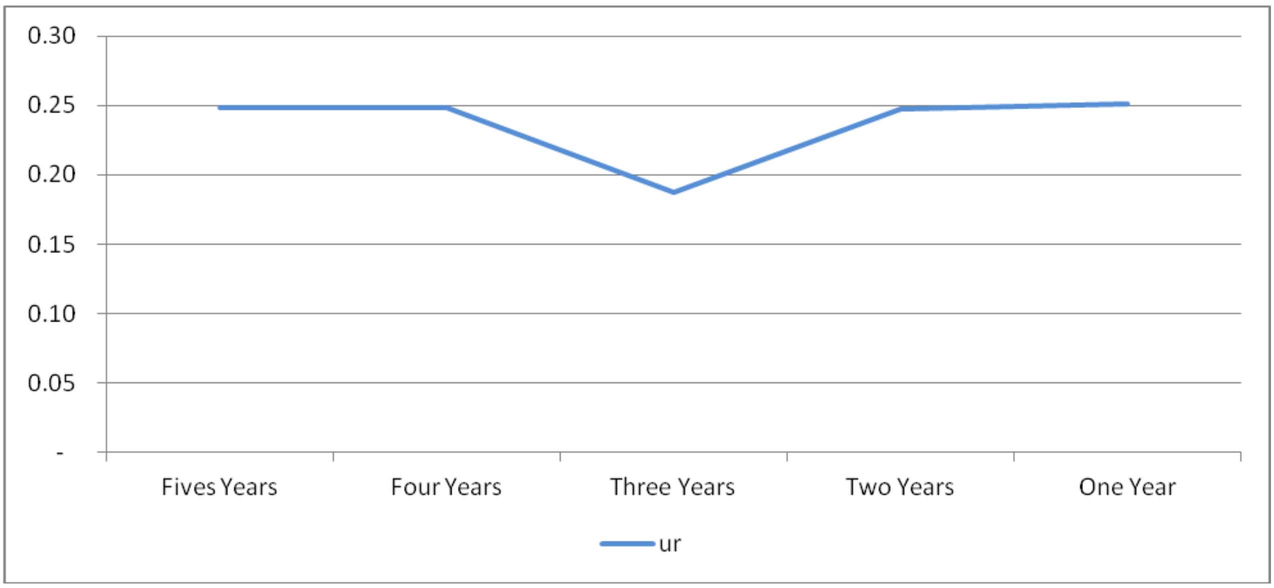
Graph 7-9: A five-year trend analysis reflecting gross domestic product



Source: own research

A downward trend is evidenced in Graph 7-9, which indicates a rather gloomy economy with the gross domestic product number reducing year-on-year. Economists believe that a struggling economy is likely to put immense pressure on small and medium sized companies. The small and medium sized companies sector is one sector that is aimed at absorbing unemployment. However, with a sluggish economic growth, reducing unemployment numbers remains difficult. This trend in economic growth is prone to inducing financial distress.

Graph 7-10: A five-year trend analysis reflecting unemployment rate



Source: own research

The unemployment rate in the last five years has been flat besides a dip in year three. This graph bears testimony to a sluggish economic growth as suggested by the gross domestic product graph. It is under such economic conditions that companies, especially small- to medium-sized tend to suffer financial distress. Such economic conditions have a multiplier tendency to social and political instability.

7.4 STATISTICAL TESTS

The study's statistical analysis follows a structured process where data is first prepared and tested using renowned statistical tests in regression analysis. The significance of data preparation and testing is to maintain the reliability and the integrity of the model by ensuring that all relevant statistical requirements are adhered to.

The first statistical test that is conducted in preparing the data is checking and dealing with outliers, missing data and data transformation. Failure to cleanse the data through conducting this test may have led to incorrect conclusions.

The second test that is conducted is the normality test. The results obtained from the normality test may be the catalyst in the final decision of an appropriate statistical technique adopted for the model. There are statistical techniques that are designed or best suited to handle data that is normally distributed, equally so, there are techniques that are more appropriate to deal with data that does not follow normal distribution. Often, the normality of data largely depends on the nature of the study.

The third statistical test that is conducted is variable collinearity. Testing variables for collinearity is aimed at identifying the level of correlation between the variables, but most importantly the significance level of that correlation. The intention is to only incorporate variables that possess the predictive power into the model, while eliminating variables that appear to communicate the same message.

These tests are performed in preparing data for the regression analysis.

7.4.1 Testing for outliers, missing data and data transformation

The influence of outliers can be severe in regression analysis and may lead to incorrect inferences. Therefore, this test is conducted to mitigate that risk in trimming all variables that are identified as outliers. Outliers are inherently experienced in studies of financial distress as the sampled population would consist of companies from different economic sectors and of different sizes both economically and financially. A good example in the present study's sample is the market capitalisation of South African Breweries which has a value reaching a trillion Rand.

Another compelling reason to test for outliers is to double-check the accuracy and integrity of the data set and the running of experiments. In cases where data is found to be coded incorrectly or the statistical program may not have been run correctly, then the outlying point may be erroneous. In this case, the outlying value is deleted from the analysis or corrected if possible.

The SPSS statistical software was used to identify extreme values in the data. Once these values are identified, a winsorising technique was adopted. Winsorising is the transformation of statistics by limiting extreme values in the statistical data to reduce the effect of possible spurious outliers. The effect is the same as clipping in signal processing. However, winsorising is not equivalent to simply excluding data – which is a simpler procedure called trimming or truncation – but is a method of censoring data. In a trimmed estimator, the extreme values are discarded. In a winsorised estimator, the extreme values are instead replaced by inserting the nearest neighbouring numbers.

The approach followed in dealing with missing data was that of mean replacement of missing values. In this case, wherever there is a missing value, instead of compromising the sample size by rejecting the whole observation, the mean value of that particular variable is used to replace the missing value. It is important to note that the mean values to replace missing data are calculated within data categories or financial states. This is more prudent than deleting the observation as the same observation carries variables that are relevant to the study. For example, there are companies that have all 12 but one missing ratio. So instead of deleting an observation that has 11 other variables, it is better to replace that one missing variable with mean values.

Data transformation is also useful in modelling observations that appear out of range with the rest of the variables. Indicators that are transformed include market capitalisation over debt, price per share, earnings per share, and price over cash flow. The reason why these particular variables spew widely dispersed numbers is the size of companies. In dealing with these widely dispersed numbers, the study uses the log10 transformation. The final decision on this particular transformation technique was after several tries using square root and lognormal techniques.

7.4.2 Normality test

A normality test is conducted on the selected data before running the correlation matrix. The statistical procedures applied in this instance are the Kolmogorov-Smirnov and Shapiro-Wilk tests. These work on the basis that the null-hypothesis of the population is normally distributed. Thus, if the p-value is less than the alpha level of 0.05, then the null hypothesis is rejected and there is evidence that the data tested are not from a normally distributed population. In other words, the data are not normal. On the contrary, if the p-value is greater than the alpha level of 0.05, then the null hypothesis that the data came from a normally distributed population cannot be rejected.

The tables below depict the results of this procedure at an alpha level of 0.05. This means that if the p-value is less than the alpha level of 0.05, then the null hypothesis is rejected and there is evidence that the data tested are not from a normally distributed population.

Therefore, the developed hypotheses are as follows:

H_0: The variable from which the sample was extracted follows a normal distribution.

H_a: The variable from which the sample was extracted does not follow a normal distribution.

Table 7-9 below suggests that all selected independent variables are not extracted from the normally distributed data. This is evidenced by the computed p-value that is lower than the significance level alpha=0.05 – the null hypothesis H_0 should be rejected, and the alternative hypothesis H_a should be accepted. The risk to reject the null hypothesis H_0 while it is true is lower than 0.01%. Given the results of this critical step in regression modelling, which is testing or checking whether the data is normal or non-normal, it may be observed that the data is non-normal.

Table 7-9: Test of normality of independent variables

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
CACL	.206	100	.000	.874	100	.000
TDTA	.453	100	.000	.189	100	.000
METD	.158	100	.000	.891	100	.000
TOTA	.127	100	.000	.947	100	.000
WCTA	.434	100	.000	.209	100	.000
P/E	.155	100	.000	.895	100	.000
P/S	.182	100	.000	.828	100	.000
P/CF	.348	100	.000	.330	100	.000
GDP	.495	100	.000	.175	100	.000
UR	.488	100	.000	.279	100	.000
STATUS	.468	100	.000	.535	100	.000

Source: own research

Sig. – significance, **df** – degree of freedom

CACL – current assets over current liabilities, **TDTA** – total debt over total assets, **METD** – market capitalisation over total debt, **TOTA** – turnover over total assets, **WCTA** – working capital over total assets, **P/E** – price per earnings, **P/S** – price per share, **P/CF** – price per cash flow, **GDP** – gross domestic product, **UR** – unemployment rate

Dealing with data that does not follow normal distribution poses certain statistical requirements. In this instance, the study has to rely on nonparametric statistical procedures that do not require that data be normally distributed.

7.4.3 Multicollinearity test

Multicollinearity is present when there is linear dependency among two or more independent variables in a multivariate model. This problem arises because some of them may be measuring the same concept. Consequently, when a given IV is a linear or quasi-linear combination of other independent variables, the affected estimates are unstable and the standard errors inflated. There are different types of statistical procedures that may be utilised in testing for collinearity.

Table 7-10: The final set of variables tested for correlation

			EBITTA	TDTA	METD	TOTA	WCTA	P/E	P/S	P/CF	GDP	UR
Spearman's Rho	EBITTA	Corr. Coeff	1.00									
		Sig. (2-tailed)										
	TDTA	Corr. Coeff.	-.671	1.00								
		Sig. (2-tailed)	0.00									
	METD	Corr. Coeff.	.429	-.578	1.00							
		Sig. (2-tailed)	0.00	0.00								
	TOTA	Corr. Coeff.	-0.05	0.16	0.07	1.00						
		Sig. (2-tailed)	0.59	0.11	0.52							
	WCTA	Corr. Coeff.	.885	-.602	.302	0.12	1.00					
		Sig. (2-tailed)	0.00	0.00	0.00	0.22						
	P/E	Corr. Coeff.	-0.09	-0.01	.397	0.02	-0.15	1.00				
		Sig. (2-tailed)	0.37	0.91	0.00	0.87	0.15					
	P/S	Corr. Coeff.	0.10	-0.07	.410	0.02	0.02	.495	1.00			
		Sig. (2-tailed)	0.33	0.47	0.00	0.85	0.88	0.00				
	P/CF	Corr. Coeff.	0.04	-0.05	.638	0.06	-0.03	.708	.508	1.00		
		Sig. (2-tailed)	0.70	0.60	0.00	0.54	0.75	0.00	0.00			
	gross domestic product	Corr. Coeff.	0.04	0.13	0.10	0.19	-0.02	0.07	0.11	0.03	1.00	
		Sig. (2-tailed)	0.68	0.18	0.31	0.05	0.86	0.51	0.26	0.79		
	UR	Corr. Coeff	-0.15	0.04	-.243	-0.16	-0.07	-.285	-.237	-.339	.253	1.00

		Sig. (2-tailed)	0.13	0.71	0.01	0.12	0.46	0.00	0.02	0.00	0.01	

Source: own research

EBITTA – earnings before interest and tax over total assets, **TDTA** – total debt over total assets, **METD** – market capitalisation over total debt, **TOTA** – turnover over total assets, **WCTA** – working capital over total assets, **P/E** – price per earnings, **P/S** – price per share, **P/CF** – price per cash flow, **GDP** – gross domestic product, **UR** – unemployment rate

The final set of independent variables does not appear to suffer from correlation problems.

7.4.4 Statistical test conclusion

After having conducted the three statistical tests – including testing and dealing with outliers, missing data and data transformation; testing of data for normality; and testing of data collinearity – it is easier to choose the most appropriate statistical methodology in conducting the regression model. The fact that the data is non-normal means that the most appropriate statistical methodology is the one that may handle the data in the most appropriate way without compromising the output. Therefore, the preferred statistical methodology in the present study is the multinomial logistic analysis.

7.5 MULTINOMIAL LOGISTIC REGRESSION

The multinomial logistic analysis is a preferred statistical methodology in this study for model development mainly due to the nature of the data. The nature of the data collected is more fitted to a non-parametric statistical procedure than to a normal parametric regression procedure. With this background, the fundamental questions the study attempts to address when developing its model using logistic analysis are:

- Can the model that is based on the logistic analysis accurately predict the financial distress outcome given a set of predictors?
- What is the relative significance of each predictor variable?
- Are there interactions among predictors?
- How good is the model at classifying cases for which the outcome is known?

The logistic analysis does not make many of the key assumptions linear regression does, like general linear models based on ordinary least squares algorithms – particularly regarding linearity, normality, homoscedasticity, and measurement level.

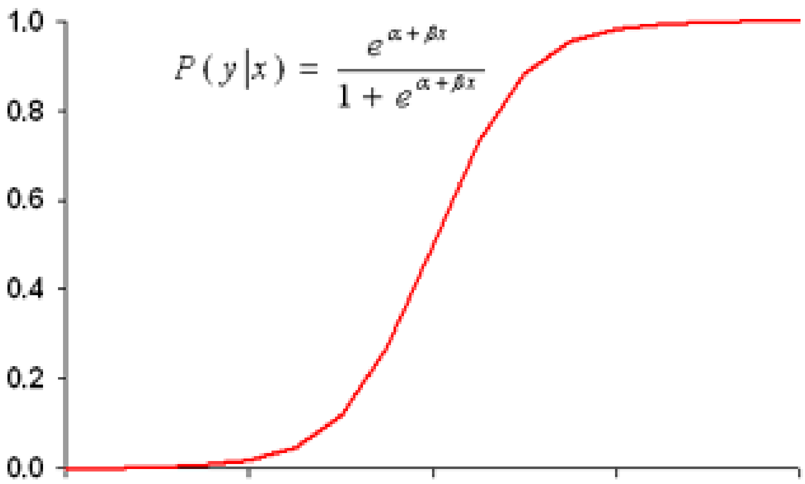
Firstly, logistic analysis does not need a linear relationship between the dependent and independent variables. Logistic analysis can handle all sorts of relationships because it applies a non-linear log transformation to the predicted odds ratio. Secondly, the independent variables do not need to be multivariate normal, although multivariate normality yields a more stable solution. Also the error terms (the residuals) do not need to be multivariate normally distributed. Thirdly, homoscedasticity is not needed.

Given a vector of application characteristics x, the probability of default p is related to vector x by the following equation:

$$\text{Logit}(p) = \text{Ln}\frac{p}{(1-p)} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots \beta_n X_n \qquad (7.1)$$

Logistic analysis provides a method for modelling a binary response variable, which takes values 1 and 0 by mapping the data on a logistic analysis curve as depicted in Figure 7-1.

Figure 7-1: The example of a binary logistic regression curve



Source: Penn State College of Science (2016)

Instead of a binary outcome, the present study has three response variables: 0 for distressed companies, 1 for depressed and 2 for healthy companies. The vector x is the vector of characteristics which are actually the fundamental data, market and macroeconomic indicators for each company. The vector w represents the variables coefficients represented by maximum likelihood estimation. In this method, a function is defined based on the probability and w, named likelihood function. Maximising the logarithm of the likelihood function will maximise the prediction rate of the model.

In developing this model, a multinomial logistic analysis equation is applied.

$$\Pr(y_i = j) = \frac{\exp(X_i\beta_j)}{1 + \sum_{j=1}^{J} \exp(X_i\beta_j)} \tag{7.2}$$

Where: j represents the response predictors and *i* the respective coefficient

Ying, Peng, Lee and Ingersoll (2002:1) use four main tests to evaluate the logistic analysis model:

(i) overall model evaluation,

(ii) statistical tests of individual predictors,

(iii) goodness-of-fit statistics, and

(iv) validations of predicted probabilities.

A logistic model is said to provide a better fit to the data if it demonstrates an improvement over the intercept-only model. An improvement over this baseline is examined using the logistic analysis or -2lnL(null)- 2lnL(model), which lnL(model) is maximum likelihood as the estimated variables are meaningful in the model, and lnL(null) is likelihood with assuming zero for all variables.

The statistical significance of individual regression coefficients is tested using the Wald chi-square statistic. If the statistic is less than 0.05, then the variable should be included in the model. Goodness-of-fit statistics assess the fit of a logistic model against actual outcomes. The inferential goodness-of-fit test is the Hosmer-Lemeshow (H–L) test. This statistic tests $H_\circ$ hypothesis of the below equation using chi-square, and if it becomes more than 0.05 it shows that the model fits well to data.

$$H_{\circ}\colon \mathrm{E}[\mathrm{Y}] = \frac{\exp\,(\mathrm{x}'\mathrm{w})}{1+\exp\,(\mathrm{x}'\mathrm{w})} \tag{7.3}$$

Logistic analysis predicts the outcome from a set of predictors, and it can be transformed back to the probability scale:

$$\mathrm{P} = \frac{exp\beta 0 + \beta 1\mathrm{X}1 + \beta 2\mathrm{X}2 + \ldots \beta n\mathrm{X}n}{1+exp\beta 0 + \beta 1\mathrm{X}1 + \beta 2\mathrm{X}2 + \ldots \beta n\mathrm{X}n} \tag{7.4}$$

The resultant predicted probabilities can then be revalidated with the actual outcome to determine if high probabilities are associated with events and low probabilities with non-events. The degree to which predicted probabilities agree with actual outcomes is expressed as either a measure of association or a prediction results.
The present study uses prediction results for assessing the logistic analysis model, the cut-off point should be considered. The pre-defined cut-off point value in statistical and econometrics software such as SPSS, is usually 0.5. The best model is the one that minimises both type I and type II errors. Selecting the best cut-off point is done by minimising these errors.

7.5.1 R-squared statistics for logistic regression

Literature reveals numerous ways to calculate R^2 for logistic analysis, although there is no consensus on which is best. However, the two methods most often reported in statistical software appear to be one proposed by McFadden (1974:105) and another by Cox and Snell (1989) along with its ‘corrected’ version.

The SPSS statistical software reports the Cox-Snell measures for binary logistic analysis, but McFadden’s measure for multinomial and ordered logistic analysis.

This present study relies on the McFadden R^2 as the better choice as it contains good properties, a lot of intuitive appeal, and is easily calculated. It also seems to meet almost all of Kvalseth’s (1985:281) eight criteria for a good R^2. When the marginal proportion is around 0.5, the McFadden R^2 tends to be a little smaller than the uncorrected Cox-Snell

R^2. But when the marginal proportion is nearer to 0 or 1, the McFadden R^2 tends to be larger.

Logistic analysis is estimated by maximising the likelihood function. Let L_0 be the value of the likelihood function for a model with no predictors, and let L_M be the likelihood for the model being estimated. McFadden's R^2 is defined as:

$$R^2\,\mathrm{m}cf = 1 - \ln(L_M) / \ln(L_0) \qquad (7.5)$$

where ln(.) is the natural logarithm. The rationale for this formula is that $\ln(L_0)$ plays a role analogous to the residual sum of squares in linear regression. Consequently, this formula corresponds to a proportional reduction in "error variance". It is sometimes referred to as a "pseudo" R^2.

7.6 THE BASIC MODEL

This section deals with the development of the basic model, which is deliberately designed in a three-phased format: basic model 1, 2 and 3. The three phases relate to the loading of independent variables to the model and the analysis of these results. In basic model 1, the first set of variables that is loaded is the fundamental data, the prediction accuracy is then analysed using the prediction results. The basic model 2 sees the market indicators as the next set of variables loaded, these variables are loaded to the model in addition to the fundamental data. Again, the prediction accuracy is analysed using the prediction results. The basic model 3 is about loading the last set of variables, the macroeconomic indicators. This set is loaded in addition to the initial two sets already loaded on the model.

The intended purpose is to test whether each set of variables possesses any predictive power. Should the results improve as a direct consequence of loading the new set of variables, it would be inferred that the particular set of variables contains additional predicting power.

The analysis covers five periods – one, two, three, four and five years before failure. The different periods show whether there is deterioration on the variables as the time gets closer to failure. This perspective is analysed in a graphical trend format under section 7.3.

The trend analysis reflects a very clear deterioration of ratios as companies face failure. The trends also clearly distinguish financially distressed companies from those that are not.

In analysing the results, three tables based on the multinomial logistic analysis output are included in the study. The first table is the case processing summary table, which confirms the number of cases that are analysed and whether the model had any missing data. The second table is the model fitting information, which indicates the goodness of the model – the attention is on the -2 log likelihood, chi-square and the significance levels. The pseudo R-squared information is also included. It is very important to read this table within the context of the multinomial logistic analysis as this R-squared conceptually differs from that of ordinary least regression.

The third table is the prediction accuracy rate, which reflects the prediction results of the model as well as the accuracy percentage per category. This is the table that is used to draw conclusions on the model prediction accuracy. The fourth table is the model parameters table. This table provides an analysis of coefficient for the individual variables to one category in reference to the other.

7.6.1 Case processing summary

This table displays the number of cases loaded on the model. These cases are categorised according to their financial state. The two important indicators in this table are valid and missing entries. These two indicators validate the model in that all cases are valid and there are no missing cases.

Table 7-11: The number of cases processed in the model

Case processing summary		N	Marginal percentage
STATUS	Distressed	8	8.00%
	Depressed	14	14.00%
	Healthy	78	78.00%
Valid		100	100.00%

Missing	0	
Total	**100**	

Source: own research

As it can be seen in Table 7-11, the data contains 100 cases, comprising a combination of distressed, depressed and healthy companies. What is also evident is the different percentage composition of companies. Unlike in previous studies that are dichotomous and where the number of companies is equal for each group of failed and not failed, the present study tries to project a more realistic picture where data is analysed as obtained from the data source without any manipulation.

7.6.2 Model goodness

The model goodness table serves to provide a level of satisfaction concerning the integrity of the model or model performance. The logistic analysis model works differently to the simple regression model where R-squared values play a pivotal part in explaining the model performance. The logistic analysis model applies the maximum likelihood of the odds as an indicator of model performance. While R-squared is not calculated in the same way as in simple regression models, in the logistic analysis model there is a table that calculates the model relevant pseudo R-squared. This table may also be used as a model performance indicator.

Table 7-12: The performance of the overall model measured in goodness fit and pseudo R-squared

Variable	Statistic	One year before failure	Two years before failure	Three years before failure	Four years before failure	Five years before failure
Pseudo R^2	McFadden	0.42	0.28	0.29	0.52	0.34
-2LL	Intercept only	134.22	134.22	134.22	134.22	134.22
	Final	78.12	96.46	95.02	64.39	88.95
	Chi-square	56.10	37.77	39.20	69.83	45.27

	Sig	0.000	0.000	0.000	0.000	0.000

Source: own research

The pseudo R-squared percentage explains approximately how much variation in the outcome is explained by the model. This further suggests that the model is performing at an acceptable level, showing a strong relationship between independent variables and dependent variables.

With regard to the -2 log likelihood (-2LL), the first line shows the intercept only figures, this is intended to communicate an intercept where all independent variables are held at zero. The second line shows the final figures which represent the impact or the movement as results of adding the variables to the model. Therefore, this provides satisfaction that the independent variables impact model responsive variables. Furthermore, the level of chi-square and its significance level where the alpha is set at 0.05 are additional indicators providing confidence to the performance of the model. The achieved significance levels are all below the set alpha, which confirms that predictor variables impact the outcome variables.

7.6.3 Prediction Accuracy rate

Table 7-13 below shows percentages per financial state representing the financial distress prediction accuracy. These prediction accuracy results are based on the actual input variables per company. The output report is based on the multinomial logistic regression analysis. The model output reports are generated as each set of variables is put into the system. The intention is to observe the improvement, if any, as the new set of variables is put.

Table 7-13: The model prediction percentage accuracy table for all financial states

STATUS	Basic model 1 - fundamental					Basic model 2 - fundamental plus market variables				
	One year before failure	Two years before failure	Three years before failure	Four years before failure	Five years before failure	One year before failure	Two years before failure	Three years before failure	Four years before failure	Five years before failure
Distressed	63%	63%	50%	100%	75%	100%	100%	100%	100%	100%

Depressed	7%	14%	21%	14%	21%	14%	21%	21%	29%	14%
Healthy	100%	99%	99%	100%	97%	99%	97%	100%	100%	100%
Overall percentage	84%	84%	84%	88%	85%	87%	87%	89%	90%	88%

Source: own research

Basic model 1 in Table 7-13 shows a 63% prediction for distressed companies, 7% for depressed companies, and 100% for healthy companies. This gives an overall percentage of 84% one year before failure. In years four and five before failure, the model appears to have made a better prediction. This is contrary to a general perception found in literature suggesting that prediction accuracy deteriorates further away from distress. The model has consistently and accurately predicted approximately 100% of companies that are financially healthy for all the years before failure.

Basic model 2 shows an improvement from basic model 1. The model predicts 100% for both distressed and healthy companies – a prediction that is consistent for all the years before failure. At this stage, it may be concluded that the addition of market variables has positively improved the prediction accuracy results. However, the further addition of macroeconomic indicators does not appear to contribute positively to the accuracy results. This observation is expected as the macroeconomic indicators are constant for all categories. Resultantly, the table reflecting basic model 3, which is the combination of fundamental, market and macroeconomic indicators, is not included.

7.6.4 Determination of a cut-off point and calculation of type I and II errors in validating the model

As a mechanism of validating the model, it is important to determine the cost of error in the model. The model in the present study seeks to predict the financial state of companies – the model is expected to identify and group companies that are distressed, depressed and healthy. The model results presented in this study prove that the model is capable of making the classification at an acceptable level. However, it would be wrong to ignore the cost of errors the model has made. The cost of errors is introduced when the model identifies a distressed company as healthy, or when the model identifies a healthy company as distressed. These errors are referred to as type I and II errors.

A type I error, also known as a false positive, is the error of rejecting a null hypothesis when it is actually true. It is an error where the model classifies a healthy company as distressed. In a group of healthy companies where there is no distressed company, the model says there is a distressed company.

A type II error, also known as a false negative, is the error of not rejecting a null hypothesis when the alternative hypothesis is the true state of nature. This is an error where the model classifies a distressed company as healthy. In a group of distressed companies where there is no healthy company, the model says there is a healthy company.

The abovementioned errors could be very costly for an institutional investor or any financier dealing with large corporations. The rating agencies are also at risk when relying on this model. The magnitude of an error tends to differ at different levels of cut-off points. It then becomes very important to select a cut-off point where the errors are minimised.

Table 7-14 below depicts cut-off points with corresponding error percentages and model performance. The idea is to select a cut-off where the error is minimised.

Table 7-14: Cut-off, classifications and error determination

Cut-off	Correct prediction		Errors		Model performance		
	H	D	Type I	Type II	H	D	Overall
0.1	92	4	0%	50%	100%	50%	96%
0.2	92	4	0%	50%	100%	50%	96%
0.3	91	5	1%	37%	99%	63%	96%
0.4	91	6	1%	25%	99%	75%	97%
0.5	91	6	1%	25%	99%	75%	97%
0.6	91	6	1%	25%	99%	75%	97%
0.7	90	7	2%	12%	98%	88%	97%
0.8	89	7	3%	12%	97%	88%	96%
0.9	86	7	7%	12%	93%	88%	93%

*(H) Healthy, (D) Distressed

Source: own research

To enable a proper calculation of type I and II errors, the model results had to be rearranged into a binary format classifying companies as healthy (H) or distressed (D).

The first two cut-off points yield the same results with the overall model performance of 96%. The errors at this level are 0% and 50% for type I and II, respectively. A similar result is noticed with cut-off levels 0.4, 0.5, 0.6 and 0.7 –the overall model performance at these cut-off points is at 97%, which is a positive result. However, taking a closer look at the first three cut-off levels (0.4, 0.5 and 0.6), the sum of the two errors is 26% (1% + 25%). This means that there is a 1% chance that a healthy company may be classified as distressed. The cost of this would be a loss of interest income that could have been earned from the credit worthy customer. Conversely, there is a 25% chance that a distressed customer may be approved as healthy, thus the financier losing investment erroneously made to a credit unworthy customer.

A cut-off point at which the errors are minimal is 0.7. At this level, the model achieves a high percentage overall performance (97%), yet the sum of errors is only 14% (2% + 12%) – see the grey line on Table 7-14.

7.6.5 The estimation of coefficients for individual variables

The final number of variables employed in the model is ten: five are fundamental, three are market, and two are macroeconomic indicators. The final fundamental ratios used in model are: working capital over total assets, total debt over total assets, earnings before interest and tax over total assets, turnover over total assets and market capitalisation over total debt. The final market based ratios are: the price per earnings, price per share, and price per cash flow. The macroeconomic variables are: gross domestic product and unemployment rate.

The model outcome yields somewhat unexpected findings in that, while the overall model performance is good and significant, certain individual variables are found to be insignificant. When all variables are added together, the model indicates that some are making an insignificant contribution, yet when the same variables are loaded individually they become significant contributors. When the statistical model behaves this way, the literature suggests an element of collinearity among the variables. However, this was checked and the variables were not found to be correlated.

Of the five fundamental variables used in the basic model 1, only three variables are found to contribute significantly (p values<0.05) in classifying companies into different financial states. The other two ratios reflect coefficients with p values that are more than 0.05. In developing basic model 2 and 3, the market and macroeconomic variables are added. All coefficients in these two sets of variables reflect p-values that are more than 0.05 which suggests their insignificance in the model. Upon these results, the model is re-run now adding ratios individually. When added individually, the coefficients of the ratios are significant.

In developing the logistic analysis equation, only the significant variables are considered. Therefore, the equations drawn from the model coefficients relate only to basic model 1.

Table 7-15: The model results reflecting coefficient estimates for distressed companies

Code	Variable	Statistic	Fundamental				
			One year before failure	Two years before failure	Three years before failure	Four years before failure	Five years before failure
X_1	EBITTA	Coeff	-51.115	-11.897	-.845	-1109.00	-27.759
		Sig.	.005	.007	.635		0.02
X_2	TDTA	Coeff					
		Sig.					
X3	METD	Coeff					
		Sig.					
X_4	TOTA	Coeff	-6.616	-1.857	-1.398	-17.313	-1.792
		Sig.	.022	.136	.100	.995	0.243
X_5	WCTA	Coeff	-9.242	-12.725	-10.132	-567.148	-2.812
		Sig.	.016	.000	.001	.925	0.472
X_6	P/E	Coeff					
		Sig.					
X_7	P/S	Coeff					
		Sig.					
X_6	P/CF	Coeff					
		Sig.					
X_9	GDP	Coeff					
		Sig.					
X_{10}	UR	Coeff					
		Sig.					
	Constant	Coeff	7.115	1.005	-0.508	27.182	1.432

	Sig.	.025	.412	.266	.991	0.268

All coefficients are statistically significance between 0.05 levels. **EBITTA** – earnings before interest and tax over total assets, **TDTA** – total debt over total assets, **METD** – market capitalisation over total debt, **TOTA** – turnover over total assets, **WCTA** – working capital over total assets, **P/E** – price per earnings, **P/S** – price per share, **P/CF** – price per cash flow, **GDP** – gross domestic product, **UR** – unemployment rate

Source: own research

The grey shaded variable coefficients and respective p-values (0.05) indicate the variables that are loaded in the logistic analysis equation below. These are variables that the model has identified as making a significant contribution. The insignificant variables are not considered, although their impact is better explained in prediction results where they make a positive contribution.

Therefore, the logistic analysis function is constructed as follows:

$$\text{Logit}(p) = \text{Ln}\frac{p}{(1-p)} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots \beta_n X_n \quad (7.6)$$

Given the above model results, the log odds may be presented as follows:

Logistic analysis equation for distressed companies:

One year before failure: $\text{Logit}(p) = \text{Ln}\frac{p}{(1-p)} = 7.115 + 51.115X_1 – 6.616X_4 - 9.242X_5$

Two years before failure: $\text{Logit}(p) = \text{Ln}\frac{p}{(1-p)} = 1.005 – 11.897X_1 - 12.725X_5$

Three years before failure: $\text{Logit}(p) = \text{Ln}\frac{p}{(1-p)} = 0.508 – 10.182X_5$

Five years before failure: $\text{Logit}(p) = \text{Ln}\frac{p}{(1-p)} = 1.432 - 27.759X_1$

Where:

X_1	Earnings before interest and taxes
X_2	total debt to total assets
X_3	Market capitalisation to total debt

X_4	Turnover to total assets
X_5	Working capital to total assets
X_6	Price per earnings
X_7	Price per share
X_8	Price per cash flow
X_9	Gross domestic product
X_{10}	Unemployment rate

Table 7-16: The model results reflecting the coefficient estimates for depressed companies

Code	Variable	Statistic	Fundamental				
			One year before failure	Two years before failure	Three years before failure	Four years before failure	Five years before failure
X_1	EBITTA	Coeff	-5.385	-9.745	-.724	-4.314	3.626
		Sig.	.055	.017	.675	.322	0.21
X_2	TDTA	Coeff					
		Sig.					
X_3	METD	Coeff					
		Sig.					
X_4	TOTA	Coeff	-0.306	.045	.071	-.049	-0.046
		Sig.	.467	.909	.844	.896	0.883
X_5	WCTA	Coeff	-6.954	-6.864	-5.342	-7.385	-5.594
		Sig.	.003	.002	.003	.003	0.011
X_6	P/E	Coeff					
		Sig.					
X_7	P/S	Coeff					
		Sig.					
X_8	P/CF	Coeff					
		Sig.					
X_9	GDP	Coeff					
		Sig.					
X_{10}	UR	Coeff					
		Sig.					
	Constant	Coeff	-0.042	-0.006	-1.191	-0.315	-1.551
		Sig.	.964	.994	.073	.688	0.038

All coefficients are statistically significant at 0.05 levels. **EBITTA** – earnings before interest and tax over total assets, **TDTA** – total debt over total assets, **METD** – market capitalisation over total debt, **TOTA** – turnover over total assets, **WCTA** – working capital over total assets, **P/E** – price per earnings, **P/S** – price per share, **P/CF** – price per cash flow, **GDP** – gross domestic product, **UR** – unemployment rate

Source: own research

The logistic analysis function is therefore constructed as follows:

$$\text{Logit}(p) = \text{Ln}\frac{p}{(1-p)} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots \beta_n X_n \qquad (7.7)$$

Consequently, given the above model results, the log odds may be presented as follows:

Logistic analysis equation for depressed companies:

One year before failure: $\text{Logit}(p) = \text{Ln}\frac{p}{(1-p)} = -0.042 - 5.385X_1 - 6.954X_5$

Two years before failure: $\text{Logit}(p) = \text{Ln}\frac{p}{(1-p)} = -0.006 - 9.745X_1 - 6.864X_5$

Three years before failure: $\text{Logit}(p) = \text{Ln}\frac{p}{(1-p)} = -1.191 - 5.342X_5$

Four years before failure: $\text{Logit}(p) = \text{Ln}\frac{p}{(1-p)} = -0.315 - 7.385X_5$

Five years before failure: $\text{Logit}(p) = \text{Ln}\frac{p}{(1-p)} = -1.551 - 5.594X_5$

Where:

X_1	Earnings before interest and taxes
X_2	total debt to total assets
X_3	Market capitalisation to total debt
X_4	Turnover to total assets
X_5	Working capital to total assets
X_6	Price per earnings
X_7	Price per share
X_8	Price per cash flow
X_9	Gross domestic product
X_{10}	Unemployment rate

7.6.6 Converting log odds to probabilities

Given the nature of the data coupled with the research objective of the present study, trying to predict the probability of financial distress using linear regression has presented statistical problems, specifically since the outcome variables are multinomial with a floor at 0 and the ceiling at 2 inherent in probabilities. Therefore, the study has used the explanatory variables to predict the log odds to circumvent this problem. Effectively, logistic analysis is just a log of the odds, and odds are just a function of the probability. Hence, it is possible to convert the log odds back to odds by applying the reverse of the log, which is called the exponential or anti-logarithm, to both sides. Taking the exponent eliminates the log on the left-hand side so the odds can be expressed as:

$$\text{Logit}(p) = \text{Ln}\frac{p}{(1-p)} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots \beta_n X_n \qquad (7.8)$$

This equation can also be rearranged to find the probabilities as:

$$P = \frac{exp\beta0 + \beta1X1 + \beta2X2 + \ldots\beta nXn}{1{+}exp\beta0 + \beta1X1 + \beta2X2 + \ldots\beta nXn} \qquad (7.9)$$

which is the logistic function that converts the log odds to probabilities.

Rather than log odds or logits, the equation finds the probability of distress. The predicted percentage of probability of failure may be interpreted as: the higher the percentage, the higher the risk of failure.

In summary, employing a linear regression in the present study is inappropriate for statistical and conceptual reasons. With binary and multinomial outcomes, the form of the relationship between an explanatory variable X and the probability of Y is better modelled by an S-shaped curve.

Therefore, to convert to the probability of distress for distressed companies, the logistic analysis model may be rearranged as follows:

One year before failure: $$p = \frac{e^{(7.115-51.115*X1-6.616X4-9.242*X5)}}{1+ e^{(7.115-51.115*X1-6.616X4-9.242*X5)}}$$

Two years before failure: $$p = \frac{e^{(1.005-11.897*X1-12.725X5)}}{1+ e^{(1.005-11.897*X1-12.725X5)}}$$

Three years before failure: $$p = \frac{e^{(0.508-10.132*X5)}}{1+ e^{(0.508-10.132*X5)}}$$

Five years before failure: $$p = \frac{e^{(1.432-27.759*X1)}}{1+ e^{(1.432-27.759*X1)}}$$

Where:

X_1	Earnings before interest and taxes
X_2	total debt to total assets
X_3	Market capitalisation to total debt
X_4	Turnover to total assets
X_5	Working capital to total assets
X_6	Price per earnings
X_7	Price per share
X_8	Price per cash flow
X_9	Gross domestic product
X_{10}	Unemployment rate

Similarly, the logistic analysis equation for depressed companies is rearranged to derive the probability as per below.

The probability of distress for depressed companies:

One year before failure: $$p = \frac{e^{(-0.042-5.385*X1-6.954X5)}}{1+ e^{(-0.042-5.385*X1-6.954X5)}}$$

Two years before failure: $$p = \frac{e^{(-0.006-9.745*X1-6.864X5)}}{1+ e^{(-0.006-9.745*X1-6.864X5)}}$$

Three years before failure: $$p = \frac{e^{(-1.191-5.342*X5)}}{1+ e^{(-1.191-5.342*X5)}}$$

Four years before failure: $p = \frac{e^{(-0.315-7.385*X5)}}{1+ e^{(-0.315-7.385*X5)}}$

Five years before failure: $p = \frac{e^{(-1.551-5.594*X5)}}{1+ e^{(-1.551-5.594*X5)}}$

7.6.7 Analysis of model results

It should be stated that the negative coefficients of ratios in the developed logistic analysis model indicate that these ratios are negatively correlated with the probability of financial distress; while the ratios with positive coefficients have a positive effect on the probability of financial distress. Variables that contribute significantly to the models should have a significance value of less than 0.05 (Pallant, 2007:1).
Garc´ıa , Marqu´es & S´anchez (2015:171) also suggest that it is important to take into consideration that simple superiority of a prediction model in terms of some performance score on a test set, is not sufficient. For a complete performance evaluation, it seems pertinent to adopt some hypothesis testing in order to assert that the observed differences in performance are statistically significant, and are not merely due to random splitting effects.

The model results of the present study suggest that one variable may be statistically significant enough to determine the financial state. For distressed companies, the model suggests that there are three variables that possess a financial distress predictive power one year before failure: earnings before interest and taxes over total assets, turnover over total assets and working capital over total assets. This model also shows that as the years before failure move to two, only two variables remain significant enough to predict the financial states. Three up to five years before failure the model suggests that just one variable is enough to predict the financial states. A similar trend is evident on the financially depressed companies where two variables that possess the predictive power one year before failure and just one variable for years two to five before failure.

While it may be tempting to generalise that at least five variables should be included in the model to determine the financial state and not one variable, this may emanate from the original classical research studies where Altman (1966:589), Ohlson (1980:109), and De La Rey (1981:1) found at least five variables in their studies.

The present study presents evidence in literature of studies that have found one, two and three variables that are significant enough to determine financial distress. In one study, Altman's (1966:499), Ohlson's (1980:109), and Zmijewski's (1984:59) studies are revisited using a different set of data and the researcher concludes that not all variables that were originally identified by these authors in their studies were actually significant. Therefore, it may be inferred that there are researchers who would include all tested variables in their model function irrespective of their significant levels.

In a study conducted by Avenhuis (2013:1) where he remodelled Altman's (1968:499), Ohlson's (1980:109), and Zmijewski's (1984:59) studies, he had instances where only one variable was found to be significant. In Ohlson's (1980:109) study, nine variables were used to predict financial distress, yet Avenhuis (2013:1) concluded that only three of the nine are statistically significant indicating p-values less than 0.05. In the case of Zmijewski (1984:59), Avenhuis found that none of the variables were significant one and three years before failure, and only one variable shows p-values less than 0.05 two years before failure. The same researcher found another phenomenon contrary to the general perception in literature: a phenomenon that suggests that the model tends to be more accurate one year before failure with the prediction accuracy deteriorating as the years before failure increase. He found better performance of the model where there were more years before failure.

In a similar study in the UK conducted by Taffler and Tishaw (1977:55), they found only two significant variables in some years and three in other years before failure. The authors had a population of 92 manufacturing companies and achieved 99% successful classification accuracy. Therefore, the one and two variables found to be relevant in the present study is in line with similar previous studies.

Back, Laitinen, Sere & Van Wezel (1996:8) looked at multiple discriminant analysis, logistic analysis and neural networksin their study. They acknowledge that the number of variables that are relevant in the model for the prediction of a financial state depend on the significance levels. Therefore, variable that are found to be insignificant may not be included in the model equation. The table below shows the number of variables that were statistically significant included in the model by Back *et al.* (1996:8).

Please note the variable coding system used in the below table, the letter 'R' means ratio, and the number next to the letter 'R' represent the order number of the total variables used in their study. Therefore, R4 refers to the fourth ratio on the list, R24 refers to the 24th ratio and R28, the 28th ratio on the total list of variables. Therefore, in the column headed as one year prior failure, there are three significant ratios i.e. R4, R24 and R28.

Table 7-17: The number of variables (financial ratios depicted by R) included in the model by Back *et al*. (1996) as statistical significant

One year prior failure	Two years prior failure	Three years prior failure
R4	R14	R4
R24	R27	R5
R28	R5	
	R25	

Back *et al*. (1996)

As can be noted from the above, in one year prior to failure there are only three ratios, and three years prior to failure only two ratios are included in the logistic analysis equation. This result is in line with the findings of the present study where the lesser number of ratios indicates predictive power with three or more years before failure.

Tables 7-15 and 7-16 above indicate whether an explanatory variable makes a statistically significant contribution to predicting the outcome, but the intention is also to know the magnitude of the association. In linear regression, the coefficients (B) are the increase in Y for a one unit increase in X. However, in logistic analysis it is not about predicting a continuous dependent variable but the log odds of the outcome occurring. Thus, in logistic analysis the (B) coefficient indicates the increase in the log odds of the outcome for a one unit increase in X.

The coefficient rows in the tables reflect the estimated multinomial logistic analysis coefficients for the models. An important feature of the multinomial logistic analysis model is that it estimates *k-1* models, where *k* is the number of levels of the outcome variable. In this instance, the category of financially healthy companies is the reference group and estimated a model for financially distressed relative to financially healthy companies, and a model for financially depressed companies relative to financially healthy companies. The intercept column is the multinomial logistic analysis estimate when the predictor variables in the model are evaluated at zero.

7.6.8 Model results interpretation

Tables 7-15 and 7-16 present the results from the logistic analysis model. In line with the requirement of a multinomial logistic analysis model, financially distressed companies were given a value of 0, financially depressed companies were given a value of 1, and financially healthy companies were given a value of 2. The present study develops a three-tiered basic model for estimating the likelihood of financial distress. In the first tier, only the fundamental ratios are employed, the second tier is about the addition of market variables, and the third tier is about the further addition of macroeconomic indicators.

Analysing the multinomial model results in Tables 7-15 and 7-16, there are some intriguing observations. The basic model 1, the model with only fundamental data, appears to be statistically significant enough to predict financial distress. This is on the basis that the addition of market and macroeconomic variables does not appear to make any statistical significance contribution as individual variables yield p-value more than 0.05. Therefore, the logistic analysis function consists of the fundamental ratios only.

When liquidity is low, profitability is low, and when leverage is high, the likelihood of bankruptcy increases. Therefore, the expected signs for the coefficients for the liquidity and profitability ratios are negative. And for the leverage ratios, the expected sign is positive.

For distressed companies, there are three ratios that are significant in predicting financial distress. The ratios are: working capital over total assets, earnings before interest and taxes over total assets and turnover over total assets. These ratios point to the liquidity and profitability positions of the company. The coefficients one year before failure reflect higher values than similar values five years before failure. This may be interpreted as the increasing risk of failure over time. Another important observation is that for all years before failure similar variables are identified as the most predictive.

In the case of the depressed companies, the model also suggests the similar three ratios as significant. The ratios are: working capital over total assets, earnings before interest and taxes over total assets and turnover over total assets.

Chadha (2016:16) finds that high level of distress shows that major changes are necessary in firms. This also shows that the operations are not running smooth. The importance of companies preserving liquidity and maintaining profitability can be inferred from the above. Regarding preserving healthy levels of liquidity, management has to ensure that effective working capital management strategies are always in place. Without proper management of working capital, companies may find themselves being unable to meet short-term obligations. Also, while the company may appear financially healthy, it is important that the operations are maintained at a profitable state. Therefore, management need to proactively identify and correct unprofitable operations. As suggested by the basic model, the important ratios that require constant monitoring are both liquidity and profitability ratios.

Koh, Durand, Dai & Chang (2015:32) present such an interesting view with regard to management intervention strategies. These authors contend that the intervention strategies are, in a way, limited to the lifecycle state of the company. They say, when firms approach default, shareholders may pressure management to take action to turn the firm around. Creditors may also demand corrective measures, especially when debt covenants may be violated. While the choice of corrective measures is made by management, these may be constrained by the firm's stage in the corporate lifecycle. These authors examine the implications of the lifecycle theory on how distressed firms choose their restructuring strategies and find evidence that distress firms' recourse to different types of restructuring strategies is influenced by the stage of the lifecycle they are in. We find that firms in earlier stages of the lifecycle have a tendency to reduce their employees; mature firms are more likely to engage in asset restructuring. The influence of lifecycle is most pronounced in the choice of financial restructuring strategies such as reducing dividends or varying capital structures.

In basic model 2, the addition of market variables has yielded insignificant p-values in that the coefficients have p-values that are more than 0.05. All coefficients that yield p-values that are more than 0.05 are considered insignificant. This may be interpreted as suggesting that the fundamental ratios are sufficient predictors of financial distress. Interestingly, when the market variables are loaded one at a time and not as a set to the model, each one yields a significant p-value which is less than 0.05. The market variables that have high coefficient values are price per earning and price per cash flow. The price per share has the lowest coefficient value of the other two market ratios. Though the market variables show insignificant p-values, the addition of this set of variables to the model improves the overall prediction accuracy. The improvement of the overall prediction results is discussed in section 7.6.3 above.

A similar result to that in basic model 2 is observed in basic model 3, when a set of macroeconomic variables are load their coefficient yield insignificant p-values. However, loading them one at a time the p-values are significant. The statistical rationale in this instance that tries to explain this observation is that the macroeconomic indicators are the same for all companies and therefore do not provide any statistical information. The gross domestic product and unemployment rate are similar for all companies irrespective of the category. This is also evidenced by there being no impact on the prediction accuracy table. There is no reason that suggests that macroeconomic indicators are not relevant for the prediction of financial distress. However, it does indicate that they are not significant contributors to the response variables statistically as they are constant variables for all case. A more meaningful impact of macroeconomic variables is better explained in the trend analysis section.

7.7 CHAPTER SUMMARY

Chapter 7 starts by summarising the strategy adopted in selecting a group of fundamental, market and macroeconomic variables. In addition to that, is the strategy adopted in selecting companies used in the present study. The independent variables started as 17 after thoroughly scanning through existing literature, this number was further reduced using the forward stepwise method. The final set of variables is a combination of ten: five fundamental data, three market and two macroeconomic indicators. The final model outcome suggests that a maximum of three fundamental ratios have the most predictive power.

The selection of companies also follows a structured procedure. The study deliberately excludes the financial services and the mining sector. A list of 253 Johannesburg Stock Exchange listed companies is extracted from the INET BFA database. Thereafter, this same list of companies is cleansed – this involves identification and elimination of companies with missing data from 2005 to 2014. This process reduced the list to 92 healthy companies. The 92 companies are then split into depressed and healthy using a strict criterion. The result after the split is a total of 14 depressed companies and 78 healthy companies. As a separate process, a list of 59 delisted companies was drawn from the INET BFA database. This list is also cleansed by analysing the reasons for delisting or Johannesburg Stock Exchange suspension. Companies that were found to have delisted for reasons unrelated to financial distress are eliminated. Companies with missing information within the identified economic period are also eliminated. The result was a final list of eight distressed companies.

The statistical process then ensued with the intention of preparing the data for statistical processing. The SPSS statistical software was chosen to run the models. Using this program, four statistical tests are successfully conducted. On completion of these tests, the data is found to not be normally distributed, which immediately poses statistical restrictions. As a result, the present study relies on a nonparametric statistical procedure. In this instance, a multinomial logistic analysis is used. The regression analysis is run for five periods: one year before failure, two years before failure, three years before failure, four years before failure and five years before failure.

The results of the model are presented in detail. In summary, of the five identified fundamental data, a maximum of three were found to make a significant statistical contribution to response variables: working capital over total assets, earnings before interest and taxes over total assets and turnover over total assets. Also found in the results is the enhancement of the prediction accuracy as a result of adding market variables in the model. The macroeconomic variables were found to not make any further statistical contributions.

Interestingly, the model prediction accuracy results from five years before failure are found to be better than the prediction results one year before failure. The finding is confirmed by Avenhuis (2013:1). The logistic analysis equation is therefore developed using only variables that were found to be statistically significant. With the basic model completed, the next chapter focuses on developing the Merton model.

CHAPTER 8

THE SECOND AND THIRD TIER TO DETERMINE FINANCIAL DISTRESS

8.1 INTRODUCTION

The success of issuing a particular debt instrument by an organisation depends on three items:

i. the required rate of return on riskless debt, such as government bonds (South African treasury bills or Government long-term bonds) or very high grade corporate bonds (Eskom bonds);
ii. the various provisions and restrictions contained in the indenture, like maturity date, coupon rate, call terms, seniority in the event of default, sinking funds etc.; and
iii. the probability that the firm will be unable to satisfy some or all of the indenture requirements, such as the probability of default .

These are some of the vital considerations an issuer of a debt instrument would have to make a financial decision on. The cost of incorrect decision-making in financial institutions is likely to cause financial crises and distress. The risk to the debt issuer or the financier is that debt may be incorrectly granted to a non-deserving borrower due to the inability to detect potential financial distress, resulting in a default event. Contrary, a wrong decision may also lead to denying a good borrower and the financier losing potential business.

According to Ala'raj & Abbod (2016:89), credit granting to lenders is considered a key business activity that generates profits for banks, financial institutions and shareholders, as well as contributing to the community. However, it can also be a great source of risk. The problem associated with credit scoring is that of categorizing potential borrowers into either good or bad. Models are developed to help banks to decide whether to grant a loan to a new borrower or not using their data characteristics.

Assessment and detection of credit risk remains pivotal in the banking sector, but more importantly, the rating systems and mechanism to assess credit worthiness. In section 7.4, this study introduces one methodology of predicting financial distress that is based purely on accounting fundamentals. However, the current section embarks on an alternative mechanism of predicting financial distress based on structural data – a method developed by Merton in 1974.

Section 8.1 is the introduction of the chapter highlighting important aspects of the chapter. Section 8.2 briefly highlights the significant assumptions this method is founded on. Section 8.3 provides the step by step construction of the Merton model. The intention is to present the formula derivation without paying attention to the technical and mathematical detail. Section 8.4 contains the list of variables that are used in the formula; the study also explains some of the estimated and proxy variables. Section 8.5 provides the detailed analysis of the model results. As part of the validation of the model results, section 8.6 discusses the type I and type II errors contained in the model. Section 8.7 discusses the descriptive statistics, highlighting some of the relevant statistics in the model. Section 8.9 looks at the distance to default per economic sector and section 8.10 provides the interpretation of the model results. The chapter moves on to the introduction and development of the hybrid model covered in section 8.11. The last section of the chapter is about the model results and presentation of hypothesis; this is covered in section 8.12

For ease of reference, the list of assumptions and the construction steps of this financial distress technique are presented below again.

8.2 MERTON MODEL KEY ASSUMPTIONS

- There are no transactions costs, taxes, or problems with indivisibilities of assets.
- There are sufficient investors with comparable wealth levels – such that each investor believes that he/she can buy and sell as much of an asset as he/she wants at the market price.
- There is an exchange market for borrowing and lending at the same rate of interest.
- Short sales of all assets, with full use of the proceeds, are allowed.
- Trading in assets occurs continuously in time.

- The Modigliani-Miller (1958:261) theorem that the value of the firm is invariant to its capital structure obtains.
- The term structure is flat and known with certainty – that is, the price of a riskless discount bond that promises a payment of $1 at time *t* in the future is P(*t*) = exp[-r^{t}], where r is the (instantaneous) riskless rate of interest, the same for all time.
- The dynamics for the value of the firm, V, can be described by a diffusion type stochastic process through time.

8.3 THE CONSTRUCTION OF THE MERTON MODEL

The Merton model makes two important assumptions. Firstly, it takes an overly simple debt structure and assumes that the total value *V* of a firm's assets follows a geometric Brownian motion under the physical measure:

$$dV = \mu V dt + \sigma v V dW \qquad (8.1)$$

where *V* is the total value of the firm, *μ* is the expected continuously compounded return on *V*, *σV* is the volatility of firm value and *dW* is a standard Weiner process.

Secondly, it assumes that debt consists of a single outstanding bond with face value and maturity. At maturity, if the total value of the assets is greater than the debt, the latter is paid in full and the remainder is distributed among shareholders. However, if the total value of the assets is less than the debt, then default is deemed to occur. The bondholders exercise a debt covenant giving them the right to liquidate the firm and receive the liquidation value (equal to the total firm value since there are no bankruptcy costs) in lieu of the debt. Shareholders receive nothing in this case, but by the principle of limited liability are not required to inject any additional funds to pay for the debt.

From the above observations, shareholders have a cash flow at a particular time where the total value of the assets is greater than the debt. Symbolically, the Merton model stipulates that the equity value of a firm satisfies:

$$E = VN(d_1) - e^{-rT}FN(d_2) \qquad (8.2)$$

where *E* is the market value of the firm's equity, *F* is the face value of the firm's debt, *r* is the instantaneous risk-free rate, *N*(·) is the cumulative standard normal distribution function, *d*1 is given by:

$$d_1 = \frac{(In(V/F)+(r+0.5\sigma^2v)T}{\sigma v\sqrt{T}} \qquad (8.3)$$

and d_2 is just d_2 = d_1−$\sigma v\sqrt{T}$. While this is a fairly complicated equation, most financial economists are familiar with this formula as the Black-Scholes-Merton option valuation equation.

This model uses two important equations. The first is the Black-Scholes-Merton equation (8.2), expressing the value of a firm's equity as a function of the value of the firm. The second equation relates the volatility of the firm's value to the volatility of its equity. Under Merton's assumptions the value of equity is a function of the value of the firm and time, so it follows directly from Ito's lemma that:

$$\sigma E = \left(\frac{V}{E}\right)\frac{\partial E}{\partial E}\sigma v \qquad (8.4)$$

In the Black-Scholes-Merton model, it can be shown that $\frac{\partial E}{\partial E}$ = *N* (d_1), so that under the Merton model's assumptions, the volatilities of the firm and its equity are related by:

$$\sigma E = \left(\frac{V}{E}\right)N(d_1)\sigma v \qquad (8.5)$$

where d_1 is defined in equation (8.3).

The Merton model uses these two non-linear equations – (8.2) and (8.5) – to translate the value and volatility of a firm's equity into an implied probability of default. In most applications, the Black-Scholes-Merton model describes the unobserved value of an option as a function of four variables that are easily observed (strike price, time-to-maturity, underlying asset price, and the risk-free rate) and one variable that can be estimated (volatility).

However, in the Merton model, the value of the option is observed as the total value of the firm's equity, while the value of the underlying asset (the value of the firm) is not directly observable. Thus, while *V* must be inferred, *E* is easy to observe in the marketplace by multiplying the firm's shares outstanding by its current share price. Similarly, in the Merton model, the volatility of equity, *σE*, can be estimated but the volatility of the underlying firm, *σV*, must be inferred. In the present study, the equity volatilities, prices and market capitalisation are obtained from the INET BFA database.

The first step in implementing the Merton model is to obtain *σE*, which is sourced from the BFA database in this study. The second step is to choose a forecasting horizon and a measure of the face value of the firm's debt. For example, it is common to assume a forecasting horizon of one year (*T* = 1), and take the book value of the firm's total liabilities to be the face value of the firm's debt. The third step is to collect values of the risk-free rate and the market equity of the firm. For the risk-free rate, the present study uses a proxy of the 90-day South African Treasury bill. After performing these three steps, there are values for each of the variables in equations (8.2) and (8.5) except for *V* and *σV*, the total value of the firm and the volatility of firm value, respectively.

The fourth, and perhaps most significant step in implementing the model, is to simultaneously solve equations (8.2) and (8.5) numerically for values of *V* and *σV*. Once this numerical solution is obtained, the distance to default can be calculated as:

$$DD = \frac{In(\frac{V}{F})+(\mu-0.5\sigma_v^2)T}{\sigma v\sqrt{T}} \tag{8.6}$$

where *μ* is an estimate of the expected annual return of the firm's assets. The corresponding implied probability of default is given as:

$$PD = N\left(-\left(\frac{In\left(\frac{V}{F}\right)+(\mu-0.5\sigma_v^2)T}{\sigma v\sqrt{T}}\right)\right) = N(-DD) \tag{8.7}$$

If the assumptions of the Merton model hold, the Merton model should give very accurate default forecasts. In fact, if the Merton model holds completely, the implied probability of default defined above should be a sufficient statistic for default forecasts.

The inputs to the model are the market value of equity, the face value of debt, and the volatility of equity. As the market value of equity declines, the probability of default increases, which is both a strength and weakness of the model. For the model to work well the Merton model assumptions must be met and the markets must be efficient and well informed.

8.4 LIST OF VARIABLES AND THEIR PROXIES

There are five primary inputs to the distance to default calculation that need to be estimated. The estimation of these variables would simply mean building certain assumptions to support the model.

Table 8-1: The list of variables used in the Merton model

Variable	Proxy	Code
Asset values	Market capitalisation	(A_0)
Asset volatility	Equity volatilities	(σ_A)
Debt levels	STD* plus 50% of LTD*	(D)
Risk-free rate	Treasury bill (90 days)	(μ)
Time	One-Year	(T)

*STD – short-term debt, *LTD – long-term debt

Source: own research

8.5 MODEL RESULTS

The model is developed using 100 companies – a similar population used for the development of the basic model. In this model, the list of companies is also categorised according to the identified financial states. Once all values are introduced on the model, the distance to default and probability of default is calculated for each company for all the years under review.

The results of the calculated distance to default for individual companies are averaged and sorted from smallest to largest according to the distance to default values. The list of predicted distance to default is then compared with a list of the actual financial state outcomes to obtain percentage accuracy. The below table reflects the results.

Table 8-2: The Merton model prediction accuracy table

STATUS	distance to default		
	1.45	1.46 - 2.7	2.8
Prediction	9	14	77
Actual	8	14	78
Accuracy	**100%**	**100%**	**99%**

Source: own research

Out of a total of eight distressed companies, all eight have been correctly classified. This gives 100% model accuracy in the prediction of financially distressed companies. When comparing the number of predicted companies (9) to the actual number of distressed companies (8), there is one more company that is predicted as distressed when it is actually healthy. This one particular company that has been misclassified as distressed has scored a distance to default value falling within the range of distressed companies.

A further analysis this one particular company misclassified as distressed group reveals a large amount interesting information. This company has experienced a financial loss situation for the past five years. Its market capitalisation has been decreased from R160m (2011) to R58m (2014). In 2012 the same company was technically insolvent. This financial information explains why this company has been identified as distressed by the Merton model. This proves the robustness of the Merton distance to default model in identifying companies facing distress.

The model has identified 14 companies scoring within the range set for depressed companies. This is a 100% achievement in identifying financially depressed companies. Lastly, 77 companies are identified as financially healthy by achieving a distance to default score greater or equal to 2.8. This is a 99% accuracy prediction of healthy companies. The one company that has been misclassified has been ‘misallocated’ to distressed companies. The financial performance of the same company also suggests that the company is under severe financial pressure though the company has not failed.

These results indicate two things. On the one hand, they show that certain companies might be classified as healthy on the basis that they still meet all the Johannesburg Stock Exchange requirements and resultantly have not yet been suspended or delisted while the same companies have entered the state of financial distress. On the other hand, certain companies might be showing signs of financial distress yet the same companies may still be saved and turned around to financial stability.

8.6 TYPE I AND II ERRORS

To calculate type I and II errors for model validation or to validate the selected cut-off points, the response variables are rearranged into a binary format. Meaning, instead of three outcomes (distressed, depressed and healthy), the outcomes are changed into distressed and not distressed. In doing this, the group of depressed companies is combined with the group of healthy companies to make one group of companies that are not distressed. Therefore, this changes the data composition to 92 not distressed companies and eight distressed companies.

In performing a hypothesis test, two types of errors are possible: type I and type II. The risks of these two errors are inversely related and determined by the level of significance and the power for the test. Thus, it is deemed prudent to determine the severity of these errors so the model may be well validated. The determination of these errors also serves to check whether the model results are explained meaningfully and not by way of a random chance.

A type I error, also known as a false positive, is the error of rejecting a null hypothesis when it is actually true. In other words, this is an error where the model classifies a healthy company as distressed – in a group of healthy companies where there is no distressed company; the model says there is a distressed company.

A type II error, also known as a false negative, is the error of not rejecting a null hypothesis when the alternative hypothesis is the true state of nature. This is an error where the model classifies a distressed company as healthy – in a group of distressed companies where there is no healthy company; the model says there is a healthy company.

Table 8-3: Prediction results reflecting misclassifications

STATUS	Probability of default		
	Healthy	Distressed	Total
Healthy	91	1	92
Distressed	0	8	8
Total	91	9	100

Source: own research

In reference to Table 8-3, the top left green shaded block reflects the number of healthy companies correctly predicted as healthy – true positive. The second green shaded bottom right block reflects the number of distressed companies correctly predicted as distressed – true negative. Inversely, the top right block shaded in red, reflects the number of healthy companies predicted as distressed – false positive. The bottom left block shaded in red reflects the number of distressed companies predicted as healthy.

Table 8-3 is interpreted differently in Table 8-4, reflecting the percentages of the type I and II errors.

Table 8-4: Type I and II error percentages

STATUS	Population	Correct prediction	Correct per cent	Error per cent
Type I error	92	91	99%	1%
Type II error	8	8	100%	0%
Total	100	99	99%	1%

Source: own research

The type I error is found to be 1% while the type II error is 0%, both shaded in grey. Combined, these two percentage points form the lowest possible level found in an attempt to minimise the errors. Therefore, it is comforting that the cut-off point selected for this classification is the optimal cut-off point where the errors are minimised.

8.7 DESCRIPTIVE STATISTICS

Below are some of the important statistical tables generated from the model. These tables provide an indication on the data structure. The tables are separated according to their financial states. Bharath & Shumway (2008:1344) say that the value of equity is observed in the marketplace by multiplying the company's shares outstanding by its current share price. This observation is in line with Merton's option pricing model (1974:449) which assumes that the value of the option is observed as the total value of the company's equity, while the value of the underlying assets is not directly observable. The market value of the firm is simply the sum of the market values of the firm's debt and the value of its equity. Therefore, in line with existing literature the present observes the market value of equity in the marketplace by multiplying the company's shares outstanding by its current share price.

Table 8-5: The descriptive statistics of distressed companies used in Merton model

Variable	Code	Mean	StdDev	Median	Min	Max
Debt (Rmillon)	D	235	416.57	21.92	8.41	1 155.54
Market Value (Rmillon)	A	241.84	454	25.92	5	1 286
Expected return (%)	μ	7	1	7	6	8
Debt volatility (%)	σ_D	47	17	45	23	66
Asset volatility (%)	σ_A	145	55	134	76	226
Distance to Default	DD	0.65	0.59	0.71	-0.13	1.45
Probability of Default (%)	PD	29	19	24	7	55

Source: own research

Table 8-5 shows statistical figures used in the model. The dispersion in the asset value reflects a minimum of R5m and a maximum value of R1 286bn. The distance to default line has a mean of 0.65 with a maximum of 1.45. The probability of default goes as high as 55% for distressed companies. This is an indication of the mixture in company sizes. Even with the combination of big and small companies, the model did not find any bias against small companies as it correctly identified those that are actually distressed.

Table 8-6: The descriptive statistics of depressed companies used in Merton model

Variable	Code	Mean	StdDev	Median	Min	Max
Debt (Rmillon)	D	4 872	6 136.11	2 720.14	22.06	21 459.80
Market Value (Rmillon)	A	9 032.65	11 342.61	4 496.64	28.87	39 741.12
Expected return (%)	μ	7	0	7	7	7
Debt volatility (%)	σ_D	14	3	13	11	18
Asset volatility (%)	σ_A	24	12	19	8	48
Distance to Default	DD	4.50	1.50	4.50	2.08	6.51
Probability of Default (%)	PD	0.20	0.51	0.00	0.00	1.87

Source: own research

The interesting observation in Table 8-6 is that the distance to default increases to a mean of 4.50 compared to a mean of 0.65 for the financially distressed group. Another distinction is the probability of default figure which reduces closer to 0.2% for the depressed companies compared to distressed companies. However, this group, just like the group of distressed companies, appears to contain companies that are widely dispersed in terms of size.

Table 8-7: The descriptive statistics of healthy companies used in Merton model

Variable	Code	Mean	StdDev	Median	Min	Max
Debt (Rmillon)	D	5 838	10 643.81	1 340.81	22.66	62 870.70
Market Value (Rmillon)	A	22 155.96	52 781.12	4 214.62	13.03	267 921.72
Expected return (%)	μ	7	0	7	7	7
Debt volatility (%)	σ_D	14	4	13	6	30
Asset volatility (%)	σ_A	26	16	22	5	92
Distance to Default	DD	4.76	2.24	4.50	1.43	13.52
Probability of Default (%)	PD	0.33	1.07	0.00	0.00	7.62

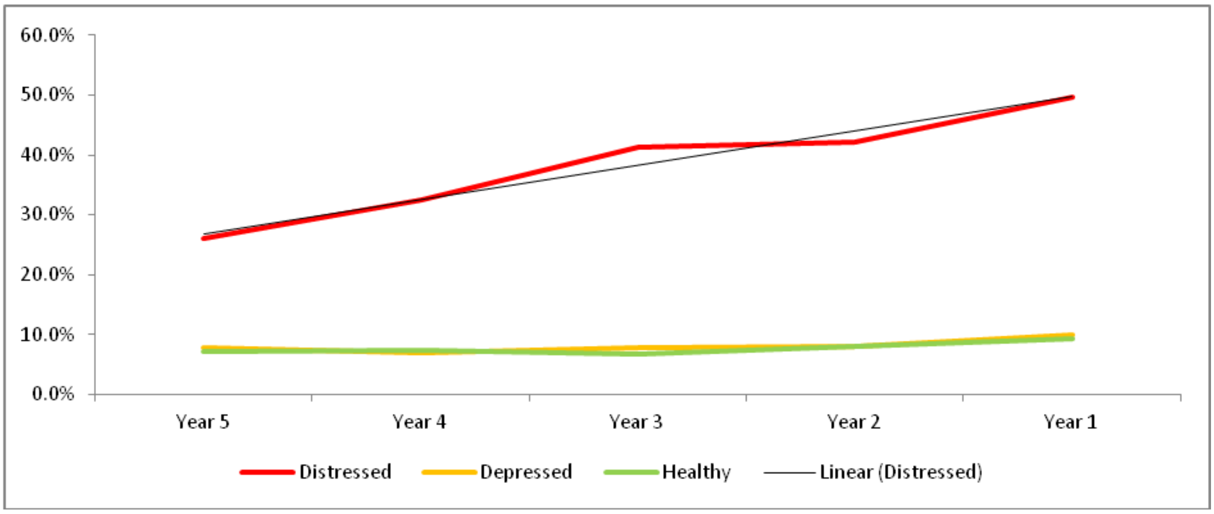
Source: own research

The financially healthy companies are a combination of small, medium and large companies. The distance to default further increases to a mean of 4.76 compared to a mean of 4.50 and 0.65 for financially distressed and depressed groups, respectively. Another distinction is the probability of default figure which reduces to 0.3% for healthy companies.

8.8 PROBABILITY TO DEFAULT TREND ANALYSIS

The below graphs seek to display a trend over the five-year horizon between three financial states. The x-axis represents the recent five years of financial performance. This is deliberately not presented as "2014-2010" as the distressed companies failed in different periods

Graph 8-1: The probability of default for all companies as calculated in Merton model



Source: own research

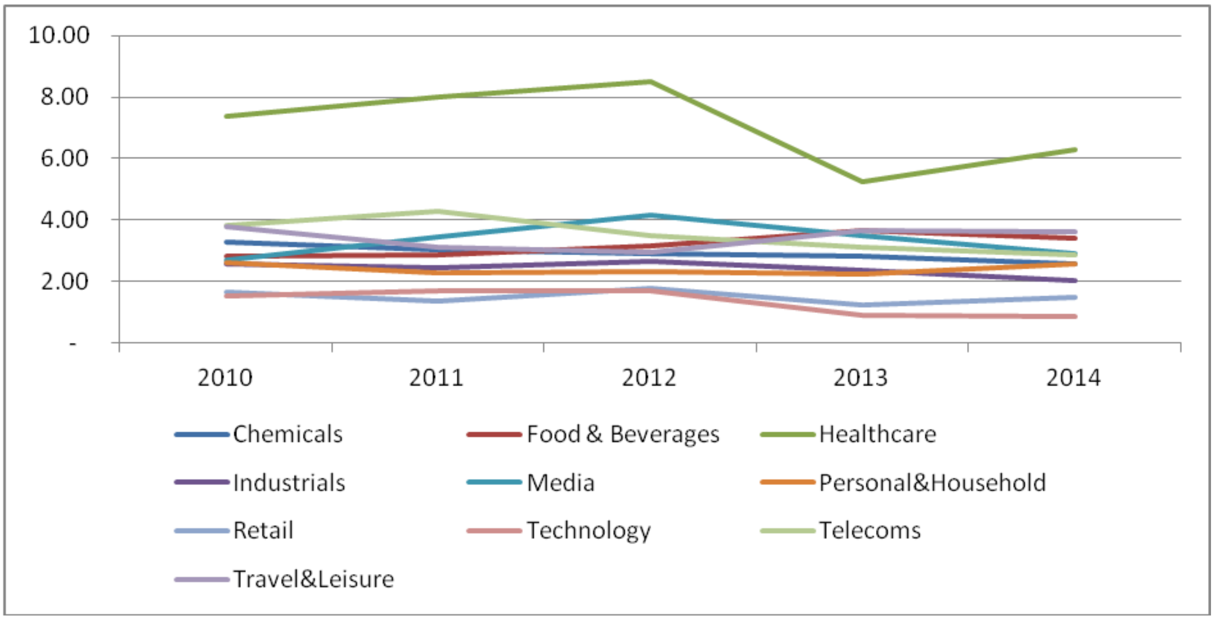
The probability of default trend for financially distressed companies reflect an upward movement indicating worsening signs of financial distress as it gets closer to actual failure. A gap is observed in the comparison with companies that have not failed. The trend for these companies is somewhat flat indicating financial stability. Again, the comparison of the financially depressed with that of healthy companies proves the very close proximity of these two groups. Hence, the model shows high levels of misclassifications between these groups.

The data is also sorted to reflect the variability between economic sectors based on their calculated distance to default. A trend analysis graphical presentation is conducted for economic sectors.

8.9 DISTANCE TO DEFAULT PER ECONOMIC SECTOR

The dimension of data that is presented is the distance to default sorted by the economic sector. Graph 8-2 intends to highlight economic sectors that are further away from financial distress as computed in Merton model.

Graph 8-2: The Distance to default per economic sector as calculated in Merton model



The x-axis represents the recent five years of financial performance. This is deliberately not presented as "2014-2010" as the distressed companies failed in different periods.
Source: own research

Graph 8-2 suggests that the healthcare sector has a comfortable distance to default. When interpreted in terms of the probability of financial distress, the bigger the number, the lower the probability of financial distress. Therefore, this ranks the healthcare sector in a much better position than other sectors regarding the probability of default. The healthcare trend is then followed by a cluster of sectors within the range of 4-2 with the lower number being riskier than the higher number. The positive is that this group of economic sector reflects a somewhat flat trend, which indicates financial stability. The riskiest economic sector with the lowest distance to default is the technology sector closely followed by the retail sector.

8.10 INTERPRETATION OF MODEL RESULTS

The Merton model appears to be performing robustly given the percentage accuracy in classifying companies according to their financial state based on the calculated distance to default. The model achieved 100% prediction for distressed and depressed companies and a 99% prediction for healthy companies. This prediction accuracy is based on the following cut-off points: Distance to Default<1.45, 1.45>distance to default<2.7 and distance to default>2.7 for the distressed, depressed and healthy states, respectively.

Interestingly, the analysis behind the company has been misclassified. The financial results of this company seem to point in the same direction as the model outcome results. The same company suffered a loss situation for the past five years. Furthermore, its market capitalisation is showing a downward spiral. The model did not categorise this company as depressed, although it was categorised as distressed. Such a company should have been classified as depressed in the first place, however, the criteria set in the present study looks at the movement year-on-year. So, while this particular company reflects losses, the movement year-on-year is not necessarily negative. Their loss situation is reflecting a slightly improving trend.

8.11 THE HYBRID MODEL

Thus far, the present study has successfully developed the basic and Merton models with positive results. The Merton model performed significantly well, achieving 99% compared to the basic model with an overall percentage accurate prediction performance of 90%. Even the 90% is achieved four years before failure with other years reflecting a lower percentage. In the basic model, the prediction results were enhanced with the addition of market variables to the model. Now that the first two models of the study have been developed with very good results, the hybrid model is developed. The hybrid model is a combination of the basic and Merton models in that it incorporates variables from both models.

8.11.1 Multicollinearity test

For the robustness and the integrity of a regression model, testing for collinearity among independent variables is very important. While ten independent variables have already been tested with no correlation being found, the addition of another independent variable in the form of the distance to default necessitates that the test is run again. The below table reflects the correlation matrix where all independent variables are included.

Table 8-8: The correlation matrix table incorporating all variables in the hybrid model

Variables	WCTA	EBITTA	TDTA	METD	TOTA	P/E	P/S	P/CF	GDP	UR	DD
WCTA Sig, (2 tailed)	**1.000** -										
EBITTA Sig, (2 tailed)	**0.230** 0.020	**1.000** -									
TDTA Sig, (2 tailed)	**-0.581** 0.000	**-0.224** 0.024	**1.000** -								
METD Sig, (2 tailed)	**0.275** 0.005	**0.605** < 0.001	**-0.524** < 0.001	**1.000** -							
TOTA Sig, (2 tailed)	**0.065** 0.517	**0.200** 0.044	**0.128** 0.200	**0.052** 0.601	**1.000** -						
P/E Sig, (2 tailed)	**-0.055** 0.581	**0.213** 0.032	**0.018** 0.859	**0.500** < 0.001	**0.099** 0.322	**1.000** -					
P/S Sig, (2 tailed)	**0.063** 0.527	**0.333** 0.001	**0.024** 0.810	**0.486** < 0.001	**0.052** 0.605	**0.459** < 0.001	**1.000** -				
P/CF Sig, (2 tailed)	**-0.035** 0.726	**0.363** 0.000	**-0.070** 0.481	**0.654** < 0.001	**0.123** 0.218	**0.684** < 0.001	**0.527** < 0.001	**1.000** -			
GDP Sig, (2 tailed)	**-0.111** 0.265	**-0.261** 0.011	**0.111** 0.266	**-0.220** 0.027	**-0.050** 0.618	**-0.157** 0.114	**-0.267** 0.007	**-0.196** 0.048	**1.000** -		
UR Sig, (2 tailed)	**0.323** 0.001	**0.440** < 0.001	**-0.179** 0.072	**0.514** < 0.001	**0.217** 0.029	**0.446** < 0.001	**0.391** < 0.001	**0.347** 0.000	**-0.379** < 0.001	**1.000** -	
DD Sig, (2 tailed)	**0.020** 0.841	**0.142** 0.155	**-0.125** 0.210	**0.205** 0.038	**-0.128** 0.201	**0.215** 0.030	**0.278** 0.005	**0.235** 0.018	**-0.381** 0.000	**0.291** 0.003	**1.000** -

Source: own research

EBITTA – earnings before interest and tax over total assets, **TDTA** – total debt over total assets, **METD** – market capitalisation over total debt, **TOTA** – turnover over total assets, **WCTA** – working capital over total assets, **P/E** – price per earnings, **P/S** – price per share, **P/CF** – price per cash flow, **GDP** – gross domestic product, **UR** – unemployment rate, **DD –** distance to default

Table 8-8 reflects the correlation matrix results of all independent variables. The numbers in bold represent the correlation and the numbers below the bold represent the p-values. It can be noted from the numbers in bold that there is no correlation between the independent variables. Again, a Spearman correlation test was used as the statistical technique.

With the above results, the numbers of eleven variables are used in a new hybrid model again using the logistic analysis technique. The model results tables as are explained below.

8.11.2 Case processing summary

This table displays the number of cases loaded on the model. These cases are categorised according to the financial state. Two important indicators are the valid and missing entries. These two indicators give confidence in the model, in that all cases are valid and there are no missing cases.

Table 8-9: The number of cases processed in the hybrid model

Fundamental, market, macroeconomics and Distance to Default			
		N	**Marginal percentage**
STATUS	Distressed	8	8.00%
	Depressed	14	14.00%
	Healthy	78	78.00%
Valid		100	100.0%
Missing		0	
Total		**100**	

Source: own research

As it can be seen in Table 8-9, the data contains 100 cases of distressed, depressed and healthy companies. The different percentage composition of companies is also evident. Unlike in previous studies that are dichotomous in nature and where the number of companies is equal for each group of failed and non-failed, the present study tries to be more realistic as data is analysed as it is obtained from the data source without any manipulation.

8.11.3 Model goodness

The model goodness tables serve to provide a level of satisfaction regarding the integrity of the model or model performance. The logistic analysis model works differently to the simple regression model where R-squared values play a pivotal part in explaining the model performance. The logistic analysis model applies the maximum likelihood of the odds as an indicator of model performance. While R-squared is not necessarily calculated in the same way as in simple regression models, there is an output table for the logistic analysis model that calculates the model relevant pseudo R-squared. These tables may also be used as a model performance indicator.

Table 8-10: The performance of the overall hybrid model measured in goodness fit and pseudo R-squared

Variable	Statistic	Hybrid
Pseudo R2	McFadden	0.95
-2LL	Intercept only	134.22
	Final	6.23
	Chi-square	127.99
	Sig	0.000

Source: own research

The pseudo R-squared analysis confirms the goodness of the hybrid model. As depicted in the above table 8-10, pseudo R-squared is 95% indicating a very good model fitting. It also indicates how much the independent variables explain the variability in the dependent variables. With regard to the -2 log likelihood – the intercept line assumes no independent variables that are used in the model. The final -2LL reflects the impact of using the various independent variables. From this observation it may be inferred that the independent variables influence the dependent variables. That is, the model is working fine. Another important factor is the chi-square and the significance level. With the alpha set at 0.05, the model p-values are below the alpha threshold reflecting the significance of the selected independent variables.

8.11.4 Prediction Accuracy rate

The prediction results reflect the model accuracy in predicting the financial distress position of companies. The addition of the distance to default to the variables appears to have improved the results. The below table reflects a 100% prediction for all financial states.

Table 8-11: The hybrid model prediction percentage table

STATUS	Hybrid
Distressed	100%
Depressed	100%
Healthy	100%

Source: own research

These results prove one of the developed hypotheses that say a hybrid model performs better on than individual models. The next section presents the estimation of coefficients for individual variables.

8.11.5 The estimation of coefficients for individual variables

Table 8-12 below investigates the influence of individual variables on the outcome or response variables. It is important to note that the reference category in the below table is set as healthy. Therefore, in reading the numbers, the table shows the odds likelihood of distressed or depression in reference to healthy.

The grey shaded variable coefficients and respective p-values (0.05) indicate the variables that are used in the logistic analysis equation. These are variables that the model has identified as making a significant statistical contribution. The insignificant variables are therefore not considered. However, their impact is better explained in the overall prediction accuracy where they make a positive contribution.

Table 8-12: The hybrid model results reflecting coefficient estimates

Distressed				Depressed			
Code	**Variable**	**Statistic**	**Hybrid**	**Code**	**Variable**	**Statistic**	**Hybrid**
X_1	CACL	Coeff Sig.	0.51 0.72	X1	CACL	Coeff Sig.	-7.66 0.00
X_2	TDTA	Coeff Sig.	18.86 0.00	X2	TDTA	Coeff Sig.	9.59 0.00
X3	METD	Coeff Sig.		X3	METD	Coeff Sig.	
X_4	TOTA	Coeff Sig.		X4	TOTA	Coeff Sig.	
X_5	WCTA	Coeff Sig.	-10.68 0.41	X5	WCTA	Coeff Sig.	-33.16 0.00
X_6	P/E	Coeff Sig.	0.13 0.22	X6	P/E	Coeff Sig.	1.07 0.00
X_7	P/S	Coeff Sig.	-0.13 0.85	X7	P/S	Coeff Sig.	-0.00 0.96
X_6	P/CF	Coeff Sig.	-0.13 0.06	X8	P/CF	Coeff Sig.	0.19 0.00
X_9	GDP	Coeff Sig.	-243.92 0.17	X9	GDP	Coeff Sig.	-131.84 0.95
X_{10}	UR	Coeff Sig.	-1 635.87 0.01	X10	UR	Coeff Sig.	-293.38
X_{11}	DD	Coeff Sig.	-1.26 0.10	X11	DD	Coeff Sig.	0.52 0.00
	Constant	Coeff Sig.	380.20 0.01		Constant	Coeff Sig.	63.41 0.30

All coefficients are statistically significance between 0.05 levels. **CACL** – current assets over current liabilities, **TDTA** – total debt over total assets, **METD** – market capitalisation over total debt, **TOTA** – turnover over total assets, **WCTA** – working capital over total assets, **P/E** – price per earnings, **P/S** – price per share, **P/CF** – price per cash flow, **GDP** – gross domestic product, **UR** – unemployment rate, **DD** – distance to default

Source: own research

The logistic analysis function is therefore constructed as follows:

$$\text{Logit}(p) = \text{Ln}\frac{p}{(1-p)} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots \beta_n X_n \qquad (8.8)$$

Given the above model results, the log odds may be presented as follows:

Distressed companies: $\text{Logit}(p) = \text{Ln}\frac{p}{(1-p)} = 380.20 + 18.86X_2 - 0.13X_8 - 1\,635.87X_{10}$

Depressed companies: $\text{Logit}(p) = \text{Ln}\frac{p}{(1-p)} = 63.41 - 7.66X_1 + 9.59X_2 - 33.16X_5$
$+ 1.07X_6 + 0.19X_8 + 0.52X_{11}$

It is possible to convert the log odds back to odds by applying the reverse of the log (the exponential or anti-logarithm) to both sides. Taking the exponent eliminates the log on the left-hand side so the odds can be expressed as:

$$\text{Logit}(p) = \text{Ln}\frac{p}{(1-p)} = \beta_0 + \beta_1X_1 + \beta_2X_2 + \ldots \beta_nX_n \qquad (8.9)$$

This equation can also be rearranged to find the probabilities as:

$$P = \frac{exp\beta0 + \beta1X1 + \beta2X2 + \ldots\beta nXn}{1+exp\beta0 + \beta1X1 + \beta2X2 + \ldots\beta nXn} \qquad (8.10)$$

which is the logistic function that converts the log odds to probabilities.

Therefore, to convert to the probability of distress for distressed companies, the logistic analysis model may be rearranged as follows:

Distressed companies: $$p = \frac{e^{(380.20+18.86*X2-0.13X8-1638.87X10)}}{1+ e^{(380.20+18.86*X2-0.13X8-1638.87X10)}}$$

Depressed companies: $$p = \frac{e^{(63.41-7.66*X1+9.59X2-33.16X5+1.07X6+0.19X8+0.52X11)}}{1+ e^{(63.41-7.66*X1+9.59X2-33.16X5+1.07X6+0.19X8+0.52X11)}}$$

Where:

X_1	Earnings before interest and taxes
X_2	total debt to total assets
X_3	Market capitalisation to total debt
X_4	Turnover to total assets
X_5	Working capital to total assets
X_6	Price per earnings
X_7	Price per share
X_8	Price per cash flow
X_9	Gross domestic product
X_{10}	Unemployment rate
X_{11}	Distance to default

A similar behaviour is observed in developing the hybrid model in that certain variables respond as statistically insignificant. The variables have an outcome of p-values greater than an alpha of 0.05. All variables are checked and confirmed to be correlated. Nevertheless, the overall model fit suggests a very good fit and it is also statistically significant. Also, the calculated R-squared reflects very good percentages. In terms of the model prediction accuracy, there is a great improvement with the addition of the distance to default variable.

8.12 RESULTS AND PRESENTATION OF HYPOTHESIS

The preceding sections of this chapter present and discuss the results of the three-tiered approach to determine the financial distress of companies. This section further discusses the model results, contrasting them with formulated hypotheses. The research hypothesis and alternative hypothesis are confirmed or rejected by the empirical findings.

8.12.1 Results and presentation of hypothesis one

Hypothesis one is set as follows:

H_1: The financial distress model using a multinomial specification is able to distinguish between the three financial states of a company: distressed, depressed and healthy.

H_0: The financial distress model using a multinomial specification is not able to distinguish between the three financial states of a company: distressed, depressed and healthy.

Model results

This hypothesis is founded on the basis that there should be a clear-cut trajectory that leads to financial distress – that is, financial distress should not come as a surprise but should follow a period of poor financial results. Therefore, should there be financial indications that a company requires attention; management is expected to engage turnaround strategies to salvage or avoid distress situations. Therefore, this may suggest that at any given point a company may be identified as financially healthy, depressed or distressed.

Section 7-3 of this chapter discusses the trend analysis results as mapped out from the total list of companies. The results of this exercise, as depicted graphically under the same section, reflect a clear drop or deterioration in the financial state of companies that eventually land in distress. The graphical presentation also depicts a clear gap between distressed companies and those that are not. The identification of financially distressed companies is also proven statistically. In reference to the prediction results, the multinomial logistic analysis model is able to identify a good percentage indication of the three financial states.

When moving to the split between the financially healthy companies and those that are declared as financially depressed, the graphical results (as presented under section 7.3) also reflect a split between the two groups. However, this split is relatively small. It should be noted that these are companies that have not failed but are not doing well in terms of their reported financial performance. Statistically, the prediction results identify an average of 100% of financially healthy companies.

Therefore, in this case, the research hypothesis is accepted as the model is able to distinguish between the three zones of a company: healthy, depressed and distressed. The alternative hypothesis is then rejected.

8.12.2 Results and presentation of hypothesis two

Hypothesis two is set as follows:

H_1: The prediction accuracy of a financial distress model is enhanced when combining fundamental, market and macroeconomic variables.

H_0: The prediction accuracy of a financial distress model is not enhanced when combining fundamental, market and macroeconomic variables.

Model results

The development of the basic model is presented in three phases. These phases are about the systematic use of independent variables. The intention is to test whether the research hypotheses may be accepted or rejected. In the event that there is no enhancement in the prediction results in using additional variables, the alternative hypotheses are accepted.

The accuracy rate of prediction in Table 7-13 shows prediction results for basic models stages 1, 2 and 3 with the clear enhancement of prediction accuracy as new information is added. While no improvement could be noticed by adding the macroeconomic variables, there is a definite improvement in adding the market variables.

With this outcome, the research hypothesis that states that adding variables to the fundamental data enhances the prediction results is therefore accepted. The alternative hypothesis is rejected.

8.12.3 Results and presentation of hypothesis three

Hypothesis three is set as follows:

H_1: The Merton model produces prediction accuracy results that are within 5% of the accuracy results of the basic model.

$H_{0:}$ The Merton model produces prediction accuracy results that are more than 5% of the accuracy results of the basic model.

Model results

The results indicate that the basic model achieved a maximum of 90% prediction accuracy considering the five-year average, while the Merton model achieved a 99% prediction accuracy resulting in a 9% percentage variance. Therefore, in this instance, the research hypothesis may not be accepted as the percentage difference is greater than 5%. This finding suggests that the Merton model is a better performing model than the basic model. The alternative hypothesis is accepted.

8.12.4 Results and presentation of hypothesis four

Hypothesis four is set as follows:

H_1: Although the prediction ability of a financial distress model based on the logistic analysis approach is very close to the Merton-based approach, combining the variables from these two models give better prediction results.

$H_{0:}$ Although the prediction ability of a financial distress model based on the logistic analysis approach is very close to the Merton-based approach, combining the variables from these two models does not give better prediction results.

Model results

In testing this hypothesis, the results of individual models are tabled below. The hybrid model is loaded with the full combination of variables which includes fundamental, market, macroeconomics and distance to default.

Table 8-13: Model performance

Model performance	Basic model	Merton model	Hybrid model
Overall percentage	90%	99%	100%

Source: own research

The results in Table 8-13 indicate that the hybrid model financial distress prediction performance is better than the alternative two models, albeit only marginal. Therefore, this information leads to the acceptance of the research hypothesis that combining the variables from these two models gives better prediction results. Hence, the alternative hypothesis is rejected.

8.13 CHAPTER SUMMARY

Given the results of the Merton model financial distress prediction performance, it may be inferred that this model could be preferred as an alternative to the basic model. This is purely based on the fact that it produced 99% accuracy in predicting the financial distress. There were eight distressed companies, 14 depressed and 78 healthy. The Merton model picked nine distressed, 14 depressed and 77 healthy. This means one healthy company as defined by the financial distress definition used in this study, was classified as distressed by the Merton model. A further analysis to the results is the analysis of the type I and II errors. The errors combined reflect 1% as the lowest possible level. This result suggests that the cut-off point selected is the best possible. While this model has performed excellently in this study, its critics have hammered on its theoretical assumptions and estimation of certain variables. However, it remains in use by reputable agencies like Moody's.

Once the basic and Merton models were developed, the study constructed a hybrid model. This model sees the combination of the basic model variables with the Merton distance to default score. The intention was to observe whether the prediction results would improve using a hybrid model. The end results suggested an enhancement of the statistical results prediction results showed a financial distress prediction of 100%. After these results, the study then reflected on the earlier developed hypotheses.

The first hypothesis that was tested looked at the model being able to distinguish between the three financial states of a company (healthy, depressed and distressed). The research hypothesis in this instance was accepted as the model was able to produce results for the three states. The second hypothesis asks whether the combination of different sets of variables enhances the prediction results. Again, the research hypothesis is also accepted as the model produced better prediction results when market variables were added.

However, regarding the third hypothesis, the alternative hypothesis is accepted. This hypothesis says the prediction results of the basic model and that of the Merton model produced results that are within 5% of each other. The study findings disproved this hypothesis as the Merton model performs 9% better than the basic model. The last hypothesis was about the prediction accuracy benefits in using a hybrid model. This also proved to be true as the prediction accuracy reflected 100% prediction on the hybrid model. All the three models have been developed covered in chapter 7 and 8. The next chapter concludes this present study reflecting on the findings and areas for future research.

CHAPTER 9

CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

9.1 INTRODUCTION

This chapter concludes the study and provides recommendations for further research after having laid a solid theoretical and empirical foundation for a three-tiered approach to determine financial distress. Having introduced the study and provided appropriate background in Chapter 1, a thorough theoretical framework is discussed in Chapters 2 and 3. The aim of deliberately splitting the literature review was to clearly review the extant literature on models that are based on fundamental data, and to incorporate the impact of market and macroeconomic indicators. This model, referred in the present study as the basic model, is compared with the Merton model, which is driven by market parameters. The development of these two separate models was aimed at an eventual combination of the two and the development of a hybrid model. The hybrid model yielded better prediction accuracy than the individual two models, although only marginal.

Therefore, this chapter focuses on providing a synopsis of the findings in line with set research objectives, highlighting the contribution of the present study to the existing body of knowledge on financial distress prediction, and suggesting further areas for future research.

Section 9.2 of this chapter briefly highlights the recap of the theoretical background of the present study. Section 9.3 provides a concise summary of the research objectives and the empirical findings of the study. Section 9.4 highlights the main contributions to existing research. And section 9.5 discusses lessons learnt and areas for future research.

9.2 THEORETICAL BACKGROUND OF THE STUDY

The financial distress prediction models aim to assign a probability of failure, default or a credit score to firms over a given period of time. Without a functioning banking system the economy would grind to a halt with individuals and businesses unable do business. To ensure financial stability in the banking sector the Basel committee is there to strengthen the regulation, supervision and practices of banks worldwide. Following the financial crisis in 2008, the Basel committee issued for consultation a package of proposals to strengthen global capital and liquidity regulations with the goal of promoting a more resilient banking sector.

In order to strengthen and enhance credit risk management banks have had to tighten their credit assessment mechanisms. The Basel II document says banks that have received supervisory approval to use the Internal Rating-Based approach may rely on their own internal estimates of risk components in determining the capital requirement for a given exposure (Basel II:48). The same document further suggests that the risk components include measures of the probability of default, loss given default, the exposure at default, and effective maturity. South African as a member of the Basel Committee operates under the same banking regulations.

The academic researchers appear to show continued interest in further researching the financial distress prediction models. The literature review, as covered in detail in chapter 2 of the present study, reveals the dominance of classical financial distress prediction models. These classical prediction models are: (multiple discriminant analysis, logistic regression analysis and the option pricing frame). However, considering the contemporary research, literature does reveal significant strides mostly in the selection of variables.

The present study uses the logistic regression analysis in developing the basic and the hybrid model. The prediction accuracy results derived from the three models are compared with the objective of identifying a model with the highest prediction percentage. In the first stage the basic model is compared with the Merton model, with the latter producing better results. In the second stage the hybrid model is compared with both the basic and Merton model. The accuracy results derived from the hybrid model are better that the other two models. This finding is line with the theoretical review covered in chapter 2 that suggests that hybrid models seem to posses higher prediction ability that individual models. This may be due to the fact that the hybrid model contains both the fundamental and the market based indicators.

9.3 RESEARCH OBJECTIVES AND THE EMPIRICAL FINDINGS

At the beginning of this study, various research objectives were highlighted. Below is a reminder of these objectives – the aim is to look at the empirical findings and check if the present study has managed to meet its set research objectives.

Therefore, the research objectives for the present study are as follows:

(i) To develop a financial distress prediction model that incorporates three variables: fundamental, market and macroeconomics data. This model shall be referred to as the basic model.

(ii) To develop a structural financial distress model to calculate distance to default. This model is referred to as the Merton model.

(iii) To develop a hybrid model incorporating the outcomes of the basic and Merton models, and it shall be referred to as the hybrid model.

(iv) To investigate which of the two models is better at differentiating defaulting and non-defaulting firms. In this way, the study assesses the extent to which different failure prediction models may yield significantly different distress prediction results.

(v) To explore the extent of gains (if any) that can be realised from developing a hybrid model.

The research objective (i) is well covered in Chapter 7 where the basic model is developed. This model presents a scenario where the impact of a systematic loading of independent variables is analysed. The first set of variables that is loaded is the fundamental variables. One year before financial distress, the model results suggest that 63% of the distressed companies could be classified as distressed, 7% as depressed, and 100% of healthy companies are correctly predicted. This performance is further confirmed with the trend analysis covered in section 7-3. This section clearly distinguishes the trends between companies that have failed, or are depressed or healthy. The distressed companies tend to reflect a highly volatile trend reflecting financial instability within the company. Furthermore, the trend tends to show deterioration as the company faces failure.

The next step in developing the basic model was the loading of the market and the macroeconomic indicators on top of the fundamental ratios. The market indicators were loaded first, followed by the macroeconomic indicators. There was a significant improvement in the Prediction results the moment market variables were added to the model – this confirmed the positive impact caused by adding market variables to the fundamental data. The prediction accuracy results improved from a low of 84% to a high of 90% when market variables were added. The present study found that the further addition of macroeconomic variables does not further enhance the prediction results.

Research objective (ii) is discussed in Chapter 8 and deals with the development of the Merton model. The framework of this model is based on the estimation of five variables:

- (i) asset values,
- (ii) asset volatilities,
- (iii) risk-free interest,
- (iv) debt level, and
- (v) time period.

The proxies used for asset values and asset volatilities are equity values and equity volatilities; for the risk-free interest, the present study used the 90-day treasury bills; the debt levels came from the financial statements made up of 50% of long-term debt plus current debt; and all this is calculated over a time period of one year. This is in line with the Merton equation. This aim in this formula is to determine the distance to default and then calculate the probability of default.

This model managed to identify nine distressed companies, 14 depressed and 77 healthy companies. This is a 99% prediction as the study contained eight distressed, 14 depressed and 78 healthy companies. The one healthy company was actually misclassified as distressed. The model also tended to classify certain healthy companies as depressed and depressed as healthy. While this observation points to type I and II errors, this is expected as there is a very thin line between depressed and healthy companies. This observation is further confirmed in section 7.6 where trend analysis is discussed. A close link between these two financial states is noticeable.

Research objective (iii) is aimed at checking whether combining the basic and Merton models in developing a hybrid model would improve the accuracy prediction results. This was done by allocating the distance to default score as an additional variable to the basic model. The prediction results containing the prediction accuracy was analysed, which reflected a 100% correct prediction for all financial states. This result serves as a confirmation that hybrid models tend to produce better prediction accuracies that individual models.

It can be observed that each set of variables communicate a certain angle of the company's financial position. In that, the fundamental data communicate relevant internal affairs about the company, whilst the market and macroeconomic indicators communicate relevant external imperatives about the company. When these are combined the model is expected to perform better as it tends to communicate more comprehensively.

Research objective (iv) seeks to establish which model performs better between the basic and Merton models. This objective is in line with the hypothesis that said: the financial distress model based on Merton technique produces results that are within 10% of the results of a financial distress model based solely on fundamental variables, and derived through the logistic analysis. The results indicate that the basic model achieved a maximum of 90% considering the five-year average, while the Merton model achieved 99% resulting in a 9% percentage variance. This confirms the hypothesis and achieves the research objective.

The last research objective (v) was to explore the gains (if any) realised from developing a hybrid model. Even though the results of the hybrid model reflect a marginal improvement, this model should be considered more than individual models. This is on the basis that they contain variables that communicate comprehensively.

9.4 CONTRIBUTION TO THE EXISTING RESEARCH

The contribution made by the present study is that the basic model in itself is a hybrid in nature as it combines fundamental, market and macroeconomic variables. The objective achieved in developing such a model is the enhancement of prediction accuracy in combining two sets of variables. Another contribution is the exploration of the Merton model theory and going further to develop this model using Johannesburg Stock Exchange companies. The Merton model produced much better results than the basic model identifying 99% of the companies in their correct category. The present study further develops a unique hybrid model that incorporates the distance to default factor that is derived from the Merton model with the fundamental data. This combination yield even better results than the Merton model identifying 100% of the companies in their categories.

9.5 AREAS FOR FUTURE RESEARCH

There are good academic reasons for such studies being based on companies that are listed on the stock exchange. Among these reasons, are the credibility and reliability of data, the availability of data, and the ease of reference and comparison with similar global research. Therefore, the selected companies in the present study are limited to those companies that were listed on the Johannesburg Stock Exchange between 2005 and 2014. In compiling the list of distressed companies, the study relied on the Johannesburg Stock Exchange list of suspended or delisted companies. However, these companies were further analysed to detect the reasons that are viewed to be related to financial distress. Companies that delisted for other reasons were not part of the population.

Another identified area for future research is the uniformity on the utilisation of independent variables. Many research papers tend to rely on certain common ratios. The present study, much like those research papers, picked commonly used ratios that were found to be successful in previous studies. The choice of statistical software was also informed by existing research, with the present study relying on the SPSS package. Similarly, existing research also assisted in selecting data sources. The present study used the INET BFA database to extract all financial and market ratios. It also relied on the South African Reserve Bank website for macroeconomic indicators. The advantage that comes with utilising data from the INET BFA database is that the researcher does not have to calculate all the ratios from the start. The inherent risk in calculating all ratios using Microsoft Excel is the potential room for error, but moreover using the formula that is not industry acceptable in calculating a particular ratio.

The future development of financial prediction studies could deal with the prediction of only companies that have not failed. The intention would be to identify companies that are likely to experience financial distress in the near future. The accuracy can only be tested at a later stage to check whether the company did actually experience financial distress. Current studies have the advantage of already knowing which companies have or have not failed. Regarding the statistical methodology, the South African academic community still needs to explore the performance of neural networks in predicting financial distress. While this methodology is widely used globally, not enough research is found in South Africa.

9.6 CHAPTER SUMMARY

This chapter provides the conclusion of the entire study. It embarks with the theoretical background of this study and moves to test whether the research objectives have been met given the empirical study findings. This chapter also highlights the contributions made to existing academic knowledge base and most importantly it concludes with the suggested areas for future research.

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APPENDIX A – LIST OF COMPANIES

List of companies				
Nictus Ltd	The Spar Group Ltd	Cashbuild Ltd	African Oxygen Limited	Bowler Metcalf Ltd
Cullinan Holdings Ltd	Super Group Ltd	Howden Africa Hldgs Ltd	Avi Ltd	Astral Foods Ltd
Distribution and Warehousing	Combined Motor Hldgs Ltd	Clicks Group Ltd	Aeci Limited	Mr Price Group Ltd
Allied Electronics Corp	Barloworld Ltd	Metrofile Holdings Ltd	Tiger Brands Ltd	Oceana Group Ltd
Datatec Ltd	Iliad Africa Ltd	Nu-World Hldgs Ltd	Distell Group Ltd	Truworths Int Ltd
Aveng Group Limited	Pinnacle Hldgs Ltd	Value Group Ltd	Illovo Sugar Ltd	Italtile Ltd
Murray & Roberts Hldgs	Compagnie Fin Richemont	Metair Investments Ltd	Datacentrix Holdings Ltd	African & Over Ent Ltd
Basil Read Holdings Ltd	Imperial Holdings Ltd	Sasol Limited	Remgro Ltd	Eoh Holdings Ltd
Group Five Ltd	Mtn Group Ltd	Steinhoff Int Hldgs N.V.	The Foschini Group Limit	Hudaco Industries Ltd
Jasco Electron Hldgs Ltd	Masonite Africa Ltd	Naspers Ltd -N-	Trencor Ltd	Crookes Brothers Ltd
Verimark Holdings Ltd	Elb Group Ltd	Woolworths Holdings Ltd	Caxton Ctp Publish Print	Netcare Limited
Mustek Ltd	Shoprite Holdings Ltd	Cargo Carriers Ltd	Argent Industrial Ltd	Transpaco Ltd
Bidvest Ltd	Grindrod Ltd	Sovereign Food Inv Ltd	Invicta Holdings Ltd	Famous Brands Ltd
Cognition Holdings Ltd	Adaptit Holdings Limited	Aspen Pharmacare Hldgs L	Rex Trueform Cloth Co Ld	Mediclinic Internat Ltd
Winhold Ltd	Astrapak Limited	Nampak Ltd	Ppc Limited	JCI Ltd
Onelogix Group Ltd	Spur Corporation Ltd	City Lodge Hotels Ltd	Omnia Holdings Ltd	Beget Holdings Ltd
Zaptronix Ltd	Sherbourne Capital Ltd	Sherbourne Capital Ltd	Bell Equipment Ltd	Massmart Holdings Ltd
Intertrading Ltd	Ardor SA Ltd	Mobile Industries Ltd	Comair Limited	Pick N Pay Holdings Ltd
Telkom Sa Soc Ltd	Spanjaard Limited	Reunert Ltd	Sun International Ltd	Sabmiller Plc
Delta Emd Ltd	Rcl Foods Limited	Advtech Ltd	Tsogo Sun Holdings Ltd	Phumelela Game Leisure