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# A classic statistical model developed towards predicting financial distress

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A research project handed in to the Gordon Institute of Business Science, University of Pretoria in partial fufillment of the requirements for the degree of Masters in Business Administration.

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## Abstract

To date there has been significant research on the topic of financial distress prediction, due to its relevance to various stakeholders. Beaver (1966), Altman (1968) and Ohlson (1980) are generally regarded as the pioneers in this field of study, despite heavy criticism their models are widely accepted and used. Studies by Grice & Ingram (2001); Grice & Dugan (2001) and Sudarsanam & Taffler (1995) have shown that these models require to be updated regularly with new variables and coefficients due to various factors. This study proposes to add to the body of knowledge by developing a distress prediction model using a classic statistical method and financial ratios, calculated on published company data of organisations listed on the Johannesburg Stock Exchange.



## Keywords

Financial distress prediction; financial ratio analysis; Beaver; Altman Z-score

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## Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

Marrelie le Roux | Date

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# DEDICATION

To my best friend and husband Gerhard le Roux, you have been a inspiration to me with your relentless support. Thank you for all the cups of tea and encouragement during the past year. I love you dearly.

♥♥♥♥♥♥♥♥♥♥♥♥♥

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# 1 Introduction

The 2008 global financial crisis and the subsequent recession have created an increasingly tougher economic environment in which to conduct business. Globally, giants of industry received financial aid and those 'too big to fail' have failed.

South Africa has not been left unscathed as there have been several high-profile cases where organisations have filed for business rescue. These include Velvet Sky Aviation airlines in February 2012, the construction group Sanyati in July 2012, and 1Time Holdings in August 2012 (Bowman Gilfillan, 2012). Liquidation and insolvencies have seen a decreasing trend since the business rescue laws came into effect under the Companies Act 2008, in May 2011: they have decreased from 3 992 in December 2011 to 2 716 in December 2012 (Statistics South Africa, 2013); however there has been an increase in the number of companies that have applied for business rescue assistance, indicating the increasing level of distress experienced by organisations (Bowman Gilfillan, 2012; Du Preez, 2013).

In the current uncertain environment financial decisions and their impact on entities are more difficult, as illustrated in the previous paragraphs. Although, globally, entities seem to focus on corporate governance and ethics as a form of prevention of financial distress, the early prediction of distress is still crucial (Muller, Steyn-Bruwer, & Hamman, 2009). By predicting financial distress in an organisation, corrective management-led action can be taken in order to renew the organisation and avoid business rescue or liquidation, and investors and lending institutions can decrease their associated risk.

Owing to the importance of their prediction, financial distress and failure have provided a key topic of debate and research. To date the research has led to a number of prediction models, some using complex statistical processes and others relying on measures as simple as understanding the movement in one accounting ratio. There is however little consensus on the definition of financial distress, which techniques provide the highest accuracy or which input variables should be used. Each of these points will be discussed later on in the report.

## *1.1 Purpose of the study*

This study endeavours to develop a model to predict financial distress of companies which are listed on the Johannesburg Stock Exchange (JSE) using a selected classic statistical approach based on a proven historical track record and characteristics of financial information.

## *1.2 Context and significance of the study*

### 1.2.1 Awareness of distress

Research into the sources of decline and distress has been categorised into two groups: the group arising from external factors and the group resulting from internal factors. These two categories have been accepted in the two-stage model developed by Pearce & Robbins (1993). Pearce and Robbins (1993) indicated that the course of action which should be taken is strongly influenced by the cause of the organisational decline.

The external causes which research has shown to be causes of decline include environmental jolts (including subtle environmental changes), new and disruptive technological changes, demographic changes and competitor landscape changes (Pearce & Robbins, 1993; Trahms, Ndofor, & Sirmon, 2013). Internal causes of decline have been attributed to a misalignment between a firm, its resources and its environment, structural characteristics such as size and operating procedures, ineffective top management, and leadership (Pearce & Robbins, 1993; Trahms et al., 2013; Xu & Wang, 2009)

According to section 76(3) of the Companies Act 71 of 2008, directors have the responsibility of being accountable to stakeholders in a company and of acting in the best interests of the company at all times. While the causes themselves would be indicators of potential financial distress, these changes are often missed by management when making decisions. In order to be in a position to fulfil these duties, directors need to be aware of areas of concern (GTI Corporation example to follow) and of the impact which their current decisions will have on the entity.

Financial decisions are shrouded in risk and uncertainty due to their nature and possible impact. By providing tools to gain insight into the prediction of the general health of the organisation, some of the risk and uncertainty is reduced (Alireza, Parviz, & Mina, 2012)

Failure prediction models are among such tools that can be used to assist businesses in identifying problems and the possible impact of complications stemming from decisions which, if remedial action were not implemented, could result in failure (Altman, 2000). Failure prediction models can also be used in the assessment of strategic plans, providing organisations with the opportunities to revise plans in order to avoid distress (Samkin, Low, & Adams, 2012). The closer these model assessments and predictions are to reality, the better the action which can be taken (Alireza et al., 2012).

A number of these accounting-based prediction models have been developed, the best-known being those of Beaver (1966), Altman (1968), and Ohlson (1980), all of whom used accounting-based statistical models. An American study conducted in 2007 which aimed to identify the metrics that provided the most insight into return to shareholders and financial health, identified the Altman Z-score (Altman, 1968; Altman, 2000) as the most significant performance metric (Calandro, 2007) . A case study done more than 30 years ago by Altman (1975) and the CEO of GTI Corporation, James K La Fleur, illustrated the impact that the Z-score can have as a strategic and performance management tool. To summarise, the entity GTI, an electronics components manufacturing firm, experienced significant growth in its earnings per share ('EPS') figures but, despite this, it struggled to repay its debt obligations. La Fleur (1975) tracked GTI's changing Z-score and compared that to the increasing EPS; Altman and La Fleur concluded that the change in Z-score better reflected the entity's financial position than did the EPS (Altman & La Fleur, 1981).

Despite being criticised, models using financial ratios based on financial statement information still constitute a widely accepted tool for predicting financial distress. They are believed to be suitable because they are simple to use and understand; information is readily available and the models have proven predictive capabilities (Alireza et al., 2012; Manisha, 2012).

### 1.2.2 Significance of the study

Financial models are widely "used in a variety of business situations involving prediction of bankruptcy and financial stress situations" (Grice & Ingram, 2001, p. 1). Commercial bankers use these models as part of the loan review process (Chen & Du, 2009; Grice & Ingram, 2001; T. Lin, 2009), while investment bankers use them as part of security and portfolio analysis (Alireza et al., 2012; Chen & Du, 2009; Grice & Ingram, 2001; T. Lin, 2009). Furthermore these tools have been employed as analysis tools by auditors to assess going concern abilities (Grice & Ingram, 2001; T. Lin, 2009), and as strategic management tools (Calandro, 2007; Grice & Ingram, 2001).

The study attempts to develop a simple financial prediction model using a classic statistical approach, which would alert all stakeholders to the potential financial distress.

### 1.2.3 Scope of the study

Failure and distress prediction is a dichotomous testing process. Generally speaking, there are four different types of approaches which can be used for this purpose: "classical statistical techniques, recursive partitioning analysis (or tree classification), neural networks, and genetic algorithms" (Ooghe & Balcaen, 2007, p. 35). This study focuses on the classic statistical techniques and models. Being a multilinear discriminant analysis (MDA), logistic regression and because of its simplicity, the univariate approach.

As highlighted earlier, a number of factors are essential, and do require consideration in the development of a model with predictive capabilities. These are the following:

- the definition of distress or failure
- the statistical method employed and
- the variables to be used

The study aims to develop a financial distress prediction model using a classic statistical method. The research is not aimed at defining what constitutes financial distress and failure or success, but rather at providing an indicator which leads up to financial distress, using the company-specific information of JSE listed entities. The model will not endeavour to incorporate non-financial information.

## *1.3 Defining financial distress*

Financial failure is a vast field to define; it appears that each study develops its own 'fit for purpose' definition and there is little overall consensus, while others fail to even propose a definition, relying on the readers' understanding of the occurrence (Pretorius, 2009). Some studies have defined financial failure as filing for bankruptcy (Altman, 1968; S. Lin, Ansell, & Andreeva, 2012; Ohlson, 1980; Wu, Gaunt, & Gray, 2010); others have viewed it as periods of consecutive negative earnings, structural changes to the organisation or delisting or a combination of thereof (Agarwal & Taffler, 2008; Balcaen, Manigart, Buyze, & Ooghe, 2012; Maricica & Georgeta, 2012; Trahms et al., 2013). As a result of the non-consensus on the definitions of financial failure and distress, the repeatability and use of current prediction models have significant limitations.

In his study of the definition of failure, Pretorius (2009) found that there are three groups of definition perspectives which are used in studies, namely decline focused definitions, failure focused definitions and turnaround focused definitions and, within each of these categories, there are various key characteristics of what would constitute the definition in that category. The description of the above-mentioned categories of definitions supports Cybinski's (2001) description of the concept of 'failure' and 'non-failure' as firms lying on a continuum instead of in two boxes marked 'failed' and 'non-failed', because there is no clear cut-off point between the two. Between the two extreme points on this line, one finds financial distress, which itself takes on numerous shapes and forms ranging from the point of health to decline, distress and eventually failure.

Financial decline and failure were defined by Pretorius (2009) as follows:
"Decline: A venture is in decline when its performance worsens over consecutive periods and it experiences distress in continuing operations. Distress is a natural precursor to failure.

Failure: A venture fails when it involuntarily [sic] cannot attract new debt or equity funding to reverse decline. Consequently it cannot operate under the current ownership or management. Failure is the endpoint of discontinuance and when it is reached judicial action commences [sic]."

Financial decline is the precursor to financial distress defined in section 128(1) of the Companies Act 71 of 2008:

"Financial distress":
"(i) it appears to be reasonably unlikely that the company will be able to pay all of its debts as they fall due and payable within the immediately ensuing six months; or
(ii). it appears to be reasonably likely that the company will become insolvent within the immediately ensuing six months"

A company in a position of distress as defined above, is allowed to file for business rescue in terms of section 129(7) of the Companies Act 71 of 2008 If unsuccessful the venture would be liquidated and deemed to have failed.

The above three definitions are 'series based', meaning that the definitions follow one another, based on the situation the entity finds itself in: decline, distress, failure.

In most studies, liquidating or filing for bankruptcy has been the most commonly used criterion for financial distress (Muller et al., 2009). Filing for bankruptcy or liquidating a business is a legal event influenced by business creditors and financiers in their attempt to recover outstanding debt (in creditor-orientated countries) or alternatively the legislation is designed to keep companies as going concerns, which is the case in the United States (Muller et al., 2009). The previous explanation is given to provide context to various reasons for filing for bankruptcy as an action which takes place despite the organisation's historically 'strong' financial health, and done as part of a strategy to eradicate rising debts or as a result of 'an act of God' which has crippled the organisation (Balcaen & Ooghe, 2006; Muller et al., 2009)

As is clear from the preceding paragraphs, defining financial distress for the purposes of this study is of utmost importance, in order to replicate the study in future as well as for increased usability of the predictor. It is also clear from the preceding that the action of liquidation is not always a true reflection of financial distress. Taking this into account, the definition of financial distress in this study is based on that of section 128(1) of the Companies Act 71 of 2008, financial distress:

> "(i) It appears to be reasonably unlikely that the company will be able to pay all of its debts as they fall due and payable within the immediately ensuing six months; or
> (ii) it appears to be reasonably likely that the company will become insolvent within the immediately ensuing six months."

The definition as stated above is still vague and allows for interpretation. To eliminate this, a single criterion is used for classification purposes, this being the current ratio. The current ratio is calculated as follows: current assets divided by current liabilities. The assumption is that a ratio of less than one to one will result in the organisation being unable to service its short-term liabilities, with resultant classification as being in financial distress.

Current assets and current liabilities are respectively defined by International Accounting Standards (IAS) as follows:
"Current assets are cash; cash equivalent; assets held for collection, sale, or consumption within the entity's normal operating cycle; or assets held for trading within the next 12 months. All other assets are non-current. [IAS 1.66]" (Deloitte, 2013); and
"Current liabilities are those expected to be settled within the entity's normal operating cycle or due within 12 months, or those held for trading, or those for which the entity does not have an unconditional right to defer payment beyond 12 months. Other liabilities are non-current [IAS 1.69]" (Deloitte, 2013).

South Africa uses IAS and the International Financial Reporting Standards (IFRS) in its reporting of company financial statements, making the above definitions standardised in terms of JSE listed company information. Further to this, the definition of financial distress allows for the study to be recreated, as well as to be usable in the determination of potential candidates for chapter six.

The purpose of this study is not to define the terms of what constitutes decline, distress or failure but, rather, to provide a predictor of organisational distress. By expanding the failure group to include organisations in distress and not remain focused on bankruptcy a more robust model can be developed (S. Lin et al., 2012).The words *decline, distress* and *failure* are used interchangeably in the research that follows; however what is important is that the organisational decline is contextualised in a predictor for financial distress.

# 2 Literature review

The literature review focuses on the main factors of consideration in developing a financial distress prediction model:

i. The classic statistical methods: a review of the evolution of ratio analysis, financial distress models and their related techniques by placing focus on the initial and better-known models in each category
ii. Financial information: a review of the characteristics of and criticism shrouding financial information
iii. Financial ratios as variables: a review of previous studies and the variables that were used

## *2.1 The history of financial analysis and distress predictors*

Ratio analysis is the process of identifying the financial strengths and weaknesses of a firm by establishing the relationship between items on the annual financial statements (Manisha, 2012). Various parties find ratio analysis – including investors, suppliers, customers and employees – relevant (Manisha, 2012). This was detailed earlier.

Researchers have been fascinated by the topic of financial distress and bankruptcy and have been predicting these events since the Industrial Revolution of America in the second half of the 19th century (Alireza, Parviz, & Mina, 2012). As companies' management of accounting matters became more scientific, the analysis of financial statements in terms of ratios became more widely used and key ratios were identified as indicators of potential success, one being the ratio between current assets and current liabilities (Alireza et al., 2012). This evolution of ratio analysis saw Winakor and Smith (1930) conclude in the 1930s that financial ratios provided an efficient method of predicting financial distress in an entity, supported by findings from literature made by Horrigan (1968) during this period.

### 2.1.1 Univariate model

A univariate model is the simplest of them all and does not require high levels of statistical knowledge. It is based on the principle of identifying a value for each individual ratio and then a cut-off point at which the ratio value discriminates between the two groups, falling into either one or the other. The approach does however make an assumption that there is a linear relationship between all measures and the 'failure' status (Ooghe & Balcaen, 2006).

The methodology in the study conducted by Beaver (1966) was univariate in nature, placing focus on individual signals of impending problems; viewed in isolation the ratios are often misunderstood or misinterpreted. As an example, an organisation with high profit margins or sales growth could be interpreted as doing very well; however their sales and profit might not be translating into cash, resulting in an extremely poor liquidity (cash) position. A univariate approach has the potential to isolate the 'most important' factors to consider and can act as a starting point to identify the root cause of a problem. While univariate analysis will not allow for a robust model, the process of univariate analysis can be applied for purposes of identifying the ratios which have strong discriminative capabilities.

***Beaver***

Beaver (1966) assessed the relationship between accounting information and business failure. A sample of 79 failed firms was identified for the study, using information from the Moody's Industrial Manual and a list provided by Dun and Bradstreet (an organisation focused on credit scoring). Failure was the term used in relation to those companies that have filed for bankruptcy (Beaver, 1966), meaning that the organisation could no longer afford to pay its creditors who called for liquidation of the organisation's assets. Beaver used a matched pair approach, matching the bankrupt firms with non-bankrupt firms in the same population, with a similar asset size and from the same industry.

The study identified 30 financial statement ratios, based on popularity, use in previous studies and association with a 'cash flow' concept (Beaver, 1966). Beaver concluded that the prediction of failure was the strongest when using the cash flow to total debt ratio; error predictions amounted to 13% in the first year prior to failure and 22% five years prior to failure (Beaver, 1966).

Viewed in isolation the ratio is of little meaning and therefore a benchmark, comparison or cut-off point is required to put the results into perspective, which is the standard work done in many cases by financial analysts to provide context for a company situation. In his study, Beaver (1966) highlighted the fact that the actual ratio number or ratio level could provide further insight into the probability of failure, meaning that the more it strays from the cut-off point for the two dichotomies, the greater the probability of failure or 'success'.

It is difficult to comprehend that one ratio on its own has the predictive power to indicate future financial distress or failure, without considering the organisation age, reputation, products, competitors, macroeconomic environment et cetera. However the intention of this study was to illustrate the usefulness and insights which could be gained from financial accounting information, and not to provide a single predictor of bankruptcy (Beaver, 1966).

A logical process of failure will commence when an organisation is no longer efficient in its operations, resulting in a decline in profitability; the declining profitability will impact liquidity and leverage as funders become unwilling to further fund the organisation, which ultimately leads to failure. Based on this premise and taking into account Beaver's definition of failure (bankruptcy), the debt to cash flow ratio would in theory be the best predictor of failure, as defined by Beaver (1966), since this would be a clear indicator of the organisation's inability to repay its debts. An argument could therefore be made that there were earlier signals provided by ratios which could have pointed to the inevitable bankruptcy to follow.

### 2.1.2 Multiple Discriminant Analysis

The basic principle of Discriminant Analysis (DA) is to determine whether two or more groups differ in terms of a mean variable; based on the difference in the mean variable, membership to a group is determined. Multiple Discriminant Analysis takes DA one step further by adding variables to the equation. The approach assumes a linear relationship between the various variables and a normal distribution (Pallant, 2011). The result of the linear equation which is derived categorises the sample into the various groups based on predefined cut-off points. The results are therefore not intuitively usable.

### *Altman*

The purpose of Altman's (1968) paper was an attempt to assess the quality of ratio analysis as an analytical technique, while the prediction of corporate bankruptcy was used for illustrative purposes (Altman, 1968). As indicated earlier, past studies were predominantly univariate in nature, placing focus on individual signals of impending problems (Beaver, 1966). However, such an isolated view of ratio analysis could result in misinterpretation and confusion. As a result Altman in 1968 was the first researcher to use an MDA approach incorporating a number of variables into a predictive model (Altman, 1968).

A matched pairs approach was used and the Group 1 sample was selected first. It comprised of 33 previously listed bankrupt firms, U.S. manufacturers which filed for bankruptcy under Chapter X of the National Bankruptcy Act during the period 1946 to 1965, with a mean asset size of $6.4million (Altman, 1968). The Group 2 sample of non-bankrupt firms was matched to Group 1 in terms of asset size, industry and timing of financial information available (Altman, 1968).

The 22 selected variables which were included in the study were identified, based on their popularity in previous literature, and potential relevancy to the study, as well as a number of 'new' ratios. The selection process used is at the heart of some of the strong criticism levelled against the model, because the process used was not based on theory (Agarwal & Taffler, 2008; Grice & Ingram, 2001). Although the criticism towards the selection process above does have elements of truth, there are indications that the variables used are of little consequence in the overall predictive power since the variables are correlated, as they are from the same set of financial information (Beaver, McNichols, & Rhie, 2005).

The ratios selected were classified into five ratio categories: liquidity, profitability, leverage, solvency and activity (Altman, 1968). From this original list five variables were selected, using criteria of statistical significance, inter-correlation, observations of predictive capabilities and analyst judgement (Altman, 1968).

The final discriminant function published by Altman in 1968, as the Altman Z-score, is as follows:

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

Where:

$X_1$ = Working capital / Total assets

$X_2$ = Retained earnings / Total assets

$X_3$ = Earnings before interest and tax / Total assets

$X_4$ = Market value of equity / Total liabilities

$X_5$ = Sales / Total assets

Index:

>2.99 = tend not to fail

1.81>2.99 = grey area

<1.81 = tend to fail

The score related to two distinct groups – bankrupt and non-bankrupt companies, he concluded: two thresholds. Z-scores higher than 2.99 companies would be regarded as financially healthy while a score lower than 1.81 would predict bankruptcy up to two years prior to failure (Altman, 1968). The model proved accurate in correctly predicting bankruptcy in 94% of the initial sample, and additional findings were that bankruptcy can be accurately (72%) predicted up to two years prior to actual failure (Altman, 1968).

Subsequent to the initial study, Altman enhanced the model to increase accuracy of prediction, developing the ZETA® model in 1977 – an enhanced Z-score model which could be deployed for use in manufacturing and non-manufacturing entities as well as privately owned companies (Altman, 2000). The commercially available ZETA® model appears to have superior performance when compared to the original Z-score (Altman, 2000) showing 96.2% accuracy one year prior to bankruptcy.

The Altman Z-score (Altman, 1968) has long been used in determining the financial health of organisations (Alireza et al., 2012; Chen & Du, 2009; Grice & Ingram, 2001) and, although it is widely used, there is compelling criticism against its generalised use as a bankruptcy predictor and distress indicator. Criticism relates largely to the use of financial information as well as to the limitations associated with the statistical method and sample size.

The study consisted of two populations both from the manufacturing industry, with underlying similarities of asset size and timing of financial information (Altman, 1968). Each of the two dichotomous groups was represented by a sample of 33 with a normal distribution. A statistical objection relates to the use of a relatively small data sample and to the data being matched pairs, which is deemed to be non-representative of the actual population (Grice & Ingram, 2001; Li & Rahgozar, 2012; T. Lin, 2009).

The generalised use of the model is also a point of criticism. Studies have shown that the predictive powers of the model do not transfer to industries and time periods other than those used in the development of the model: accuracy and effectiveness of the model tend to decline (Grice & Dugan, 2001; Grice & Ingram, 2001; Sudarsanam & Taffler, 1995). Other findings supported this notion, indicating that separate models should be developed to assess the financial health of unlisted firms and industries since the distributional properties of these entities are different (Agarwal & Taffler, 2007; Mensah, 1984; Samkin et al., 2012).,

Despite the criticism, recent studies have shown the effectiveness of the Altman model at predicting financial distress (Alkjatib & Al Bzour, 2011; Li & Rahgozar, 2012; Lifschutz & Jacobi, 2010; Wang & Campbell, 2010), while others have shown a significant decline in the effectiveness of the model when compared to the original results (Grice & Ingram, 2001; Lugovskaya, 2009; Ooghe & Balcaen, 2007). The decline in results has been ascribed to some of the above factors.

### 2.1.3 Logistic regression

Like MDA, logistic regression has the potential to categorise a sample or population into two or more categories, based on the characteristics of the independent variables. And, as an ordinary regression does, it provides a coefficient which measures the independent variable contribution to the variation in the dependent variable (Pallant, 2011).

The function representing logistic regression is as follows:

P(x)= 1 / [1+e – (b0 + b1 x X1 + b2 x X2+……bn x Xn) ]

Where: P(x) is the probability of distress for a firm bi is the coefficient for each independent variable.

While logistic regression gives each independent variable a coefficient 'b' which measures its independent contribution to variations in the dependent variable, the dependent variable can only take on one of the two values: 0 or 1 (healthy or distressed)(Pallant, 2011). What we want to predict from a knowledge of relevant independent variables and coefficients is therefore not a numerical value of a dependent variable as in linear regression, but rather the probability (P) that it is 1 rather than 0 (belonging to one group rather than the other). As with normal regression, it obtains a best fit line using the maximum likelihood of finding the function that will maximise the ability to predict the probability of the dependent variable (distressed or healthy) based on what we know about the independent variables (ratios) (Pallant, 2011).

### *Ohlson*

Ohlson (1980) employed conditional logit analysis in 1980 for his failure prediction model. The approach was followed in order to avoid some of the stumbling blocks which he had identified with the use of MDA – to be discussed in due course in the study. Logit analysis is similar to logistic regression, the difference being in interpretation –the coefficients of the logistic regression being the log odds referred to in logit analysis (Field, 2009)

The sample data used in developing the model included 105 bankrupt and 2 058 non-bankrupt firms from 1970 to 1976, the definition of bankruptcy being filing for Chapter X (Ohlson, 1980). In contrast to previous studies, assumptions on the timing of released information was incorporated and not gathered from Moody's as in previous studies, but from the 10K submission done by the organisations (Ohlson, 1980).

Ohlson (1980) used nine measures, concentrating on 'simplicity' as selection criterion in order to develop his model:

Ohlson= $-1.3 - 0.4X_1 + 6X_2 - 1.4\,X_3 + 0.8X_4 - 2.4X_5 - 1.8X_6 - 0.3X_7 - 1.7X_8 - 0.5X_9$

$X_1$ . SIZE= log (total assets/GNP price-level index). The index assumes a base value of 100 for

| | | |
|---|---|---|
| | | 1968. |
| $X_2$ | TLTA | Total liabilities divided by total assets |
| $X_3$ | WCTA | Working capital divided by total assets |
| $X_4$ | CLCA | Current liabilities divided by current assets |
| $X_5$ | OENEG | One if Total liabilities exceed total assets, zero otherwise |
| $X_6$ | NITA | Net income divided by total assets |
| $X_7$ | FUTL | Funds provided by operations divided by total liabilities |
| $X_8$ | INTWO | One if net income was negative for the last two years, zero otherwise. |
| $X_9$ | CHIN | =(NIt-NIt-1)/(│NIt│+│NIt-1│), where NIt is net income for the most recent period. The denominator acts as a level indicator. The variable is thus intended to measure change in net income. |

Percentages of 96.1 and 95.6 of entities were correctly classified as distressed one and two years prior to bankruptcy, respectively (Ohlson, 1980). Criticism of the model focuses on the fact that it did not incorporate market-based ratios or information (Ohlson, 1980) Furthermore the studies have shown that the generalisability of the model is limited to the industry referenced, and that the model is more useful in predicting financial distress than failure, as defined by Ohlson in different environments (Grice & Dugan, 2001; Ohlson, 1980)

***Zmijewski***

Basing his research on the performance of financial ratios that measured firm performance, leverage and liquidity in prior studies, Zmijewski selected these to develop his probit-based model for distress prediction (Zmijewski, 1984). The model was developed using 40 bankrupt and 800 non-bankrupt firms during the period 1972 to 1978. While past studies mostly used non-random sampling, this study employed random sampling to test the effect of choice-based samples and selection-sample bias (Zmijewski, 1984). The findings concluded that, although the results did show bias, it did not appear to affect the statistical interpretations or the overall classification rates (T. Lin, 2009; Zmijewski, 1984)

The function derived from the Zmijewski (1984) study:

$X= -4.3 - 4.5X_1 +5.7X_2 – 0.004X_3$

$X_1$ = Net income/ Total assets

$X_2$= Total debt/ Total assets

$X_3$= Current assets/ Current liabilities

### 2.1.4 Modern approaches

More recently work has been done to forecast financial distress and bankruptcy using artificial neural networks ('ANN'), a process which harnesses the computing power of technology in the prediction of financial distress variables (Chen & Du, 2009; T. Lin, 2009).

The Nobel-prize-winning Black & Scholes model was developed by Fischer Black and Myron Scholes. The model is used to price options and, in this capacity, can be used to determine financial decline. The market-information-based model is deemed to provide better insight and accuracy when applied to determining future distress (Li & Rahgozar, 2012; Vassalou & Xing, 2004). The nature of this market-based prediction model, together with the information it requires, result in its being used to forecast distress of listed entities rather than privately owned enterprises.

### 2.1.5 Summary

Despite the criticism, accounting-based financial bankruptcy and distress models are still widely researched (Alireza et al., 2012; Alkjatib & Al Bzour, 2011; Bardia, 2012; Cohen, Doumpos, Neofytou, & Zopounidis, 2012; Li & Rahgozar, 2012; Lifschutz & Jacobi, 2010; S. Lin et al., 2012; Lugovskaya, 2009; Samkin et al., 2012; Tomas & Dimitric, 2011; Wang & Campbell, 2010) and used. This is possibly due to these models being simpler and their results easier to interpret (Alireza et al., 2012). Despite the research, there is still very little consensus on the best statistical approaches to use, and results of the studies are mixed.

## *2.2 Financial distress and its multiple dimensions*

As highlighted earlier, financial health and distress should be viewed on a continuum (Cybinski, 2001) and not as a dichotomous dataset, which, in many studies, fails to acknowledge and incorporate the multi-dimensions of the reality of financial distress

(Balcaen & Ooghe, 2006). Confirming this, Samkin et al. (2012) state that statistical models fail to emphasise the importance of non-financial factors and the effect that these have on distress prediction. Tomas & Dimitric, (2011) explain these statements as follows: financial distress indicators should not be viewed in isolation when determining distress, but should take into account the cyclical and macroeconomic changes which result in systematic risk, which impacts the volatility of business cash flow.

In support of the above, the financial prediction models – specifically MDA (Altman Z-score) – are assumed to be stable for various economic conditions over time, such as inflation, recessionary environment, interest rates and so on, while research has shown that the accuracy and structure of the model changes over time (Grice & Ingram, 2001; Mensah, 1984; Sudarsanam & Taffler, 1995). Furthermore, studies have found that the predictive powers of these models are not transferrable to industries and time periods other than those used in the development of the model: the accuracy and effectiveness of the model tends to decline (Grice & Ingram, 2001; Grice & Dugan, 2001; Sudarsanam & Taffler, 1995).

The researcher does not refute the importance of the external environment in the prediction of distress: it is with this reasoning that the research is being conducted and an 'updated' model developed. Logically, there is a correlation between the external environment and distress, as supported by the above. However, while these realities might not be captured explicitly in an accounting ratio model, they are captured implicitly, since the impact of these would be incorporated in the financial results of an organisation.

## *2.3 Financial information*

At the heart of the prediction models is the financial information which is used. The age-old proverb of 'garbage in garbage out' also rings true in this situation (Huang, Tsai, Yen, & Cheng, 2008; Maricica & Georgeta, 2012). Quality of financial information, changes in accounting standards, and manipulation of data have the potential to influence model results. The following section reviews the leveraged criticism of the use of financial statement information for the purpose of financial distress models.

### 2.3.1 Historical information

Since accounting-based models use financial statement information which is essentially backward looking, the suggestion is that these models do not have predictive capabilities (Gharghori, Chan, & Faff, 2006; Li & Rahgozar, 2012). Furthermore, financial statements are prepared on a going-concern basis; firms are presumed not to file for bankruptcy, which is inconsistent with the forward-looking measure (Li & Rahgozar, 2012) . To counter these arguments and as previously highlighted, financial distress which leads to failure is not a sudden event, since there is a period of decline, followed by distress and ultimately failure, if corrective action is not initiated. The period of decline and distress should therefore be captured in the financial information (Agarwal & Taffler, 2008). The focus of this study being more towards the period preceding the point of distress known as the period of decline, the assumption above is still applicable.

### 2.3.2 International Accounting Standards

The purpose of ‘standardised accounting statements’ and additional disclosures in the financial statements of organisations is to ensure that the information is useful and relevant to investors and other users. With more disclosure and the goal of IAS and IFRS being greater transparency and standardisation, one can deduce that the quality of financial statement information and its predictive capabilities should be enhanced.

Samkin et al. (2012) investigated the collapse of financial services entities in New Zealand, and found significant changes in the classification levels in specifically the Altman Z-score, with a change in accounting policies from New Zealand Generally Accepted Accounting Practice to IFRS. Changes in accounting statements and policies over the last 47 years have been immense, specifically in terms of fair value accounting and the importance of intangible assets et cetera – all areas which play a significant role in the financial health of an organisation and which could allow for manipulation (Beaver et al, 2005).

The evolution of accounting standards towards a fair value focus, has allowed for a perceived increase in the level of discretion entering financial statements in the form of value of intangible assets et cetera.  These changes could in turn allow for the manipulation of financial and accounting data, which can influence the accuracy of a ratio and ultimately a financial prediction model's score (Agarwal & Taffler, 2008; Cohen et al., 2012; Mensah, 1984).

Manipulation of financial and accounting data would be management led and would therefore indicate that management is aware of signs of decline or have overpromised to investors. Whatever the reason for the manipulation, a rational person could assume that, because the financial information as disclosed in the annual financial statements is by section 30(2) of the Companies Act 71 of 2008 required to be audited, they are not manipulated and fairly represent the financial position of a listed entity (public company). Even though the contrary has occurred in the past, Enron can be used as an example. Trust is required.

### 2.3.3 Double entry system

The double-entry system of accounting will in theory ensure that window dressing of accounts or change in accounting policies will have minimal effect on ratios measured (Agarwal & Taffler, 2008). However, just as with any measure, if it is known, it can be manipulated. "Show me how you will measure me and I will show you how I will behave." (Goldratt, 1990 p.26) To this end, the importance of the cash flow statement plays a role since these figures are far more difficult to manipulate.

### 2.3.4 Outdated information

Another criticism of financial statement information is that, while it is historical-looking, in many cases it is 'outdated': companies have a six-month period post year end to release annual financial statement (Johannesburg Stock Exchange, 2014). Timelines of financial information are crucial and could influence the results of a financial model. In addition to this the argument can be made that, viewing only company-specific financial information in isolation, without taking into account macro-economic factors, and industry and competitor considerations, could cause confusion. However, market-related company data have already absorbed underlying financial information as well as containing all recent publicly available information. The assumption can therefore be made that, by including additional market-related information in the variables, the predictive capabilities of a distress model would be increased because it contains the most recent associated financial, industrial and economically available information relating to a company (Agarwal & Taffler, 2008; Campbell, Hilscher, & Szilagyi, 2008; Vassalou & Xing, 2004).

Despite the above factors, the financial statement information provided by companies is the only company-specific information which is available to the public, and trust should be placed in management that the information accurately reflects the position of the company. Therefore the use of this information is key to the development of a distress predictor model.

### 2.3.5 Summary

Although an argument can clearly be made against the use of financial statement information, it is the only true reflection of an organisation's performance which is available to the public and the only form of information which summarises the performance of a company in a given period of its management.

## *2.4 Financial ratios as variables*

Accounting ratio-based models are typically built by data mining large numbers of ratios and assigning weights to them, based on a sample of failed and non-failed firms. Findings indicate that the relationship between financial ratios and financial distress changes over time (Grice & Ingram, 2001; Sudarsanam & Taffler, 1995), which necessitates the update of the statistical models used for purposes of predicting financial distress. This supports the proposed study.

The numbers of variables which have been used in distress (as defined by the various studies) prediction models in the past are enormous. Ratio-based financial distress and bankruptcy models focus on three key areas: profitability, cash flow generation, and leverage (Beaver et al., 2005). In most of the preceding studies an empirical approach was used to identify the relevant variables to be featured, and this process was another object of the major criticisms of past studies.

Beaver et al. (2005) pointed out that the combinations of variables or ratios which are selected in the various studies have little influence on the overall predictive capabilities of the model since the financial variables are correlated; Altman in his 2000 report contended that these correlations are of little consequence in a statistical approach and that the influence and insight which each of the variables has in terms of predicting the level of distress is of far more importance (Altman, 2000).

A review of a number of previous studies on predictive models was conducted in order to identify those ratios which were frequently used as well as to highlight the accuracy of the various statistical methods mentioned. These are reflected in Table 1
Summary of predictive models developed in the past.

Table 1
*Summary of predictive models developed in the past*

| Author | Method | Sample size | Variables | Predictive accuracy (1yr) |
| --- | --- | --- | --- | --- |
| (Beaver, 1966) | Univariate analysis | 79 “Distress” and 79 “Healthy” | 1. Cash flow /Total debt<br>2. Net income / Total assets<br>3. Total debt / Total assets<br>4. Working capital / Total assets<br>5. Current ratio<br>6. No credit interval | 87% |
| (Altman, 1968) | MDA | 33 “Distress” and 33 “Healthy” | 1. Working capital /Total assets<br>2. Retained earnings/ Total assets<br>3. EBIT/Total assets<br>4. MV of equity/BV of debt<br>5. Sales/Total assets | 95% |
| (Deakin, 1972) | MDA | 23 “Healthy” and 11 “Distress” | 1. Cash flow/Total debt<br>2. Net income/ Total assets<br>3. Total debt/Total assets<br>4. Current assets/Total assets<br>5. Quick assets/Total assets<br>6. Cash/Total assets<br>7. Working capital/Total assets<br>8. Current assets/Current liabilities<br>9. Quick assets/Current liabilities<br>10. Cash/Current liabilities<br>11. Current assets/Sales | 87% |
| (Ohlson, 1980) | LR | 2058 “Healthy” and 100 “Distress” | 1. Total liabilities / Total assets<br>2. Working capital / Total assets<br>3. Current liabilities / Current assets<br>4. Net income / Total assets<br>5. Cash flow from operations / Total liabilities<br>6. Change in net income<br>7. Log (Total assets / GNP deflator) | 96% |

| Author | Method | Sample size | Variables | Predictive accuracy (1yr) |
|---|---|---|---|---|
| (Zmijewski, 1984) | Probit | 800 “Healthy” and 40 “Distress” | 1. Net Income/ Total liabilities<br>2. Total liabilities/ Total assets<br>3. Current assets / Current liabilities | |
| (Platt & Platt, 1991) | LR | 182 “Healthy” and 182 “Distress” | 1. Cash flow / Total assets<br>2. Net fixed assets / Total assets<br>3. Total debt / Total assets<br>4. Short term debt / Total debt<br>5. Sales growth<br>6. Industry output x Cash flow to sales<br>7. Industry output x Total debt / Total assets | Period 1: 80.5%<br>Period 2: 86.5%<br>Period 3: 80% |
| (Laitinen, 1991) | MDA | 40 “Healthy” and 40 “Distress” | 1. Return on investment<br>2. Rate of growth of assets<br>3. Net sales/Total assets<br>4. Cash flow/Net sales<br>5. Total liabilities/Total assets<br>6. Current assets/Current liabilities | c.90% |
| (Thorley Hill, Perry, & Andes, 1996) | Event History | 257 firms in any given year | 1. Cash/Total Assets<br>2. Income before extraordinary items/ Total assets<br>3. Total liabilities/ Total assets<br>4. Natural log of sales<br>5. Qualified or unqualified audit opinion | - |
| (Beaver, McNichols, & Rhie, 2005) | LR | 544 “Healthy” and 4237 “Distress” | 1. Return on assets<br>2. Earnings before depreciation, interest and tax / Total liabilities<br>3. Total liabilities / Total assets | In sample :91%<br>Out of sample: 86% |
| (Pompe & Bilderbeek, 2005) | MDA | 1500 “Healthy” and 476 “Distress” | 1. Cash flow/ Total assets<br>2. Added value/Total assets<br>3. Income taxes/Added value<br>4. (Investments + cash financial debts)/Current assets<br>5. Trade receivables/ Total assets<br>6. Equity/Total assets<br>7. (Reserves+accumulated profit)/Total assets | 80% |

| Author | Method | Sample size | Variables | Predictive accuracy (1yr) |
|---|---|---|---|---|
| (Agarwal & Taffler, 2007) | MDA | 232 “Distressed” | 1. Profit before tax/ Current liabilities<br>2. Current assets/ Total liabilities<br>3. Current liabilities/ Total assets<br>4. Non credit interval | 96%<br>*Secondary test of ability |
| (Pindado, Rodrigues, & de la Torre, 2008) | LR | 1 583 US companies & 2 250 G7 companies of which 4.1% & 7.6% “Distressed” | 1. Earnings before interest and tax / Replacement value of total assets *<br>2. Financial expenses / Replacement value of total assets *<br>3. Retained earnings / Replacement value of total assets *<br>*Replacement value of tangible fixed asses + Total assets book value – Book value of tangible fixed assets | 87% (mean value correct classification over a period) |
| (Muller et al., 2009) | MDA, LR | MDA 648 “Healthy” and 148 “Distress”<br>LR 648 “Healthy” 112 “Distress” | 1. Log (total assets/GNP deflator)<br>2. Total cash/Total liabilities<br>3. Equity/Total liabilities<br>4. Accounts receivable/Sales<br>5. Working capital/ Sales<br>6. Profit after tax/ Sales<br>7. Cumulative profit for the last three years/ Cumulative sales for the last three years<br>8. Cash flow from operating activities /Sales<br>9. Cumulative cash flow from operating activities for the last three years /Cumulative sales for the last three years<br>10. Cash flow from operating activities / Total liabilities<br>11. Cumulative cash flow from operating activities for the last three years / Total liabilities<br>12. Cash flow from financing activities / Total liabilities<br>13. Cumulative cash flow from financing activities for the last three years / Total liabilities | MDA 68% LR 83.5% |

| Author | Method | Sample size | Variables | Predictive accuracy (1yr) |
|---|---|---|---|---|
| | | | 14. Cash flow from investing activities / Total liabilities<br>15. Cumulative cash flow from investing activities for the last three years / Total liabilities | |
| (T. Lin, 2009) | MDA, LR | | 1. Total debt/ Total assets<br>2. Market value of equity/ Book value of total debt<br>3. Sales/ Total assets<br>4. Current Assets / Current liabilities<br>5. Income before tax, interest and depreciation / Total assets<br>6. Retained earnings/ Total assets<br>7. Gross profit/ Net sales<br>8. Bad debt expenses / Net sales<br>9. Cash from operations/ Current liabilities<br>10. Interest costs/ Average borrowings<br>11. Growth rate of gross profit<br>12. Growth rate of income before tax<br>13. Growth rate of Equity<br>14. Growth rate of depreciable assets<br>15. Interest costs/ Net income + Interest expenses x (1- tax rate)<br>16. Debt / Equity<br>17. Contingent liabilities/ Equity<br>18. Net sales/ Average receivables<br>19. Cost of goods sold/ Average inventory | MDA 28.95%<br>LR 89.47% |
| (Lugovskaya, 2009) | MDA | 260 “Healthy” and 260 “Distress” | 1. Cash/Current liabilities<br>2. Current asset/ Current Liabilities<br>3. (Cash + Short term Debtors)/Current liabilities<br>4. Return on Assets<br>5. Cash / Total assets | 68.1% |

| Author | Method | Sample size | Variables | Predictive accuracy (1yr) |
|---|---|---|---|---|
| (Wu et al., 2010) Multi period LR and Hazard model all with expanded set of variables | MDA, LR | 49 724 "Healthy" and 887 "Distress" | 1. Earnings before interest and tax /Total assets<br>2. Working capital/ Total assets<br>3. Total liabilities divided by market value of total assets<br>4. Total liabilities/ Market value of total assets<br>5. Change in Net Income<br>6. Various market and diversification indicators | 89.22% |
| (Alireza et al., 2012) | MDA | 56 "Healthy" and 35 "Distress" | 1. Current asset flow<br>2. Inventory development<br>3. Percentage of assets<br>4. Equity/ Total liabilities<br>5. Equity / Long term liabilities | 94% |
| (Astebro & Winter, 2012) | LR | 299 "Healthy" and 77 "Distress" | 1.Total sales<br>2.Cash/Total assets<br>3.Total liabilities/ Total assets<br>4.Current assets/ Current liabilities<br>5.Net income/Total assets<br>6.R&D expenses/Total sales<br>7.Intangible assets/Sales | - |

| Author | Method | Sample size | Variables | Predictive accuracy (1yr) |
|---|---|---|---|---|
| (Maricica & Georgeta, 2012) | Univariate | 43 "Healthy" and 20 "Distress" | 1. Return on assets<br>2. Return on equity<br>3. Total assets<br>4. Total sales<br>5. Market capitalisation<br>6. Self-financing capacity<br>7. Gross profit<br>8. Current assets/ Current liabilities<br>9. (Current assets- Inventory)/Current liabilities<br>10. Change in net working capital<br>11. Change in working capital<br>12. Total liabilities/Total assets<br>13. Long term liabilities/Equity<br>14. Operating profit/Total assets<br>15. EBITDA/Interest<br>16. Cash flow / Total liabilities<br>17. Interest / Total liabilities<br>*note a comprehensive list | Significant mean differences |

## 2.5 Conclusion

The classic statistical models have been widely used in the development of corporate failure prediction models, the univariate, MDA and logistic regression approaches all falling into this category. The approaches all have the commonality of classifying a firm within a failing or distressed category.

The "principal aim of a classic statistical model is to summarize information to determine whether a firm's profile more closely resembles the profile of a failing firm or that of a non-failing firm" (Ooghe & Balcaen, 2007, p. 77). Judging from a review of past models and findings in a South African study, it is still unclear what the best statistical approach is when constructing a financial distress prediction model (Muller et al., 2009). Balcaen & Ooghe (2006) propose that this decision is best left to the researcher and the intended study.

Accounting ratio based models do not provide an explanatory theory of failure or success, but rather a pattern recognition device akin to a thermometer used by a doctor (Agarwal & Taffler, 2007). The models aim to aggregate the effects of various individual indicators into a single performance measure, using the principle that the whole is more than the sum of its parts (Agarwal & Taffler, 2007). This research is not focused on the reasons for financial distress and does not propose that the contextual information should be ignored, but rather contends that this information should be incorporated and considered in conjunction with the results of a distress predictor in the course of decision making.

# 3 Research question

The literature study has illustrated the potential usefulness of the classic statistical financial prediction models as well as the confusion relating to their generalised use. As the literature findings illustrate, there is a relationship between financial ratios and financial distress – although not causal – and that these change over time (Grice & Ingram, 2001; Sudarsanam & Taffler, 1995). The associated reasons are not limited to the industrial and statistical methods used but include the impact of changes on financial reporting (Lugovskaya, 2009).

Studies have shown that new models should be developed and that merely updating coefficients of the current models does not reflect the current financial dimensions and profiles of companies (Agarwal & Taffler, 2007; Mensah, 1984; Samkin et al., 2012)

## *3.1 Proposition*

The study proposes to utilise a classic statistical method to develop a distress prediction model which can predict financial distress in the South African context as defined in this study. The definition of distress used for the model is in line with section 128(1) of the Companies Act 71 of 2008.

There is an extensive body of literature endeavouring to ascertain which of the classic statistical modelling techniques have greater predictive success, and the studies reach mixed conclusions (Muller et al., 2009; Wu et al., 2010). Owing to the lack of consensus and clarity on the subject, and since there appears to be no superior modelling method for failure prediction (Balcaen & Ooghe, 2006; Ooghe & Balcaen, 2007), the selection of a modelling technique is best left to the researcher. To guide researchers in their selection decision, Balcaen & Ooghe (2006) did state that there is evidence indicating that simple modelling methods do produce greater accuracy, while the more complex techniques yield only small marginal improvements in the model accuracy.

As two dichotomous groups are being used, logistic regression is preferred over MDA, this as logistic regression does not assume a linear relationship between the dependent and independent variables (Ooghe & Balcaen, 2007). Secondly the independent variables need not be normally distributed or linearly related or of equal variance within each group (Ooghe & Balcaen, 2007) and are easier to interpret. In support of a logistic regression statistical approach Barnes (1982) made the following statement "Financial ratios are not normally distributed and skewness exits" (Barnes, 1982 p.51). Furthermore there is a view that In general LR is far less demanding than MDA analysis (Muller et al., 2009; Ooghe & Balcaen, 2007).

Based on the preceding findings this study proposes to develop a classical statistical model using a logistic regression technique in the determination of a revised failure prediction model.

In order to develop the model a number of hypothesis will be constructed to determine to what extent the various independent variables (financial ratios) which will be selected discriminate between the two categories of organisations, those deemed as Distressed ("D") and those deemed Healthy ("H"). A non-parametric approach will be used in determining if there is a significant discrimination between distressed and healthy organisations variables. For each variable ("R"):

$R_n$

$H_0$: There is no statistically significant difference in the Mann Whitney U results of H and D organisations

$H_1$: There is a statistically significant difference in the Mann Whitney U results of H and D organisations

$H_0$ states that for variable n the results of a Mann Whitney U test does not significantly discriminate between H and D organisations.

$H_1$ states that for variable n the results of a Mann Whitney U test does significantly discriminate between H and D organisations.

# 4 Research methodology

## 4.1 Introduction

The research conducted is loosely based on that of Altman who pioneered the introduction of statistical models in the prediction of financial distress. “Research methodology considers and explains the logic behind research methods and techniques” (Welman, Kruger, & Mitchell, 2005, p. 2) Based on this definition of research methodology, the purpose of this chapter is to describe the logic behind the techniques that were used to test the proposition outlined in chapter 3, as well as the methods imposed to gather and analyse the research data for the proposed study.

## 4.2 Methodology

The research to be conducted is causal and predictive in nature: causal since there are a number of variables which are used to predict the effect; and predictive because, while the true cause of distress is not determined or explained by the variables being used to predict it, past studies show that variables do have predictive powers, as illustrated in chapter two.

The research was conducted using a quantitative design, based on sampled data specified below; information will be factual and numerical in nature. The quantitative design was selected as it was best suited to the nature of the information.

The basic steps which were used for the research analysis were:

i. Data were collected on the basis of the determined population and the population was allocated – the basis of the predetermined definition – to the categories of *healthy* or *distressed*.
ii. The 19 financial ratios were calculated as independent variables for the periods preceding the distress.
iii. Data were analysed to determine the statistical approach to be used to establish the probability function.
iv. Suitable variables were selected for the model.
v. The probability function was determined.

## 4.3 Unit of analysis

The units of analysis were the JSE-listed organisations in the Consumer Discretionary and Consumer Staples sectors for the period 2000 to 2012.

### 4.3.1 Data collection

Financial information from JSE-listed entities was used as data since the financial statements are publicly available from their date of listing. The McGregor BFA database was used as source of the financial information, and financial statements (*statement of financial position*, *income statement* and the *cash flow statement*) were used to calculate the variables. In addition, the relevant average share price was used where required.

### 4.3.2 Standardised financial information

The question was raised as to whether standardised financial information should be used or, alternatively, the published financial information. In terms of section 29(1) of Companies Act 71 of (2008) the financial position of the company must "present fairly the state of affairs and business of the company, and explain the transactions and financial position of the business of the company; show the company's assets, liabilities and equity, as well as its income and expenses, and any other prescribed information". These regulations lead to the assumption that the financial statements and disclosures to be used in the study are correct. It is worth noting that fair value accounting and interpretation of information have featured significantly in manipulation of financial information (Agarwal & Taffler, 2008; Cohen et al., 2012; Mensah, 1984)

Based on the above, the study used a standardised format of financial statements sourced from McGregorBFA; the standardisation process is derived by applying a number of fixed rules to the published financial statements in order to eliminate the effects of interpretive accounting standards and differing accounting policies. The standardisation of the financial statements is done by McGregor in order to make financial statements more comparative across various companies.

Financial information for a period of three years was incorporated in the study, year one being the year directly preceding distress.

## 4.4 Population Sector

Companies listed in the Consumer Discretionary and Consumer Staples sectors of the JSE in the period between 2000 and 2012 were considered, while their financial information included in the study reflected the period 1995 to 2012. The selection of these sectors was not a scientific one and will be discussed in the following paragraphs.

Not all listings on the JSE were used in the study, this being due to the structural differences in the entities which encompass the various sectors and, in some cases, industries. As an example, the metals sector which represents approximately R2.6 trillion on 31 December 2013 of the JSE market capitalisation, has its revenue and success strongly influenced by international market conditions such as the gold price, exchange rates et cetera. It is therefore difficult to compare a company within this industry with a financial services organisation.

Therefore the first step in the process of determining the population was to identify an industry or sector in which the study could be conducted. The Global Industry Classification Standard ('GICS') codes were used for company classification purposes. GICS is an industry taxonomy developed by MSCI and Standard & Poor's (S&P) for use by the global financial community. The GICS structure consists of 10 sectors, 24 industry groups, 68 industries and 156 sub-industries into which S&P has categorized all major public companies (MSCI, 2014). For the purpose of this study two sectors according to their GICS codes were selected, these being Consumer Discretionary (code 25) and Consumer Staples (code 30).

The selection of the sector was not a scientific one; it was based on a JSE requested report highlighting the fact that a total of 30 companies delisted from these two sectors from the start of 2004 to 2013, Consumer Discretionary (28) having the highest number of delistings. Consumer Staples (2) were added to the "population" to increase the number of potential distressed entities, thereby increasing the population and potential sample.

The point of delisting was used by earlier studies as a point of financial failure, this being the reasoning for using delistings as the starting point for this study. In support of this thought process, the sector also contains a vast number of industries reflected in Table 2 GICS sector and industry codes.

Table 2
*GICS sector and industry codes*

| Code | Sector | Subcode | Industry Groups |
|---|---|---|---|
| 25 | Consumer Discretionary | 2510 | Automobiles and components |
| | | 2520 | Consumer durables & apparel |
| | | 2530 | Hotels restaurants & leisure |
| | | 2540 | Media |
| | | 2550 | Retailing |
| 30 | Consumer Staples | 3010 | Food & drug retaining |
| | | 3020 | Food, beverage & tobacco |
| | | 3030 | Household & personal products |

Adapted from Wikipedia. (2013). Global industry classification standard. Retrieved December/01, 2013, from http://en.wikipedia.org/wiki/Global_Industry_Classification_Standard

Combined, the two sectors represented circa R3.8 trillion of the total JSE market capitalisation of circa R10.6 trillion at 31 December 2013. The result of the above was a total of 103 companies, over a period of 14 years, illustrating the limitation experienced in terms of the number of organisations which could be considered for this study.

The limitation of the study to a focus area or sector of the economy is in line with the studies conducted by Altman, (1968), Beaver (1966), Ohlson (1980) and a number of other relevant studies.

### 4.4.1 Dependent variable: Group classifications

The selection of the firms for the dichotomous groups was determined as follows: those firms in financial *distress* ('D') and those entities who were financially *healthy* ('H'). The definition which was used in determining financial distress for this study was that of section 128(1) of the Companies Act 71 of 2008, namely when a firm is in financial distress it:

"appears to be reasonably unlikely that the company will be able to pay all of its debts as they fall due and payable within the immediately ensuing six months; or

appears to be reasonably likely that the company will become insolvent within the immediately ensuing six months."

In order to effectively categorise the organisations between being distressed or not, the current ratio was used. This is calculated as current assets divided by current liabilities, a result of less than one meaning that the organisation will in all likelihood not be able to cover its short-term obligations.

### 4.4.2 Sub-population one: distressed firms

The initial period of financial information sourced, spanned a period of 17 years, being the standardised annual financial statements for the period 1995 to 2012. The period of 1995 to 2000 was included to ensure that the organisations which do fall into the distress category in 2000 have historic information and can be included in the study, endeavouring to predict distress three years prior to its occurrence.

Based on the definition of a distressed organisation (discussed earlier) the initial population was split into two categories: *healthy* organisations and *distressed* organisations. The distressed population numbered 47 organisations, with a first year of distress falling between 2000 and 2012, the balance of 46 being classified as healthy.

The eliminating factor being those entities with a history of less than five years and not missing values, this resulted in an ultimate sample of 28, with organisations experiencing their first year of distress during the period 2000 to 2012.

### 4.4.3 Healthy firms

The population of healthy firms numbered 46 and included firms which delisted during the period 2004 to 2013. It is not known if all these organisations are still in existence. While the study has no knowledge of the fate of the delisted entities, their exclusion from the distressed firm population means that, according to the study definition, they were not in distress during the period prior to their delisting.

Due to the small population available and the factors limiting the available data relating to the distressed firms, it did not make sense to limit the distressed organisation sample by any factors other than information available.

Ratios essentially express a relationship between two points, implying that the effect of size is decreased (Altman, 1968; Baruch & Sunder, 1979). Despite this, a matched pairs approach was used in an attempt to limit the potential impact of industry.

A judgemental or purposive sampling method was employed in the process of sampling the healthy population. As indicated earlier, a matched pairs approach was used as initial sampling method for the healthy population, the organisations being matched in terms of their asset size as far as possible.

Conflicting results have been highlighted in terms of the economic cycle influence captured in "time"; some have found these to be of little consequence (Muller et al., 2009) while others have cited them as influencing factors (Grice & Dugan, 2001) The study by Muller et al. (2009) was conducted in South Africa during the period 1997 to 2002 and, based on their findings, the author does not think the misalignment of organisational results in terms of size or time in matched pairs limits the study. Owing to the short time frame and the sample used in this study, an exact match for financial information in terms of time was not feasible; however, overlapping time periods between the matched pairs were used as far as possible.

### 4.4.4 Sample

A sample is deemed to be representative if its members tend to have the same characteristics as the population from which they were selected (Weiers, 2011). Since a purposive sampling method was used, evaluating the extent to which the samples are representative of the underlying population is regarded as impossible. This is viewed as a limitation to the study.

### 4.4.5 Independent variables: Financial ratios

The most frequently used financial ratios in the various studies are those associated with profitability, liquidity and leverage (Altman, 1968; Beaver, 1966; Muller et al., 2009; Thorley Hill et al., 1996; Zmijewski, 1984).

The most widely used method of selecting variables appears to be based on popularity in previous research or simply popularity (Altman, 1968; Beaver, 1966; Muller et al., 2009; Wu et al., 2010), reducing the number of variables based on sample observations. Balcaen and Ooghe (2006) indicated that there are drawbacks to selecting variables based on an empirical approach, namely that variables tend to be sample specific and, as a result, the model is sample specific and, secondly, the empirical results may differ from the way the coefficients would have intuitively been interpreted. In contrast to these findings, Beaver et all (2005) indicated that the combination of variables is less important because they are correlated in some form, and that the insights provided by the ratio are far more important. These findings were taken into consideration and the researcher reserved the right to apply an empirical approach to the selection of variables. The process conducted in order to determine the independent variables was as follows:

1 In order to identify variables which have been successfully used in the past, a review of previous literature and studies was conducted. These variables were summarised in Table 1.

2 Logic and rationalisation reduced these ratios to a shorter representative list of 19 reflected in Table 3. The selection was based on the following:

   i. Cash flow is crucial to the success of a business (Muller et al., 2009). This is also the area which is least susceptible to manipulation by accounting interpretations.

   ii. In the earlier literature review the importance of including market-related ratios was indicated (Shumway, 2001; Zmijewski, 1984) because these ratios would encompass all current financial and non-financial information on the market price.

   iii. The assumption is that the inclusion of ratios from all five of the generally accepted categories (liquidity, leverage, solvency, activity and profitability) would allow a representative view of the organisation. These categories generally follow the decline of an organisation as previously noted. The selection process also took into consideration the findings of Beaver et all. (2005), that a combination of the three variables (ROA, CFO: TL, TA:TL) captured essentially all of the explanatory power of the financial statement variables used in the Ohlson, Zmijewski and Shumway models.

   iv. A Mann Whitney U test was performed on each of the 19 variables to determine if there is a statistically significant difference between the variables of D and H organisations.

   v. Based on the results of the Mann-Whitney-*U* test and Spearman rho- which determined multi-colliniarity, six final independent variables were identified. Steps (iv) and (v) will be discussed in more detail later on.

The ratios have been grouped according to the following categories: liquidity, leverage, solvency, activity, profitability and market ratios.

Table 3
*Independent variables*

| Ratio | | Measurement |
|---|---|---|
| **Liquidity** | | |
| C:S | Cash to sales ratio | Cash and cash equivalents / Total sales |
| CA:TA | Current assets to total assets ratio | Current assets / Total assets |
| CFO:S | Cash flow from operating activities | Cash flow from operating activities / Turnover |
| CFO:TL | Cash flow from operating activities | Cash flow from operating activities / Total liabilities |
| 3CFO:3S | Cumulative cash flow from operating activities | Cumulative cash flow from operating activities over the last three years / Cumulative turnover over the last three years |
| 3CFO:TL | Cash flow from operating activities | Cumulative cash flow from operating activities over the last three years / Total liabilities |
| **Leverage** | | |
| TL:E | Debt to equity ratio | Total liabilities /Total equity |
| **Solvency** | | |
| TL:TA | Debt to asset ratio | Total liabilities /Total assets |
| EBIT:I | Interest cover ratio | Earnings before interest and tax / Interest paid |
| **Activity ratios** | | |
| WC:TA | Working capital to assets ratio | (Accounts receivable + Inventory – Accounts payable) / Total assets |
| WC:S | Working capital to sales ratio | (Accounts receivable + Inventory – Accounts payable) / Turnover |
| AR:S | Accounts receivable to sales ratio | Accounts receivable / Turnover |
| INV:S | Inventory to sales ratio | Inventory / Turnover |
| **Profitability** | | |
| PAT:S | Net profit margin | Profit after tax / Turnover |
| ∆ PAT | Change in net income | (Profit after tax year two – Profit after tax year one) / Profit after tax year one |
| ROA | Return on assets | Profit after tax / Total assets |
| ROE | Return on equity | Profit after tax / Equity |
| **Market-related ratios** | | |
| MV:TL | Market value of equity/ Total liabilities | (Share price x issued shares) / Total liabilities |
| PE | Price earnings ratio | |

## *4.5 Process of data analysis*

The preceding steps dealt with the collection of data and the identification of variables. The process of analysing the data is described in the following paragraphs.

### 4.5.1 Clean sample data

Key to the study is the completeness of data. Several values were missing from the distressed population; a review of these organisations was done and the level of required information was assessed. As pointed out earlier, an organisation had to have a minimum history of five years prior to its distress in order to be included in the study and, furthermore, missing variable values were excluded from the study. Due to a matched pair approach being followed, discarding a variable in the Distressed sample resulted in a discard of the matched Healthy organisations variable and vice versa.

### 4.5.2 Time periods

The three periods prior to distress were lumped into one larger group of data points, on the assumption that the years closer to distress would provide a naturally higher indicative result than the results in previous years, and therefore no weighting was included in the time periods for the ratios.

### 4.5.3 Descriptive statistics and outliers

The initial analysis following the above data cleansing process entailed descriptive statistics to determine the nature and characteristics of the data and the approach required to determine the statistical model.

Focus was placed on kurtosis and skewness in determining the level of normal distribution. These findings are highlighted in chapter five.

As a second focus point and area of importance, outliers were identified using descriptive statistics. The mean was compared to the trimmed mean, a value calculated by eliminating the top and bottom 5% of the values from the sample and a revised mean calculated. A cut-off point of 10.1% was used to determine what the impacts of outliers between these two points were.

To reduce the impact of the outliers, they were eliminated to the point where the variance amounted to 10.1% between the two means and, where this was not possible, the matched pair ('MP') of the variable was excluded from the study. As with the treatment of missing values, an outlier was eliminated from the applicable period in both the matched samples.

### 4.5.4 Statistical significance

In view of the small sample collected, only a limited number of variables can be included in the LR analysis. To reduce the number of variables to those that are statistically significant, in the prediction of distress, a non-parametric t-test (Mann-Whitney-*U*) was completed and supported by a review of correlations of each of the statistically significant variables.

This test measures the statistical significance of differences between two samples. Only those variables that are significant were included in the LR, statistical significance being determined if $p < 0.05$.

A Spearman rho correlation test was performed to ensure that correlation between the variables is below a rho <0.5 threshold to avoid 'overemphasising' certain financial effects on the model. Where the correlation between variables was greater than this, one of the variables was eliminated from the study.

Taking logic into account, the researcher made the final selection of variables on the basis of the results of the tests mentioned above.

Following the above, an LR was done to determine the probability function.

## *4.6 Limitations*

Limitations have been identified as the following:

### 4.6.1 Financial statement information

While the use of standardised financial information can be viewed as limiting the impact of interpretive accounting statements, the standardisation process could also dilute or neglect the impact of information in specific areas. This could have a limiting effect on the model.

### 4.6.2 Organisational age

Organisational age was not considered in the sampling process, due to the limited data available. The impact of age should be considered because, in many instances, the age of the organisation will influence the level of its prediction accuracy, specifically relating to its *retained earnings to total assets,* although not used in this study (Altman, 1968). As and example younger entities will generally have a lower ratio value due to lower retained earnings, making them more susceptible to being classified as financially distressed as well as making financial distress more difficult to predict (Pompe & Bilderbeek, 2005). While this age is not explicitly included in the study, the effect is still relevant.

### 4.6.3 Sample size

The sample size is seen as a significant limitation to the study, in view of the recommendation that a minimum of 50 cases per independent variable (Utexas, 2013) be used in order to obtain a more accurate result.

In addition to the above, as a result of taking the matched pairs approach, the generalisability of the study could be reduced and the overall study could be viewed by some as not representative of the JSE listed shares. Using a matched pairs approach allowed for the view that there is an oversampling of bankrupt firms since the occurrence of distress in organisations is less than that of health, which further supports the above criticism levelled against the sampling method (Thorley Hill et al., 1996) .

### 4.6.4 Test population

Again, owing to a limited population and sample size, an independent secondary data set is unavailable to test the accuracy of the function that was derived. This is a significant limitation of which a potential user must be made aware. The model accuracy can therefore not be confirmed with confidence and caution should be exercised.

### 4.6.5 Failure process

According to Laitinen (1991) there are three different failure processes: organisations whose performance never rises above poor before failure, organisations which show significant growth before failing, and those that show good performance over a long period of time and then experience distress. This study assumes a ‘uniform process’ of distress across the sample. This assumption influenced both the variables which were selected as well as the coefficients and could potentially make the model more sample specific, limiting the potential for generalised use and insights.

### 4.6.6 Summary

The limitations highlighted in respect of this study focuses on the financial information, sample size, bias and the lack of out of sample testing. At this juncture it is important to note that the purpose of the study is not to replace or challenged the models already in existence but rather to add to the body of knowledge of distress models in the South African context.

# 5 Results

## 5.1 Introduction

In chapter four the methodology used to test the proposal and hypothesis identified in chapter three was explained – hence the presentation of the results in alignment with chapter three. In terms of the methodology described in chapter four, the results are reflected in chapter five. This chapter contains the descriptive statistics, after the results of the Man-Whitney *U* test on the variable hypothesis. Finally the proposed probability function to be used as predictive tool, is discussed. As introduction to the above, an overview of the sample of matched pairs is provided.

Sample selection was done using MS Excel while statistical analysis was done using the IBM SPSS 20 statistical software program.

## 5.2 Matched pairs

As described in chapter four of the study, a matched pairs approach was used, based on asset size at year zero of the distressed firm; distressed and healthy organisations in the population were selected. Table 4 provides the results of the matched pair sample: the sign '✓' indicates the variables for the year used in the statistical analysis and 'x' indicates that the information for that period was discarded.

Two of the companies which were included in the sample where less accurately matched than the others, these being Nictus Beperk (NCS) and Sun International Limited (SUI) with their matches to Money Web Holdings Limited (MNY) and Pioneer Food Group Limited (PFG) respectively.

Table 4

*Indicating the matched pairs in terms of total assets and the years in which information was paired*

| | Distressed | | | Healthy | | | |
|---|---|---|---|---|---|---|---|
| **Matched pair # (MP)** | **Ticker** | **Total Assets R'000** | **YR 0** | **Ticker** | **Total Assets R'000** | **YR0** | **Asset size variance** |
| 1 | ADH | R 414 304 | 2000 | SOV | R 411 919 | 2006 | -0.6% |
| 2 | AET | R 540 779 | 2010 | BSB | R 522 398 | 2007 | -3.5% |
| 3 | AFR | R 7 457 000 | 2011 | CFR | R 7 364 000 | 2005 | -1.3% |
| 4 | AHL | R 32 592 | 2008 | PAL | R 32 374 | 2007 | -0.7% |
| 5 | ARL | R 3 008 766 | 2008 | SER | R 3 007 472 | 2007 | 0.0% |
| 6 | BEG | R 370 027 | 2010 | LAR | R 361 292 | 2003 | -2.4% |
| 7 | CKS | R 313 198 | 2004 | BRC | R 314 234 | 2003 | 0.3% |
| 8 | CLH | R 385 246 | 2001 | KGM | R 398 188 | 2007 | 3.3% |
| 9 | CLS | R 3 691 757 | 2009 | AVI | R 3 631 800 | 2007 | -1.7% |
| 10 | COM | R 801 739 | 2005 | ITE | R 801 131 | 2004 | -0.1% |
| 11 | CUL | R 310 582 | 2001 | AOO | R 319 141 | 2011 | 2.7% |
| 12 | DON | R 137 857 | 2001 | VMK | R 138 484 | 2012 | 0.5% |
| 13 | ELE | R 7 817 500 | 2000 | ECO | R 7 833 000 | 2006 | 0.2% |
| 14 | FBR | R 516 218 | 2012 | CNL | R 521 639 | 2007 | 1.0% |
| 15 | IFH | R 871 887 | 2010 | AMA | R 869 191 | 2007 | -0.3% |
| 16 | ILV | R 5 178 300 | 2001 | TRU | R 5 221 000 | 2010 | 0.8% |
| 17 | JNC | R 12 098 200 | 2001 | TBS | R 12 370 400 | 2011 | 2.2% |
| 18 | MTO | R 92 312 | 2001 | ITR | R 95 675 | 2003 | 3.5% |
| 19 | NCS | R 30 467 | 2000 | MNY | R 35 162 | 2012 | 13.4% |
| 20 | NPN | R 10 436 523 | 2004 | TFG | R 10 415 600 | 2011 | -0.2% |
| 21 | PIK | R 3 428 300 | 2000 | CAT | R 3 404 761 | 2005 | -0.7% |
| 22 | PMA | R 1 229 965 | 2000 | TIW | R 1 207 030 | 2000 | -1.9% |
| 23 | SAB | R 24 564 000 | 2000 | SHF | R 23 603 286 | 2006 | -4.1% |
| 24 | SHP | R 6 199 458 | 2002 | LEW | R 6 114 300 | 2012 | -1.4% |
| 25 | SUI | R 7 459 182 | 2001 | PFG | R 9 116 662 | 2011 | 18.2% |
| 26 | TRT | R 1 065 695 | 2007 | CSB | R 1 021 017 | 2007 | -4.4% |
| 27 | TSH | R 1 238 205 | 2001 | MTA | R 1 200 823 | 2004 | -3.1% |
| 28 | WHL | R 8 182 000 | 2012 | JDG | R 8 106 000 | 2005 | -0.9% |

## 5.3 Data description and normality

Normality is a requirement for most parametric tests, one of these being the MDA technique also used by Altman (1968), which was considered as prediction modelling method for this study. Normality is the probability distribution which is known to have characteristics of skewness and kurtosis of nil (Pallant, 2011), therefore data description is crucial to the assessment of normality of the distribution of data points and ultimately influences the statistical tests to be conducted.

The following section provides insight into the characteristics of normality: skewness and kurtosis, as well as the identification of outliers using a trimmed mean approach. The tables provide information on both the distressed and healthy samples as well as on the combined sample. The discussion in chapter six will be focused on the combined sample.

### 5.3.1 Skewness

"Skewness of a distribution provides insight into the symmetry of the distribution" (Pallant, 2011 p.57). The symmetry of the distribution is relevant to the decision of which parametric tests to conduct, the majority of which require a normal distribution. Table 5 Liquidity descriptive statistics, Table 6 Leverage descriptive statistics, Table 7 Solvency descriptive statistics, Table 8 Activity ratios descriptive statistics, Table 9 Profitability descriptive statistics and Table 10 Market-based ratios descriptive statistics, illustrate that the distributions relating to the sample and variables are not normally distributed, making parametric tests less desirable. The combined sample data mostly reflect a positively skewed set, meaning that the majority of data lie towards the left at the lower end of values.

### 5.3.2 Kurtosis

"Kurtosis provides information about the 'peakedness' of the distribution" (Pallant, 2011, p.57). The sample dataset analysed showed positive kurtosis by all variables, with the exception of two: WC:TA and CA:TA. Positive kurtosis illustrates the fact that the data are clustered around a centre point, with long thin tails, while negative kurtosis illustrates a 'flatter' distribution.

### 5.3.3 Outliers

Outliers are defined as "values which are well below and well above the others" (Pallant, 2011, p.43). Significant outliers on the combined sample were identified using the trimmed mean function in SPSS. The trimmed mean function eliminates the top and bottom 5% of the data points and calculates a revised mean value. If the trimmed mean and original mean values are significantly different, the outliers have a significant impact on the data. Table 5 Liquidity descriptive statistics, Table 6 Leverage descriptive statistics, Table 7 Solvency descriptive statistics, Table 8 Activity ratios descriptive statistics, Table 9 Profitability descriptive statistics and Table 10 Market-based ratios descriptive statistics reflect the results of this process.

There are no defined rules related to what constitutes an outlier and the treatment thereof. A variance of more than 10.1% was deemed significant and the related outliers treated, by eliminating either the highest or lowest outlying values, reducing the outliers' impact to a 10.1% level; when eliminating the outlier, its matched data point for that variable was also excluded. When the threshold could not be reached within a reasonable number of exclusions, the variable was eliminated from the study. Two variables were deleted from the study in this manner, these being, EBIT:I and C:S.

### 5.3.4 Overview

This section reviewed the requirements of normally distributed data, namely kurtosis and skewness; it is also a review of the method of identification and the impact of outliers on the study. The tables which follow provide the descriptive statistics for each of the variables, grouped according to liquidity, leverage, solvency, activity, profitability and market-related ratios. The grouping is not a scientific one and is based on prior studies and the researcher's own opinion.

Table 5

*Liquidity descriptive statistics highlighting mean, median & outliers based on the results of the trimmed mean difference and data normality based on skewness and kurtosis*

| | | **Healthy** | | **Distressed** | | **Combined sample** | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Liquidity descriptive** | | **Excluding outliers** | | **Excluding outliers** | | **Including outliers** | | **Excluding outliers** | |
| Category | | Statistic | Std. Error | Statistic | Std. Error | Statistic | Std. Error | Statistic | Std. Error |
| C:S | Mean | 0.0655 | 0.0071 | 0.0998 | 0.0113 | 0.1004 | 0.0103 | 0.0827 | 0.0068 |
| | 5% Trimmed Mean | 0.0594 | | 0.0917 | | 0.0835 | | 0.0744 | |
| | Difference | | | | | 20.2% | | 11.1% | |
| | Median | 0.0518 | | 0.0661 | | 0.0608 | | 0.0589 | |
| | Skewness | 1.7840 | 0.2908 | 1.1846 | 0.2908 | 3.5322 | 0.1993 | 1.5589 | 0.2078 |
| | Kurtosis | 3.9242 | 0.5740 | 0.7793 | 0.5740 | 19.1655 | 0.3961 | 2.2562 | 0.4127 |
| | n | 68 | | 68 | | 136 | | 136 | |
| CA:TA | Mean | 0.7349 | 0.0174 | 0.5293 | 0.0277 | 0.6321 | 0.0182 | 0.6321 | 0.0182 |
| | 5% Trimmed Mean | 0.7399 | | 0.5354 | | 0.6437 | | 0.6437 | |
| | Difference | | | | | -1.8% | | -1.8% | |
| | Median | 0.7596 | | 0.5710 | | 0.6715 | | 0.6715 | |
| | Skewness | -0.2511 | 0.2627 | -0.3801 | 0.2627 | -0.7372 | 0.1873 | -0.7372 | 0.1873 |
| | Kurtosis | -0.9443 | 0.5197 | -1.1597 | 0.5197 | -0.2169 | 0.3725 | -0.2169 | 0.3725 |
| | n | 84 | | 84 | | 168 | | 168 | |
| CFO:S | Mean | 0.0512 | 0.0062 | 0.0552 | 0.0173 | 0.0532 | 0.0091 | 0.0532 | 0.0091 |
| | 5% Trimmed Mean | 0.0515 | | 0.0558 | | 0.0547 | | 0.0547 | |
| | Difference | | | | | -2.6% | | -2.6% | |
| | Median | 0.0529 | | 0.0688 | | 0.0557 | | 0.0557 | |
| | Skewness | -0.1116 | 0.2673 | 0.5912 | 0.2673 | 0.7219 | 0.1907 | 0.7219 | 0.1907 |
| | Kurtosis | -0.4102 | 0.5287 | 9.0346 | 0.5287 | 15.4559 | 0.3792 | 15.4559 | 0.3792 |
| | n | 81 | | 81 | | 162 | | 162 | |

| Liquidity descriptive | | Healthy | | Distressed | | Combined sample | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Excluding outliers | | Excluding outliers | | Including outliers | | Excluding outliers | |
| Category | | Statistic | Std. Error | Statistic | Std. Error | Statistic | Std. Error | Statistic | Std. Error |
| CFO:TL | Mean | 0.1692 | 0.0241 | 0.1290 | 0.0275 | 0.1491 | 0.0183 | 0.1491 | 0.0183 |
| | 5% Trimmed Mean | 0.1740 | | 0.1332 | | 0.1535 | | 0.1535 | |
| | Difference | | | | | -2.9% | | -2.9% | |
| | Median | 0.1701 | | 0.1503 | | 0.1537 | | 0.1537 | |
| | Skewness | -0.2290 | 0.2627 | -0.1726 | 0.2627 | -0.2269 | 0.1873 | -0.2269 | 0.1873 |
| | Kurtosis | 0.8990 | 0.5197 | 4.7409 | 0.5197 | 3.2613 | 0.3725 | 3.2613 | 0.3725 |
| | n | 84 | | 84 | | 168 | | 168 | |
| CFO3:S3 | Mean | 0.0504 | 0.0042 | 0.0479 | 0.0124 | 0.0491 | 0.0065 | 0.0491 | 0.0065 |
| | 5% Trimmed Mean | 0.0502 | | 0.0518 | | 0.0506 | | 0.0506 | |
| | Difference | | | | | -3.0% | | -3.0% | |
| | Median | 0.0467 | | 0.0436 | | 0.0453 | | 0.0453 | |
| | Skewness | 0.1701 | 0.2642 | -1.7072 | 0.2642 | -2.0617 | 0.1884 | -2.0617 | 0.1884 |
| | Kurtosis | 0.1854 | 0.5226 | 10.2069 | 0.5226 | 17.9409 | 0.3747 | 17.9409 | 0.3747 |
| | n | 83 | | 83 | | 166 | | 166 | |
| CFO3:TL | Mean | 0.4506 | 0.0458 | 0.2612 | 0.0490 | 0.3559 | 0.0342 | 0.3559 | 0.0342 |
| | 5% Trimmed Mean | 0.4280 | | 0.2663 | | 0.3482 | | 0.3482 | |
| | Difference | | | | | 2.2% | | 2.2% | |
| | Median | 0.4063 | | 0.2409 | | 0.3327 | | 0.3327 | |
| | Skewness | 1.0567 | 0.2627 | -0.4345 | 0.2627 | 0.1765 | 0.1873 | 0.1765 | 0.1873 |
| | Kurtosis | 2.7307 | 0.5197 | 2.0118 | 0.5197 | 2.6174 | 0.3725 | 2.6174 | 0.3725 |
| | n | 84 | | 84 | | 168 | | 168 | |

Difference < 10.1% further non-parametric testing will be conducted; distribution is classified as not normal when 0< kurtosis and 0< skewness.

Table 6

*Leverage descriptive statistics highlighting mean, median & outliers based on the results of the trimmed mean difference and data normality based on skewness and kurtosis*

| | | Healthy | | Distressed | | Combined sample | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Leverage descriptive** | | **Excluding outliers** | | **Excluding outliers** | | **Including outliers** | | **Excluding outliers** | |
| Category | | Statistic | Std. Error | Statistic | Std. Error | Statistic | Std. Error | Statistic | Std. Error |
| TL:E | Mean | 0.9771 | 0.1411 | 1.9625 | 0.4672 | 2.5203 | 0.7700 | 1.4698 | 0.2463 |
| | 5% Trimmed Mean | 1.0437 | | 1.9789 | | 1.5522 | | 1.4716 | |
| | Difference | | | | | 62.4% | | -0.1% | |
| | Median | 0.9385 | | 1.5496 | | 1.0661 | | 1.0530 | |
| | Skewness | -3.2801 | 0.2657 | -0.0319 | 0.2657 | 7.8826 | 0.1873 | 0.2407 | 0.1896 |
| | Kurtosis | 19.8946 | 0.5256 | 5.4242 | 0.5256 | 68.7533 | 0.3725 | 10.6625 | 0.3769 |
| | n | 82 | | 82 | | 164 | | 164 | |

Difference < 10.1% further non-parametric testing will be conducted; distribution is classified as not normal when 0< kurtosis and 0< skewness.

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Table 7

*Solvency descriptive statistics highlighting mean, median & outliers based on the results of the trimmed mean difference and data normality based on skewness and kurtosis*

| **Solvency descriptive** | | **Healthy** | | **Distressed** | | **Combined sample** | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | **Excluding outliers** | | **Excluding outliers** | | **Including outliers** | | **Excluding outliers** | |
| Category | | Statistic | Std. Error | Statistic | Std. Error | Statistic | Std. Error | Statistic | Std. Error |
| TL:TA | Mean | 0.5089 | 0.0201 | 0.6442 | 0.0305 | 0.5766 | 0.0189 | 0.5766 | 0.0189 |
| | 5% Trimmed Mean | 0.4964 | | 0.6431 | | 0.5684 | | 0.5684 | |
| | Difference | | | | | 1.4% | | 1.4% | |
| | Median | 0.4965 | | 0.6857 | | 0.5452 | | 0.5452 | |
| | Skewness | 1.5984 | 0.2627 | -0.1739 | 0.2627 | 0.5103 | 0.1873 | 0.5103 | 0.1873 |
| | Kurtosis | 5.0826 | 0.5197 | 0.0585 | 0.5197 | 0.6649 | 0.3725 | 0.6649 | 0.3725 |
| | n | 84 | | 84 | | 168 | | 168 | |
| EBIT:I | Mean | 22.4483 | 4.1153 | 11.1189 | 2.6223 | 31.1623 | 6.7474 | 16.7836 | 2.4770 |
| | 5% Trimmed Mean | 17.8831 | | 7.7062 | | 15.6668 | | 12.1601 | |
| | Difference | | | | | 98.9% | | 38.0% | |
| | Median | 10.0179 | | 5.4398 | | 8.4385 | | 8.2155 | |
| | Skewness | 2.7597 | 0.2829 | 5.3943 | 0.2829 | 4.9264 | 0.1943 | 3.5337 | 0.2020 |
| | Kurtosis | 9.0235 | 0.5588 | 35.1048 | 0.5588 | 26.3998 | 0.3862 | 14.7324 | 0.4014 |
| | n | 72 | | 72 | | 144 | | 144 | |

Difference < 10.1% further non-parametric testing will be conducted; distribution is classified as not normal when 0< kurtosis and 0< skewness.

Table 8

*Activity ratios descriptive statistics highlighting mean, median & outliers based on the results of the trimmed mean difference and data normality based on skewness and kurtosis*

| **Activity ratios descriptive** | | **Healthy** | | **Distressed** | | **Combined sample** | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | **Excluding outliers** | | **Excluding outliers** | | **Including outliers** | | **Excluding outliers** | |
| Category | | Statistic | Std. Error | Statistic | Std. Error | Statistic | Std. Error | Statistic | Std. Error |
| WC:TA | Mean | 0.2948 | 0.0226 | 0.0488 | 0.0208 | 0.1718 | 0.0180 | 0.1718 | 0.0180 |
| | 5% Trimmed Mean | 0.2947 | | 0.0450 | | 0.1703 | | 0.1703 | |
| | Difference | | | | | 0.9% | | 0.9% | |
| | Median | 0.2686 | | 0.0025 | | 0.1334 | | 0.1334 | |
| | Skewness | 0.1077 | 0.2627 | 0.5033 | 0.2627 | 0.2643 | 0.1873 | 0.2643 | 0.1873 |
| | Kurtosis | -0.8189 | 0.5197 | 1.1323 | 0.5197 | -0.3620 | 0.3725 | -0.3620 | 0.3725 |
| | n | 84 | | 84 | | 168 | | 168 | |
| WC:S | Mean | 0.1971 | 0.0204 | 0.0277 | 0.0209 | 0.1214 | 0.0174 | 0.1124 | 0.0160 |
| | 5% Trimmed Mean | 0.1802 | | 0.0277 | | 0.1091 | | 0.1059 | |
| | Difference | | | | | 11.3% | | 6.1% | |
| | Median | 0.1420 | | 0.0098 | | 0.0792 | | 0.0792 | |
| | Skewness | 1.6167 | 0.2705 | 0.5083 | 0.2705 | 1.1746 | 0.1907 | 0.7470 | 0.1931 |
| | Kurtosis | 3.7318 | 0.5350 | 4.6907 | 0.5350 | 4.0385 | 0.3792 | 3.3543 | 0.3838 |
| | n | 79 | | 79 | | 158 | | 158 | |
| AR:S | Mean | 0.2076 | 0.0177 | 0.1636 | 0.0119 | 0.2055 | 0.0154 | 0.1856 | 0.0108 |
| | 5% Trimmed Mean | 0.1894 | | 0.1566 | | 0.1761 | | 0.1729 | |
| | Difference | | | | | 16.7% | | 7.3% | |
| | Median | 0.1894 | | 0.1444 | | 0.1657 | | 0.1657 | |
| | Skewness | 2.7353 | 0.2756 | 1.1451 | 0.2756 | 3.1747 | 0.1919 | 2.5531 | 0.1968 |
| | Kurtosis | 10.5470 | 0.5448 | 1.8639 | 0.5448 | 12.0894 | 0.3815 | 11.1143 | 0.3911 |
| | n | 76 | | 76 | | 152 | | 152 | |
| INV:S | Mean | 0.1547 | 0.0100 | 0.0969 | 0.0113 | 0.1258 | 0.0079 | 0.1258 | 0.0079 |
| | 5% Trimmed Mean | 0.1480 | | 0.0857 | | 0.1171 | | 0.1171 | |
| | Difference | | | | | 7.4% | | 7.4% | |
| | Median | 0.1455 | | 0.0716 | | 0.1174 | | 0.1174 | |
| | Skewness | 1.2917 | 0.2774 | 2.3127 | 0.2774 | 1.5353 | 0.1980 | 1.5353 | 0.1980 |
| | Kurtosis | 2.6180 | 0.5482 | 8.5401 | 0.5482 | 4.2154 | 0.3936 | 4.2154 | 0.3936 |
| | n | 75 | | 75 | | 150 | | 150 | |

Difference < 10.1% further non-parametric testing will be conducted; distribution is classified as not normal when 0< kurtosis and 0< skewness.

Table 9

*Profitability descriptive statistics highlighting mean, median, outliers based on the results of the trimmed mean difference and data normality based on skewness and kurtosis*

| **Profitability ratios descriptive** | | **Healthy** | | **Distressed** | | **Combined sample** | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | **Excluding outliers** | | **Excluding outliers** | | **Including outliers** | | **Excluding outliers** | |
| Category | | Statistic | Std. Error | Statistic | Std. Error | Statistic | Std. Error | Statistic | Std. Error |
| OP:S | Mean | 0.1320 | 0.0111 | 0.1603 | 0.0265 | 0.1461 | 0.0144 | 0.1461 | 0.0144 |
| | 5% Trimmed Mean | 0.1270 | | 0.1410 | | 0.1328 | | 0.1328 | |
| | Difference | | | | | 10.1% | | 10.1% | |
| | Median | 0.0998 | | 0.1255 | | 0.1121 | | 0.1121 | |
| | Skewness | 1.0368 | 0.2673 | 2.2138 | 0.2673 | 2.6554 | 0.1907 | 2.6554 | 0.1907 |
| | Kurtosis | 1.2199 | 0.5287 | 13.8502 | 0.5287 | 21.3726 | 0.3792 | 21.3726 | 0.3792 |
| | n | 81 | | 81 | | 162 | | 162 | |
| PAT1:PAT2 | Mean | 0.1741 | 0.1506 | 0.2283 | 0.2293 | 0.3320 | 0.1913 | 0.2010 | 0.1363 |
| | 5% Trimmed Mean | 0.2319 | | 0.2060 | | 0.2246 | | 0.2142 | |
| | Difference | | | | | 47.8% | | -6.2% | |
| | Median | 0.1679 | | 0.2367 | | 0.1791 | | 0.1791 | |
| | Skewness | -1.6870 | 0.2774 | 0.0637 | 0.2792 | 4.2057 | 0.1974 | -0.3292 | 0.1987 |
| | Kurtosis | 12.3050 | 0.5482 | 6.2942 | 0.5517 | 39.0882 | 0.3923 | 8.5558 | 0.3949 |
| | n | 75 | | 75 | | 150 | | 150 | |
| ROA | Mean | 0.1289 | 0.0111 | 0.0802 | 0.0140 | 0.1046 | 0.0091 | 0.1046 | 0.0091 |
| | 5% Trimmed Mean | 0.1244 | | 0.0838 | | 0.1038 | | 0.1038 | |
| | Difference | | | | | 0.7% | | 0.7% | |
| | Median | 0.1223 | | 0.0821 | | 0.1062 | | 0.1062 | |
| | Skewness | 1.0537 | 0.2627 | -1.0809 | 0.2627 | -0.4847 | 0.1873 | -0.4847 | 0.1873 |
| | Kurtosis | 3.3118 | 0.5197 | 7.6471 | 0.5197 | 6.9580 | 0.3725 | 6.9580 | 0.3725 |
| | n | 84 | | 84 | | 168 | | 168 | |
| ROE | Mean | 0.2079 | 0.0488 | 0.2779 | 0.1155 | 0.4245 | 0.2475 | 0.2429 | 0.0625 |
| | 5% Trimmed Mean | 0.2430 | | 0.2249 | | 0.2358 | | 0.2357 | |
| | Difference | | | | | 80.0% | | 3.0% | |
| | Median | 0.2398 | | 0.1812 | | 0.2194 | | 0.2194 | |
| | Skewness | -4.0745 | 0.2657 | 3.1149 | 0.2657 | 10.8639 | 0.1873 | 3.1575 | 0.1896 |
| | Kurtosis | 27.5446 | 0.5256 | 25.5030 | 0.5256 | 134.2521 | 0.3725 | 38.7720 | 0.3769 |
| | n | 82 | | 82 | | 164 | | 164 | |

Difference < 10.1% further non-parametric testing will be conducted; distribution is classified as not normal when 0< kurtosis and 0< skewness.

Table 10

*Market-related ratios descriptive statistics highlighting mean, median & outliers based on the results of the trimmed mean difference and data normality based on skewness and kurtosis*

| Market related ratios descriptive | | Healthy | | Distressed | | Combined sample | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Excluding outliers | | Excluding outliers | | Including outliers | | Excluding outliers | |
| Category | | Statistic | Std. Error | Statistic | Std. Error | Statistic | Std. Error | Statistic | Std. Error |
| MVE:TL | Mean | 2.4618 | 0.2230 | 1.8728 | 0.1987 | 2.8133 | 0.3023 | 2.1673 | 0.1508 |
| | 5% Trimmed Mean | 2.3035 | | 1.6802 | | 2.2018 | | 1.9810 | |
| | Difference | | | | | 27.8% | | 9.4% | |
| | Median | 1.9399 | | 1.5193 | | 1.7606 | | 1.7201 | |
| | Skewness | 1.2612 | 0.2756 | 1.6436 | 0.2756 | 4.0857 | 0.1884 | 1.4131 | 0.1968 |
| | Kurtosis | 1.4204 | 0.5448 | 3.4131 | 0.5448 | 22.0109 | 0.3747 | 2.0759 | 0.3911 |
| | n | 76 | | 76 | | 152 | | 152 | |
| PE | Mean | 8.7348 | 0.9056 | 9.8921 | 1.2304 | 3.4328 | 6.2954 | 9.3135 | 0.7628 |
| | 5% Trimmed Mean | 8.8264 | | 9.8521 | | 10.2939 | | 9.3109 | |
| | Difference | | | | | -66.7% | | 0.0% | |
| | Median | 8.8300 | | 9.7700 | | 9.0300 | | 9.0300 | |
| | Skewness | -0.5750 | 0.2774 | -0.0709 | 0.2774 | -11.5109 | 0.1955 | -0.1624 | 0.1980 |
| | Kurtosis | 7.1533 | 0.5482 | 1.9296 | 0.5482 | 138.5302 | 0.3886 | 3.5053 | 0.3936 |
| | n | 67 | | 67 | | 134 | | 134 | |

Difference < 10.1% further non-parametric testing will be conducted; distribution is classified as not normal when 0< kurtosis and 0< skewness.

### 5.3.5 Summary

A perfectly normal distribution would have a nil score for both kurtosis and skewness. It is very seldom that a sample will be obtained which is perfectly normal (Field, 2009). From the preceding tables it is clear that this is also the case with the combined sample, which will be discussed in chapter six.

## 5.4 Hypothesis test: Mann- Whitney- U

This section will focus on the hypothesis relating to identifying those variables which have a statistically significant difference between healthy and distressed organisations.

The Mann-Whitney *U* test is used to test for differences in two independent continuous samples. It is the non-parametric version of the t-test (Pallant, 2011 p.227).. Rather than comparing means as used in parametric tests, it converts medians into ranks and ultimately compares the ranks to indicate if there is a significant difference (Pallant, 2011 p.227). The individual median values of the sample category variables are reflected in the preceding descriptive statistics tables.

The test was conducted to determine the results of the hypothesis. The result of the test is reflected in Table 10 Liquidity, leverage and solvency ratio results , Table 11 Activity and profitability ratio results, and Table 12 Market-related ratio results, $p< 0.05$, indicating a statistically significant variance (Field, 2009; Pallant, 2011). The result of the test leads to the conclusion on the null hypothesis for each of the variables to be accepted or rejected; $p> 0.05$ would imply that the null hypothesis is rejected and there is no statistically significant difference between the mean values of D and H organisations.

The effect size ('r') is calculated as a standardisation measure in support of identifying statistical significance; an indication of statistical significance does not imply importance or meaning (Field, 2009). Correlation coefficient ('r') is the most widely used in this instance (Field, 2009). In order to interpret these results there are some widely used suggestions which were made by Cohen as cited in Field (2009, p.57):

$r = 0.10$ small effect. Effect explains 1% of variance.

$r = 0.3$ medium effect. Effect explains 9% of the variance.

$r =0.5$ large effect. Effect accounts for 25% of the variance.

Table 11
*Liquidity, Leverage and Solvency Mann-Whitney U results*

| | **Liquidity** | | | | | **Leverage** | **Solvency** |
|---|---|---|---|---|---|---|---|
| | CA:TA | CFO:S | CFO:TL | CFO3:S3 | CFO3:TL | TL:E | TL:TA |
| Mann-Whitney *U* | 1 897.500 | 3 024.500 | 3 178.000 | 3 351.500 | 2 691.000 | 2 382.000 | 2 149.000 |
| Sum of ranks Healthy | 8 728.500 | 6 345.500 | 7 448.000 | 7 023.500 | 7 935.000 | 5 785.000 | 5 719.000 |
| Sum of ranks Distressed | 5 467.500 | 6 857.500 | 6 748.000 | 6 837.500 | 6 261.000 | 7 745.000 | 8 477.000 |
| Wilcoxon W | 5 467.500 | 6 345.500 | 6 748.000 | 6 837.500 | 6 261.000 | 5 785.000 | 5 719.000 |
| Z | -5.172 | -.858 | -1.110 | -.300 | -2.655 | -3.223 | -4.375 |
| Asymp. Sig. (2-tailed) | .000 | .391 | .267 | .764 | .008 | .001 | .000 |
| r | -.399 | -.067 | -.086 | -.023 | -.205 | -.252 | -.338 |

p <0.05 statistically significant, 0.5 < r large effect, r < 0.1 small effect

Table 12
*Activity and Profitability Man-Whitney U results*

| | **Activity** | | | | **Profitability** | | | |
|---|---|---|---|---|---|---|---|---|
| | WC:TA | WC:S | AR:S | INV:S | OP:S | PAT:PAT2 | ROA | ROE |
| Mann-Whitney U | 1 250.000 | 1 318.000 | 2 344.500 | 1 536.000 | 3 164.000 | 2 725.000 | 2 544.000 | 3 110.000 |
| Sum of ranks Healthy | 9 376.000 | 8 083.000 | 6 357.500 | 6 939.000 | 6 485.000 | 5 675.000 | 8 082.000 | 7 017.000 |
| Sum of ranks Distressed | 4 820.000 | 4 478.000 | 5 270.500 | 4 386.000 | 6 718.000 | 5 500.000 | 6 114.000 | 6 513.000 |
| Wilcoxon W | 4 820.000 | 4 478.000 | 5 270.500 | 4 386.000 | 6 485.000 | 5 500.000 | 6 114.000 | 6 513.000 |
| Z | -7.226 | -6.268 | -2.003 | -4.798 | -.390 | -.190 | -3.122 | -.829 |
| Asymp. Sig. (2-tailed) | .000 | .000 | .045 | .000 | .696 | .849 | .002 | .407 |
| r | -.558 | -.499 | -.162 | -.392 | -.031 | -.016 | -.241 | -.065 |

p <0.05 statistically significant, 0.5 < r large effect, r < 0.1 small effect

Table 13
*Market-related ratios Mann-Whitney U results*

| | **Market** | |
|---|---|---|
| | MVE:TL | PE |
| Mann-Whitney *U* | 2 341.000 | 2 569.000 |
| Sum of ranks Healthy | 6 361.000 | 5 419.000 |
| Sum of ranks Distressed | 5 267.000 | 5 906.000 |
| Wilcoxon W | 5 267.000 | 5 419.000 |
| Z | -2.016 | -0.915 |
| Asymp. Sig. (2-tailed) | .044 | .360 |
| r | -.163 | -.075 |

p <0.05 statistically significant, 0.5 < r large effect, r < 0.1 small effect

### 5.4.1 Summary

This section provides an overview of the results of the Mann-Whitney U test which was conducted to identify those variables which show a statistically significantly difference between healthy and distressed organisations.

## *5.5 Correlation and multicollinearity*

Correlation is used to determine the strength and direction of a relationship between two variables, the result being a number between -1 and 1, while the sign in front of the number provides the direction of correlation (negative and positive respectively) and the absolute value provides the strength of the correlation (Pallant, 2011).

We are aware, as indicated earlier in the document that, owing to the nature of the financial information used, there is a strong correlation between financial ratios (Altman, 2000). Correlation between independent variables should be minimised to limit the impact of the correlated variables on the overall regression model. This is because it is an indicator of collinearity which is a condition which negatively influences a regression model (Pallant, 2011). A Spearman rho approach was used to determine correlation and, due to the non-parametric nature of the data, the results of the test are provided in Table 13 Spearman rho results. A correlation rho > 0.5 was investigated and, based on logic, the variables were excluded.

Only those variables which were found to have a statistically significant difference in the Mann-Whitney *U* test, are reflected in the Spearman rho results which follow.

Table 14
*Spearman rho results*

| | | Category | WC:TA | WC:S | CA:TA | INV:S | TL:TA | TL:E | ROA | CFO3:TL | MVE:TL | AR:S |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Category | Correlation Coefficient | 1.000 | -.495** | -.536** | -.226 | -.485** | .481** | .381** | -.187 | -.302** | -.207 | -.178 |
| | Sig. (2-tailed) | | .000 | .000 | .056 | .000 | .000 | .001 | .115 | .010 | .081 | .134 |
| WC:TA | Correlation Coefficient | | 1.000 | .948** | .447** | .669** | -.418** | -.270* | .019 | -.087 | .105 | .506** |
| | Sig. (2-tailed) | | | .000 | .000 | .000 | .000 | .022 | .872 | .467 | .378 | .000 |
| WC:S | Correlation Coefficient | | | 1.000 | .308** | .698** | -.495** | -.298* | -.019 | -.043 | .187 | .585** |
| | Sig. (2-tailed) | | | | .008 | .000 | .000 | .011 | .874 | .718 | .115 | .000 |
| CA:TA | Correlation Coefficient | | | | 1.000 | .533** | .251* | .308** | .127 | -.368** | -.258* | .060 |
| | Sig. (2-tailed) | | | | | .000 | .034 | .008 | .289 | .001 | .029 | .616 |
| INV:S | Correlation Coefficient | | | | | 1.000 | -.128 | .113 | -.101 | -.258* | -.077 | .216 |
| | Sig. (2-tailed) | | | | | | .283 | .345 | .400 | .029 | .518 | .068 |
| TL:TA | Correlation Coefficient | | | | | | 1.000 | .684** | .024 | -.543** | -.392** | -.143 |
| | Sig. (2-tailed) | | | | | | | .000 | .839 | .000 | .001 | .232 |
| TL:E | Correlation Coefficient | | | | | | | 1.000 | -.114 | -.430** | -.386** | -.162 |
| | Sig. (2-tailed) | | | | | | | | .341 | .000 | .001 | .174 |
| ROA | Correlation Coefficient | | | | | | | | 1.000 | .225 | .478** | -.002 |
| | Sig. (2-tailed) | | | | | | | | | .057 | .000 | .984 |
| CFO3:TL | Correlation Coefficient | | | | | | | | | 1.000 | .496** | -.281* |
| | Sig. (2-tailed) | | | | | | | | | | .000 | .017 |
| MVE:TL | Correlation Coefficient | | | | | | | | | | 1.000 | .008 |
| | Sig. (2-tailed) | | | | | | | | | | | .950 |
| AR:S | Correlation Coefficient | | | | | | | | | | | 1.000 |
| | Sig. (2-tailed) | | | | | | | | | | | |

Note: Variables reflected are those which have been found based on the Mann-Whitney *U* test to have a statistically significant difference between distressed and healthy organisations.

**rho > 0.5 highlighted are regarded as highly correlated.

## *5.6 Probability function*

The proposition for this study is the development of a distress predictor. As indicated earlier, a non-parametric approach was used, based on the results of the descriptive statistics. To continue on this path, an logistic regression ('LR') was used as classic statistical method to determine the probability function.

The LR section will firstly focus on the 'goodness of fit' of the LR as developed: how well the predictor (independent) variables as identified can predict the dependent variable. Secondly, focus will be placed on the relative importance of each of the variables, and then on the accuracy of the model.

### 5.6.1 Descriptive: Model goodness of fit

The model underwent a battery of tests to determine the goodness of fit, meaning how well the predictor variables can predict the dependent variable. The first tests relating to the Cox & Snell R square and the Nagelkerke R square provide insight into what degree of "variation in the dependent variable is explained by the independent variables in the model" (Pallant, 2011, p.176), while the -2 Log likelihood ('-2LL') statistic provides insight into the degree of unexplained variance there is after the model has been fitted (Field, 2009). The Log test is interpreted as the greater the number the more unexplained variance there is and the lower the goodness of fit of the model (Field, 2009).

Table 15
*Model summary*

| -2 Log likelihood | Cox & Snell R Square | Nagelkerke R Square |
|---|---|---|
| 116.173[a] | .452 | .603 |

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.
* Cox & Snell R Square and Nagelkerke R Square can be interpreted as a percentage of variance explained.

The final test is the Hosmer and Lemeshow test indicating how well the model fits the data and is widely regarded as the best known (Pallant, 2011). The test is interpreted using Chi-square statistics and where p >0 .05 the model has support for its predictive capabilities.

Table 16
*Hosmer and Lemeshow 'goodness of fit' test*

| Chi-square | Df | Sig. |
|---|---|---|
| 13.167 | 8 | .106 |

*Interpretation of the test is different p>0.05 indicates support for the model.

The preceding conducted tests all reflect slightly different views regarding support for the LR model and its interpretation; however they should all be viewed as providing a better understanding of how significant the model is. The results of these tests will be discussed in chapter six.

### 5.6.2 Probability function variables

This section reflects the variables and their importance and contribution to the LR function construct and model as a whole.

The 'b' values are the variable coefficients which are used in the construction of the LR formula; based on the preceding sign, it illustrates the positive or negative relationship between the variable and the dependent. The interpretation of b in the LR is as follows:

6.363 - 7.331 WC:TA -5.107 CA:TA + 0.002 TL:E – 1.817 ROA – 2.987 CFO3:TL- 0.247 MVE:TL

The Wald statistic (Table 17) is used to determine the contribution of each of the variables to the predictive capability of the model, the statistic being interpreted by the related p value (Sig.).

Exp(B) provides the odds ratio ('OR') explained as the increase or decrease in probability of belonging to the dependent categories based on a one unit change in the independent variable. The final column reflects the confidence levels for the OR, interpreted as being that the model is 95% confident that the OR is between these two points (Lower and Upper).

Table 17
*Variables in the equation*

| | b | S.E. | Wald | df | Sig. | Exp(B) | 95% C.I.for EXP(B) Lower | Upper |
|---|---|---|---|---|---|---|---|---|
| WC:TA | -7.321 | 1.645 | 19.799 | 1 | .000 | .001 | .000 | .017 |
| CA:TA | -5.107 | 1.643 | 9.660 | 1 | .002 | .006 | .000 | .152 |
| TL:E | .002 | .069 | .000 | 1 | .983 | 1.002 | .875 | 1.147 |
| ROA | -1.817 | 2.140 | .721 | 1 | .396 | .162 | .002 | 10.772 |
| CFO3:TL | -2.987 | .838 | 12.712 | 1 | .000 | .050 | .010 | .260 |
| MVE:TL | -.247 | .139 | 3.168 | 1 | .075 | .781 | .595 | 1.025 |
| Constant | 6.363 | 1.388 | 21.024 | 1 | .000 | 579.923 | | |

*Wald statistic p<0.05 statistically significant contribution to the model.

### 5.6.3 Model accuracy

The following section reflects how well the model predicts the categories to which each of the cases belongs. Keeping in mind that the total sample n =168 with n=20 missing values, therefore the model accuracy will be tested on n =148, being the total number of firm years associated with the study.

Table 18
*Classification table*

| Observed | | Predicted Category: Healthy | Predicted Category: Distress | Percentage Correct |
|---|---|---|---|---|
| **Category** | Healthy | 63 $_a$ | 11 $_b$ | 85.1 |
| | Distress | 11 $_c$ | 63 $_d$ | 85.1 |
| **Overall Percentage** | | | | 85.1 |

Part of the tests to determine the accuracy of classification, are referred to as the sensitivity (true positive rate) and specificity (true negative rate) tests. Sensitivity and specificity are usually used in medical sciences to determine the accuracy of a diagnostic test in predicting the presence or absence of a disease (Pallant, 2011). In this case, they are used to determine the 'goodness of fit' of the distress prediction forecast model. Sensitivity reflects the proportion of organisations correctly classified as Healthy, while specificity reflects the proportion of organisations correctly classified as Distressed. Table 18 provides the classification results while Table 19 provides the formula and results for the sensitivity, specificity, positive predictive value, negative predictive value and accuracy of the results. These tests are closely related to the Type I and Type II error which is usually performed as part of hypothesis testing.

Table 19

*Sensitivity, specificity, positive predictive value, negative predictive value and accuracy*

| Test | Formula | Result |
|---|---|---|
| **Sensitivity** | a/(a+c) | 85.1% |
| **Specificity** | d/(b+d) | 85.1% |
| **Positive predictive value** | a/(a+b) | 85.1% |
| **Negative predictive value** | d/(c+d) | 85.1% |
| **Accuracy** | (a+d)/( a+b+c+d) | 85.1% |

## *5.7 Summary*

The chapter presents the results of the study. It focuses on the descriptive statistics used in determining the best approach for developing a prediction model, and the results of the Mann- Whitney *U* test conducted and, finally, it presents the proposed LR model for distress prediction. The results as presented in this chapter will be discussed in chapter six.

# 6 Discussion of results

## *6.1 Introduction*

Since this chapter provides a discussion of the results which were reported in chapter five, it will follow a similar outline. It will start with a discussion of the sample used and observations relating to this, followed by a discussion of the variables selected, based on the hypothesis. Finally there will be a discussion of the LR function which was derived from the preceding tests.

## *6.2 Sample*

This section highlights observations relating to the sample, which should be noted as part of the distress definition which is used. Steyn, Hamman, & Smit, (2001) showed that companies that were growing at a high rate and had large amounts of non-cash working capital would in all probability run into liquidity problems or become part of a corporate action and be classified as experiencing financial distress. As an example, these findings partly explain the inclusion of South African Breweries Ltd. (SAB), widely regarded as one of the 'most successful' South African organisations, its inclusion among those in distress being largely due to its aggressive expansion during the years after 2000.

It is important to note the above when reviewing the companies included in the sample of distressed firms because, in some cases, 'corrective action' was initiated and the companies successfully returned to health.

In his study, Laitinen (1991) highlighted three different failure processes: organisations whose performance never rises above poor before failure, organisations which show significant growth before plummeting and, finally, those that show good performance over a long period of time and then experience distress. This study assumed that a 'uniform process' of distress was experienced across the sample. The true combination of processes in the sample will influence both its variables and its coefficients (Laitinen, 1991) and this should be noted by the user.

## *6.3 Selection of independent variables*

**Each of the variables will be discussed in terms of the tests conducted on them, and focus will be placed on the exploratory data analysis reflected in Table 5 to Table 10 relating to the descriptive data analysis of each of the variables and the Mann-Whitney *U* test on Table 11,** Table 12 Table 12 and Table 13. Included in the discussion section is a portfolio analysis of the sample, indicating how the ratio's mean and median change as the company moves towards distress. This is done to provide a visual understanding of the change in the ratio in this portfolio; the review is similar to that completed by Beaver (1966).

### 6.3.1 Descriptive statistics and hypothesis

This section will be grouped on the basis of each of the following ratio classifications: liquidity, leverage, solvency, activity, profitability and market-rated ratios. The section will also present the variables, while discussion of the selected LR variables will be linked to the literature in the following section. Each of the variables will be discussed as follows:

i. descriptive statistics:
ii. missing values;
iii. outliers;
iv. kurtosis; and
v. skewness;
vi. Mann-Whitney *U* and hypothesis conclusion; and
vii. portfolio analysis of the mean and median over the three-year period preceding distress.

#### 6.3.1.1 Liquidity ratios

Liquidity ratios are those ratios which illustrate the organisation's liquid assets and ability to repay its short-term obligations. The set of ratios is closely related to the definition of distress featured this study: current assets < current liabilities.

#### *Cash to Sales (C:S)*

*Descriptive statistics*

Several values were missing from the C:S dataset, MP18, MP22, MP27 and MP28 years three, two and one. In addition to this, the data contained a number of outliers – MP15 and MP25 years two and one, MP12 year two, MP1 year three – which resulted in a mean (0.100) and trimmed mean (0.084) difference of 20%. A total of six outliers were identified and excluded from the analysis, resulting in a revised mean of 0.083 and trimmed mean of 0.074, a variance of 11%. Exclusion of additional outliers resulted in an increase in the difference, therefore no further analysis was conducted on the variable and it was excluded from further participation in the study. The null hypothesis could be neither confirmed nor rejected.

*Portfolio analysis*

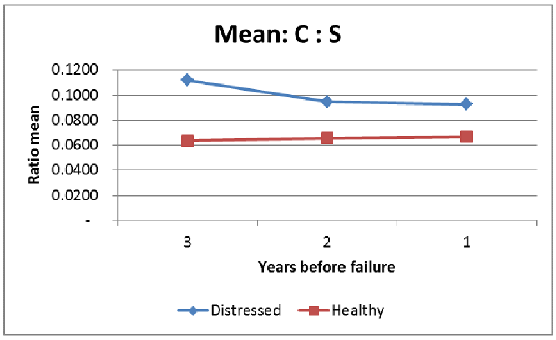


*Figure 1* Mean C:S

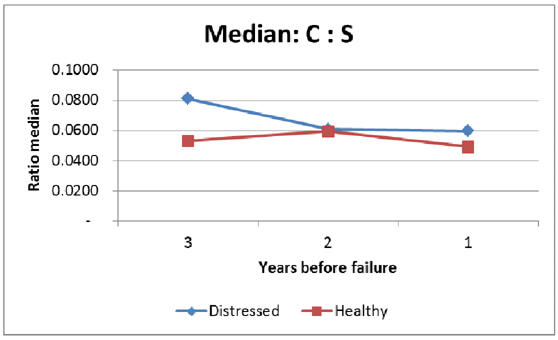


*Figure 2* Median C:S

The mean cash to sales ratio for Healthy 'H' organisations appears to be lower than that of Distressed 'D' organisations; however the scale of the difference does not appear to be significant.

The median for D organisations is higher than that for H organisations, decreasing as the number of years prior to distress decreases.

### ***Current assets to Total assets (CA:TA)***

*Descriptive statistics*

Current assets are viewed as those assets which are liquid in nature, which can easily be transformed into cash or cash equivalents. The ratio illustrates the level to which the current assets contribute to the total portfolio of assets. The sample as a whole is negatively skewed with negative kurtosis, meaning that it is not normally distributed. All data points in the sample were used and there were no outliers or missing data points. The ratio is expected to decrease in the years preceding distress, as liquidity starts to 'dry up'. This is best illustrated in **Error! Reference source not found.** Figure 3 and Figure 4.

*Portfolio analysis*

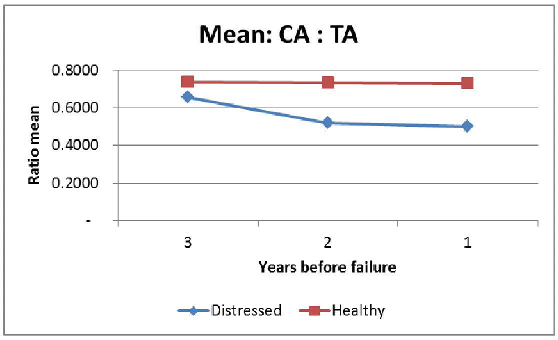


*Figure 3* Mean CA:TA

There is a distinction between the mean value of H and D organisations for the three-year period preceding the distress point.

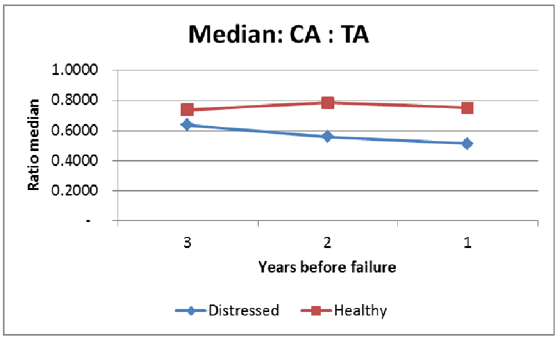


*Figure 4* Median CA:TA

Similar to the mean, there is a distinction between the median value of the H and D organisations for the three years preceding the point of distress although this is less pronounced in year 3.

*Hypothesis 2 CA:TA*

The Mann-Whitney *U* test concluded that there is a significant difference between D (Md= 0.571, n= 84) and H organisations (Md = 0.760 and n =84) for CA:TA, U = 1 897.5, z= -5.172, p= 0.000 at the 95% confidence level and that the effect size is leaning towards a higher level r =-0.399.

It can therefore be concluded that the null hypothesis is rejected in favour of the alternative suggesting that there is a significant difference between the medians of H and D organisations.

### *Cash from Operations to Sales (CFO:S)*

*Descriptive statistics*

CFO:S provides an indication of the level or rate at which sales are translated into cash. The sample had no outliers but there were three missing values from MP 27. The data points are positively skewed 0.722 (values clustered to the left), with positive kurtosis of 15.456 indicating the high peaked nature of the sample data; both these tests indicate that the data are not normally distributed and that non-parametric tests should be performed.

*Portfolio analysis*

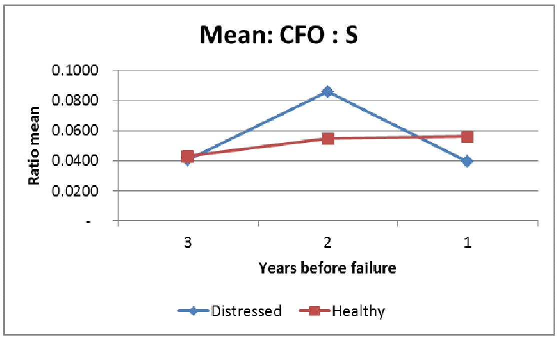


*Figure 5* Mean CFO:S

There is no visual distinction between the means of the H and D firms in year three. However this changes in year two with a strong increase in the ratio for D, after which it slumps to below the level of H in year one.

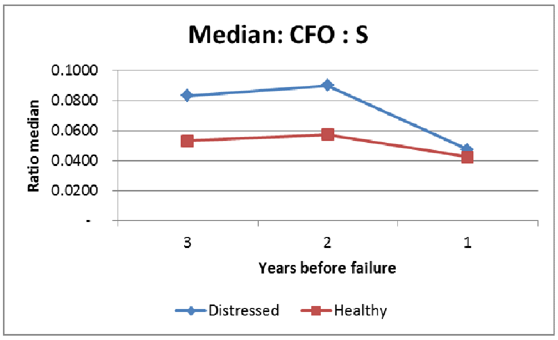


*Figure 6* Median CFO:S

There is a clear visual variance between the medians in years two and three, with both of the medians decreasing towards year one, although that of the D appears to be doing so at a greater rate. The variance however appears to be small, when taking the scale into account.

*Hypothesis 3 CFO:S*

Based on the findings of the Mann-Whitney *U* test on CFO:S (Table 11) there is no statistically significant ($p = 0.391$) difference between D (Md= 0.069, n =81) and H (Md= 0.053, n= 81) organisations, the results reflecting U = 3 025.5, z = -0.858 , r= -0.67; as a result no further analysis was conducted on the variable.

Based on the results of the Mann-Whitney *U* test, the null hypothesis is accepted at the 95% confidence level.

### ***Cash from operations to Total liabilities (CFO:TL)***

*Descriptive statistics*

The impact of outliers on the variable was negligible and no missing values were identified. As a whole, the sample was negatively skewed -0.227, with positive kurtosis 3.261. Again these descriptive statistics indicate that the data are not normally distributed. Intuitively it is expected that an H organisation would maintain a higher level of this ratio meaning, for example, lower debt levels to higher operating cash flow levels.

### Portfolio analysis

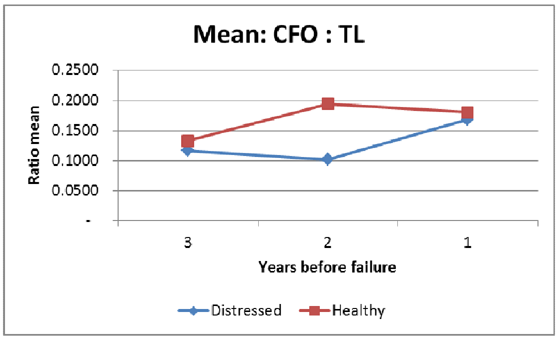


*Figure 7* Mean CFO: TL

There does not appear to be a difference between the year three data mean values of D and H companies, D and H showing a decrease and increase respectively in year two, ending at similar points in year one.

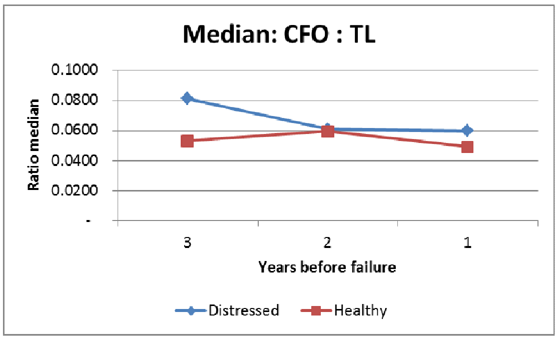


*Figure 8* Median CFO:TL

The greatest visual difference in the median occures in year three, after which both H and D move towards a similar year two point, H remaining below the D level till year one.

### Hypothesis 4 CFO:TL

There appears to be no statistically significant difference (p= 0.267) between the medians of H and D organisations, according to the Mann-Whitney *U* tests conducted, U= 3 178 , z= -1.11 and r= 0.086. In view of the results, the variable was not included in the development of the distress prediction function.

Based on the above findings, the null hypothesis is accepted at the 95% confidence level.

## ***Three years' cumulative cash flow from operations to Three years' cumulative sales (CFO3:S3)***

### Descriptive statistics

The variable was not impacted by extreme outliers as the mean (0.049) and trimmed mean (0.051) differed by 3%. The sample did have a missing value from MP27 year one, and the data points were eliminated from the CFO3:S3 analysis. The variable showed negative skewness (-2.062) and kurtosis of 17.941, highlighting the non-normality of the data set.

*Hypothesis 5 CFO3:S3*

The results of the Mann-Whitney *U* test show U= 3 351.5, z= -0.3 and r= -0.023 and p= 0.764, indicating that there is no statistically significant variance between the medians of D (Md= 0.044, n= 83) and H (Md= 0.047, n= 83). Refer to Table 5 and Table 11.

Based on the above findings, the null hypothesis is accepted at the 95% confidence level.

*Portfolio analysis*

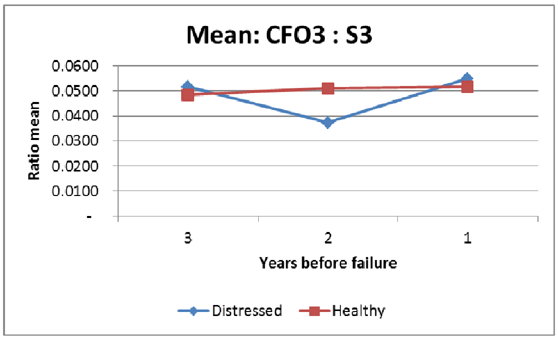


*Figure 9* Mean CFO3:S3

The trend for H appears to be stable over the period under review. The difference between H and D appears to be negligable in years three and one.

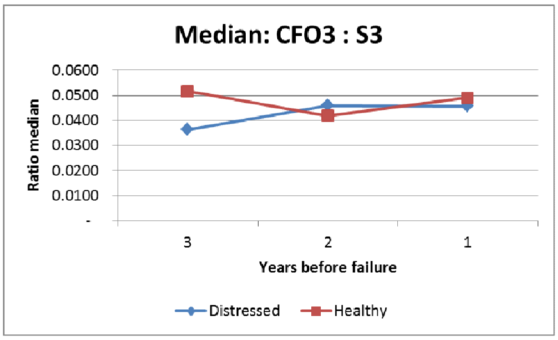


*Figure 10* Median CFO3:S3

There appears to be an insignificant difference between the samples in years two and one.

### ***Three years' cumulative cash from operations to Total Liabilities (CFO3:TL)***

*Descriptive statistics*

The ratio had no missing values and the impact of outliers was limited as indicated by the mean (0.356) and trimmed mean (0.348) comparison. The distribution of data showed positive skewness of 0.177, which is relatively low and kurtosis of 2.617. The ratio is expected to decrease the closer to distress it gets, since total liabilities are anticipated to increase – or cash flow from operations is expected to decrease.

*Hypothesis 6 CFO3:TL*

The Mann-Whitney *U* test indicated that CFO3:TL has a statistically significant difference (p= 0.008) between H (Md= 0.406, n= 84) and D (Md= 0.241, n= 84) organisations, U= 2 691, z= -2.655 and r= -0.205, the effect size of r being at the medium impact level.

The null hypothesis is rejected at the 95% confidence level in favour of the alternative and the variable was included in the statistical tests to determine a probability function.

*Portfolio analysis*

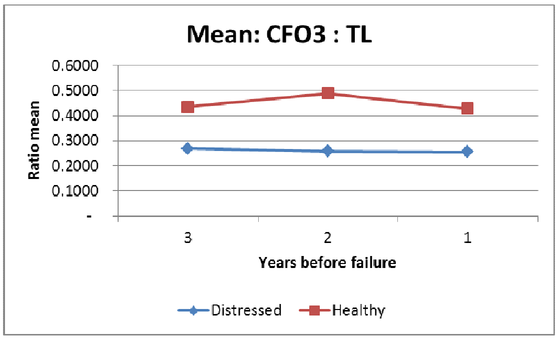


*Figure 11* Mean CFO3:TL

There appears to be a clear visual distinction between the mean values of H and D, D maintaining a position lower than that of H both, with limited fluctuation.

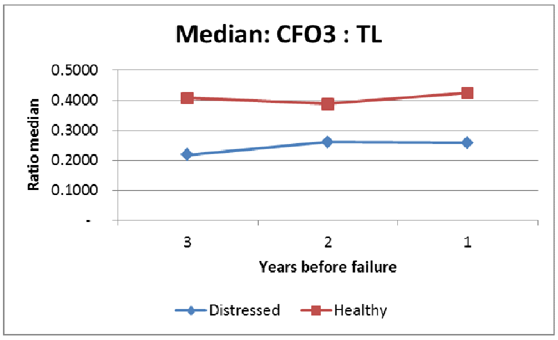


*Figure 12* Median CFO3:TL

The median value differences between the two groups appear to remain fairly unchanged with both H and D organisations remaining at a stable level, H being higher than D.

## 6.3.1.2 Leverage

### ***Total liabilities to Equity (TL:E)***

*Descriptive statistics*

The sample data for TL:E had no missing values but two significant outliers were identified, using the trimmed mean function; these related to MP14 and MP18 year one, which were excluded, as indicated earlier. The result was that the mean decreased from 2.520 to 1.470, and the trimmed mean of 1.552 to 1.472 (a difference of 62% to 0% respectively). The result of the elimination of the outliers was that a normal distribution was imitated more closely, although it still suffered from skewness (0.241) and kurtosis (10.662).

*Hypothesis 7 TL:E*

The results of the Mann-Whitney *U* test indicated U= 2 382, z=- 3.223 and p= 0.001 showing that there is a statistically significant difference between the median values of H (Md= 0.938, n=82) and D (Md= 1.550, n= 82). The effect size of the difference in TL:E being r = -0.252 indicates that the effect accounts for roughly 9% of the difference. Based on the findings, the null hypothesis is rejected in favour of the alternative and the variable is included in further statistical analysis.

Figure 13 and more so Figure 14 illustrate the expected trend for the ratio as distress becomes more evident, the level of the ratio is expected to increase as the level of total liabilities increases – or the level of equity decreases, either as a result of non-payment of debt or of taking on additional debt for cash flow purposes or, alternatively, there could be an overall slowdown in operations, resulting in decreasing profits lowering retained earnings growth. (These are examples of possible causes for the movement and do not constitute a comprehensive list.)

*Portfolio analysis*

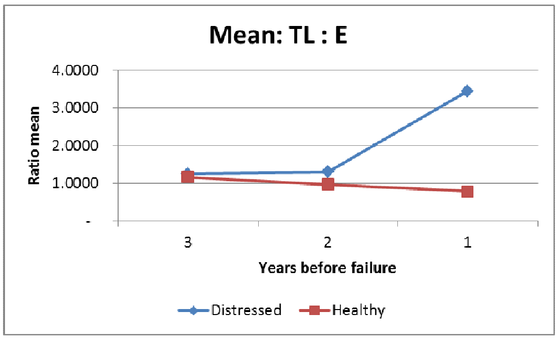


*Figure 13* Mean TL:E

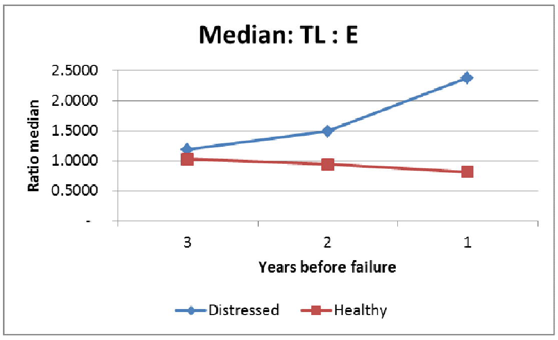


*Figure 14* Median TL:E

While there is little distinction between the mean level of the ratios in years three and two, a difference becomes clear in year-one H organisations overall, showing a downward slope, while D organisations peak in year one.

As with Figure 13 the two dychotomous groups start off at a similar point in year three, after which H organisations' median decreases slightly and D organisations' increases, peaking again in year one.

### 6.3.1.3 Solvency

***Total liabilities to Total assets (TL:TA)***

*Descriptive statistics*

The TL:TA variable showed a tendency towards a normal distribution when compared with the other variables, with skewness limited to 0.510 and kurtosis 0.665; a normal distribution has both skewness and kurtosis amounting to nil. The sample did not have any missing values nor was the distribution affected by outliers; the mean amounted to 0.576 and the trimmed mean to 0.568.

*Hypothesis 8 TL:TA*

The Mann-Whitney *U* test indicated that there is a statistically significant (p= 0.000) difference between the median value for H (Md= 0.496, n= 84) and D (Md= 0.686, n= 84) firms U= 2149, z=-4.375. The size effect is in the medium range r= 0.338. Based on these findings the null hypothesis is rejected at the 95% confidence level and as a result the variable is included in the following statistical steps.

The expectation is that the ratio should increase in a distressed organisation as liabilities increase in relation to assets. The ratio has been found in numerous studies and is viewed by the researcher as the step following the definition of distress as defined in this study, being current assets < current liabilities.

*Portfolio analysis*

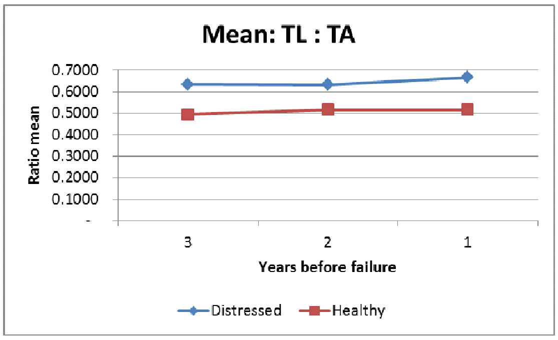

*Figure 15* Mean TL:TA

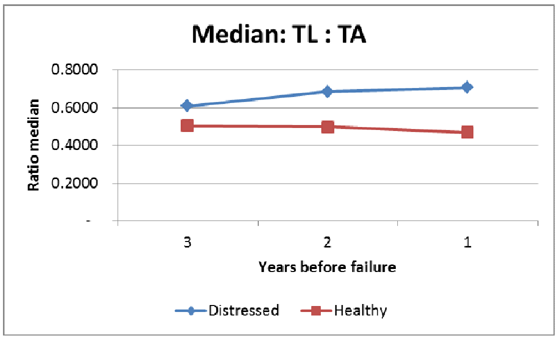

*Figure 16* Median TL:TA

The mean value for D firms is greater than that of the H organisations from year three

The median value of D organisations is similar to that of the mean graph, higher to year one, and shows little fluctuation.

than H organisations, and does not show significant fluctuation between years two and one, while the median for D firms does increase slightly between years three and two.

***Interest cover (EBIT: I)***

*Descriptive statistics*

The interest cover ratio had a number of missing values (MP1 year one, MP10 year three and two, MP16 year three, two and one); furthermore the impact of outliers on the mean 31.162 was significant compared to a trimmed mean of 15.667, a difference of 99%. Both the highest and lowest values were eliminated from the study – with their paired partners – and the difference was reduced to 38%. Since the impact of outliers was deemed to be significant, the variable was eliminated from the remaining statistical procedures and steps in determining a distress predictor. The hypothesis could not be confirmed.

*Portfolio analysis*

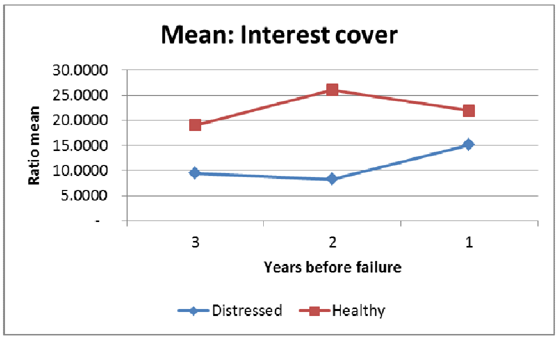


*Figure 17* Mean Interest cover

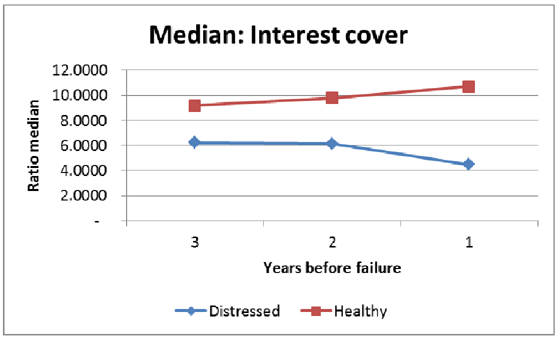


*Figure 18* Median Interest cover

There is a clear visual difference between the means of D and H organisations, with an 'inverse' relationship, H organisations starting off at a higher 'healthier' level than that of D organisations in year three, decreasing to below the level of D in year two, while H decreases to its lowest level in year one, following the increase in year two.

The median for D firms is lower than that of H firms, remaining at the lower level from year three to year one.

## 6.3.1.4 Activity ratios

### *Working capital to Total assets (WC:TA)*

*Descriptive statistics*

Although the variable is classified as part of the activity ratios, it is also regarded as a liquidity indicator. The variable was not impacted by missing values or outliers; the mean (0.172) compared to the trimmed mean (0.170) reflects a difference of 1%. The variable data are reasonably normally distributed with positive skewness of 0.264 and kurtosis of -0.362.

*Hypothesis 10 WC:TA*

The median difference between the H (Md= 0.269, n=84) and D (Md= 0.003, n=84) is statistically significant (p= 0.000), U= 1 250, z= -7.226, the size effect being r= - 0.558, the highest value in terms of the independent variables. Since the variable is deemed statistically significant with importance, it is included in the remainder of the statistical tests and study. Based on the above results, the null hypothesis is rejected at the 95% confidence level, in favour of the alternative

*Portfolio analysis*

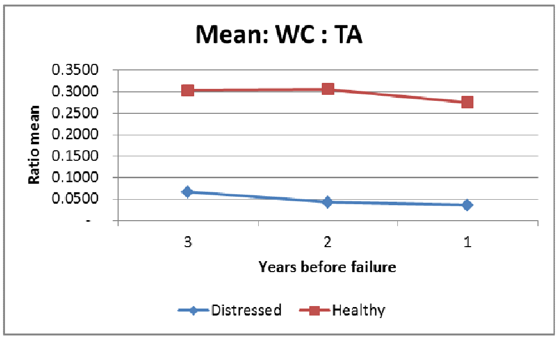


*Figure 19* Mean WC:TA

Both the H and the D organisations show little fluctuation in their mean movements from year three to year one, D being lower than the H organisations.

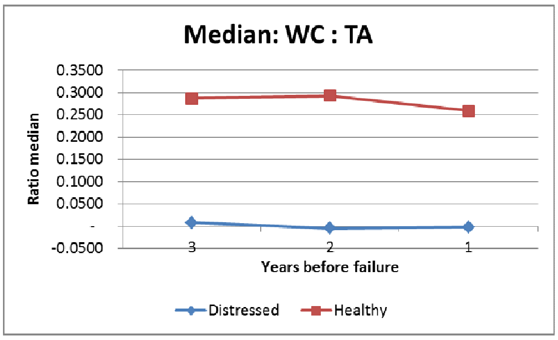


*Figure 20* Median WC:TA

The level of the median is farely stable for both D and H firms, the D median level being below that of the H organisations.

### *Working capital to Sales (WC:S)*

*Descriptive statistics*

The working capital to sales ratio data set had three missing values relating to MP27 year one, year two and year three; the missing values were excluded from the statistical analysis. Moreover, this data set also contained outliers which influenced the mean (0.121) to a trimmed mean (0.109) difference over the tolerance threshold of 10.1%, being 11%. The outliers identified as MP24 year one and year two were excluded from the study. The revised mean value amounted to 0.112 and trimmed mean to 0.106, with positive skewness of 0.747 and kurtosis of 3.354.

### *Hypothesis 11 WC:S*

The median difference between the H (Md= 0.142, n=79) and D (Md= 0.010, n=79) is deemed significant as the p- value of 0.000 is lower than the threshold of 0.05. These findings are based on the Mann-Whitney *U* test, U=1 318, z= -6.268, the related size effect being r= -0.499. The variable can therefore be viewed as statistically significant and important and, based on this, the null hypothesis is rejected in favour of the alternative and the variable incorporated in further statistical analysis.

### *Portfolio analysis*

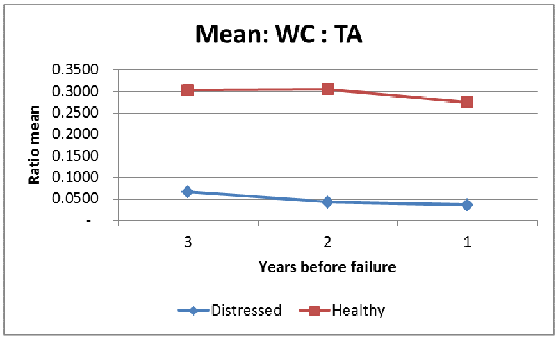


*Figure 21* Mean WC:TA

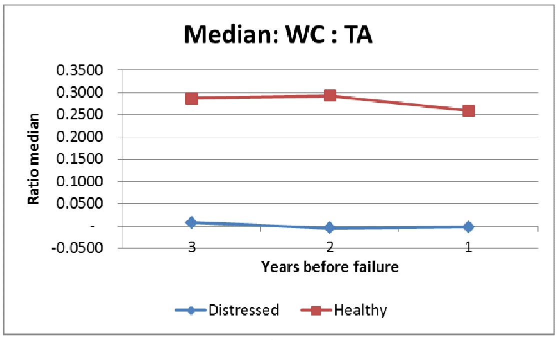


*Figure 22* Median WC:TA

The mean profile for D firms is visually lower than that of H organisations, D being below that of H and both showing limited fluctuation when scale is considered.

The median profiles of both the H and D organisations show little fluctuation between year three and year one, the D organisation median being below that of the Healthy organisation.

## ***Accounts receivable to Sales (AR:S)***

### *Descriptive statistics*

The AR:S data set was impacted by a number of missing values as highlighted in these being MP14 year three, MP27 years three, two and one. Further to this, the 5% trimmed mean differed by 17% from the mean, illustrating the impact of outliers. Four data points, as highlighted by the top 5 highest and lowest values, were excluded from the study: MP15 year three, MP28 year two and MP 24 years two and three. This ultimately resulted in a lower mean value of 0.186, a 7% difference when compared to the trimmed mean value of 0.173 and kurtosis of 11.114 and positive skewness of 2.554 indicating that the distribution is not normal.

### *Hypothesis 12 AR:S*

The result of the Mann-Whitney *U* test concluded that there is a statistically significant difference (p =0.045) between the medians of Healthy (Md= 0.189, n=76) and Distressed (Md= 0.144, n= 76) firms, albeit the effect size low r=- 0.162, the results being U= 2 344.5, z= -2,003. Based on these findings, the null hypothesis is rejected at the 95% significance level in favour of the alternative and the ratio is included in further analysis.

### *Portfolio analysis*

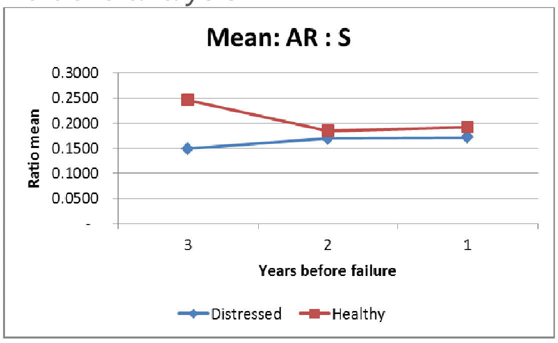


*Figure 23* Mean AR:S

The mean values for both H and D remained fairly stable during the period under review, when considering scale, D remaining at a lower value than H.

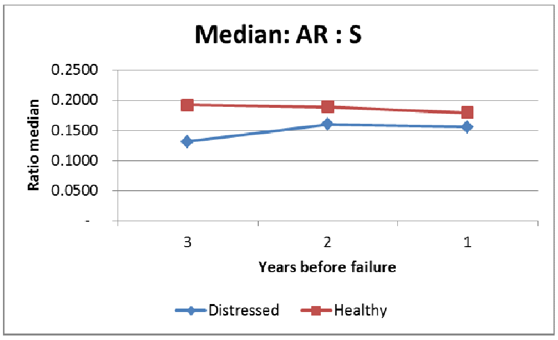


*Figure 24* Median AR:S

Both the D and H organisation medians remained stable, D increasing slightly in year two, and the H organisation median maintaining a higher position.

## ***Inventory to Sales (INV:S)***

### *Descriptive statistics*

The INV:S mean value (0.126) compared to its 5% trimmed mean value (0.117) differed by 7% below the acceptable threshold, meaning that the variable was not strongly influenced by outliers and no exclusions were required. However there were a number of missing values; MP12, MP19 and MP27 years three, two and one. The variable data set was not normally distributed because it had positive skewness of 1.535 and kurtosis of 4.215.

*Hypothesis 13 INV:S*

According to the results of the Mann-Whitney *U* test, there is a statistically significant (p= 0.000) with medium to high importance (r= -0.392) difference between the median of H (Md= 0.146, n=75) and D (Md= 0.072, n= 75) organisations, U= 1 536, z= -4.798. Owing to these results, the variable will be included in further statistical analysis and it can be confirmed that the null hypothesis was rejected at the 95% confidence level in favour of the alternative.

*Portfolio analysis*

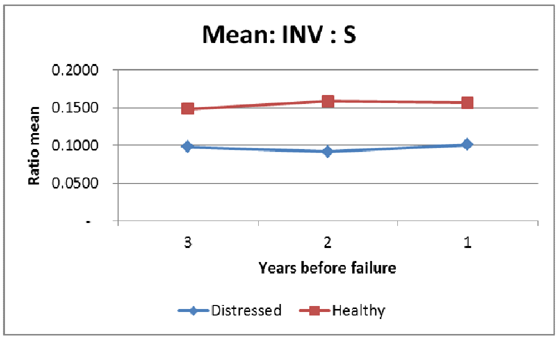


*Figure 25* Mean INV:S

The mean values for both D and H remain fairly stable during the period under review, D maintaining a position below that of H.

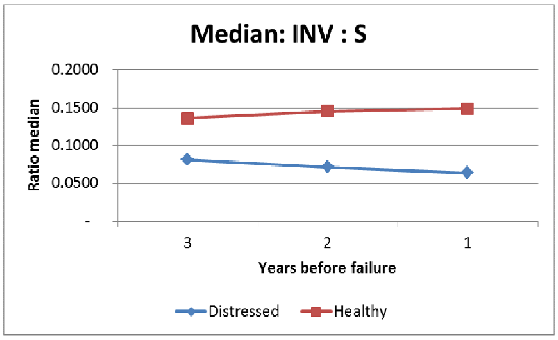


*Figure 26* Median INV:S

The median of D firms remains below that of H firms during the period under review, decreasing slightly as it approaches distress. In contrast, the median of H firms increases as years before distress decrease.

### 6.3.1.5 Profitability

#### *Operating profit margin (OP:S)*

*Descriptive statistics*

Since the OP:S mean value (0.146) compared to 5% trimmed mean value (0.133) shows a difference of 10% which is on the cusp of the threshold, it is assumed not to be influenced by outliers. The data set has three missing values, being MP27 years one, two and three, owing to lack of available turnover information. Nor is the data distribution normal since there is evidence of kurtosis of 21.373 and skewness of 2.655.

*Hypothesis 14 OP: S*

The Mann-Whitney *U* test results indicate that there is no statistically significant (p= 0.696) difference in the median values of H (Md=0.10, n= 81) and D (Md=0.126, n=81) firms, U= 3 164, z= -0.390, r= -0.031. Based on the results, the null hypothesis is accepted and no further analysis will be performed on the variable.

*Portfolio analysis*

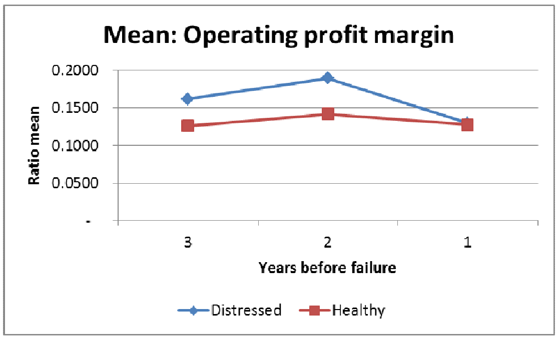


*Figure 27* Mean Operating profit margin

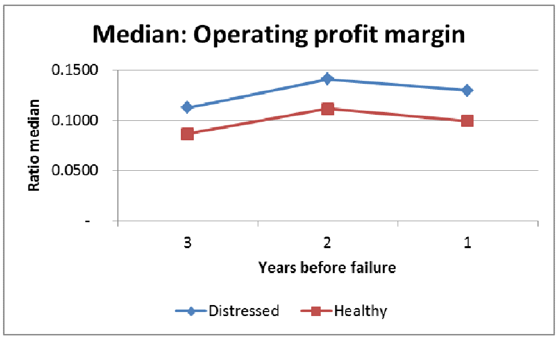


*Figure 28* Median Operating profit margin

Margin for H remains reasonably stable during the period under review, maintaining a position below that of D. D shows signs of increase in year two, decreasing sharply in year one.

The medians of both the D and the H organisations appear to fluctuate in parallel, the margin of D organisations being higher than that of H organisations.

### *Change in profit after tax (PAT1 : PAT2)*

*Descriptive statistics*

The variable had a mean value of 0.332 and a trimmed mean value of 0.225, a difference of 48%. One of the outliers was removed from the data MP19 year three: the exclusion from the study resulted in a revised mean of 0.2010 and a revised trimmed mean of 0.214, a difference of -6% which is below the threshold stipulated. Further to the removal of outliers, the data set had a number of missing values as no information was available in year four, MP1, MP2, MP13, MP17, MP22, MP23, MP25. The data set with kurtosis of 8.556 and skewness of -0.329, is not normally distributed.

*Hypothesis 15 PAT 1 : PAT 2*

The Mann-Whitney *U* test indicated that the variable does not have a statistically significant difference (p=0.849) in the median between H (Md= 0.168, n=75) and D (Md=0.237, n= 75) organisations U= 2 725, z =-0.190, r=-0.016.
The null hypothesis can therefore be concluded to be accepted and the variable will excluded from the remaining statistical steps of the study.

*Portfolio analysis*

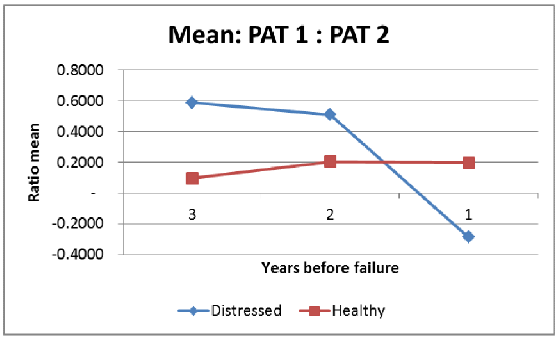


*Figure 29* Mean PAT1:PAT2

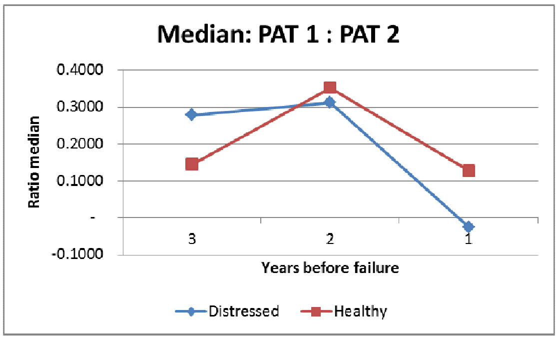


*Figure 30* Median PAT1:PAT2

H growth starts off slowly in year three, increasing to year two and maintaining that level to year one. D, in contrast, starts off at a much higher level of growth, sharply decreasing to negative growth in year one.

The median values for both H and D organisations show decline from a similar position from year two to year one. However the difference between the two sets appears to be insignificant, specifically in year two.

### *Return on Assets (ROA)*

*Descriptive statistics*

The ROA variable had no identified missing values or outliers, the mean value of the data set amounted to 0.105, while the trimmed mean was 0.104, a difference of 1%. The data set is not normally distributed, with kurtosis of 6.958 and skewness of -0.485.

*Hypothesis 16 ROA*

The Mann-Whitney *U* test results (U= 2 544) indicated that there is a statistically significant (p=0.002) difference with medium to low importance (r= -0.241) between the median values of H (Md= 0.122, n= 84) and D (Md= 0.082, n= 84) organisations, z= -3.122. Based on these findings, the null hypothesis is rejected in favour of the alternative and the variable will be used in further statistical tests associated with this study.

*Portfolio analysis*

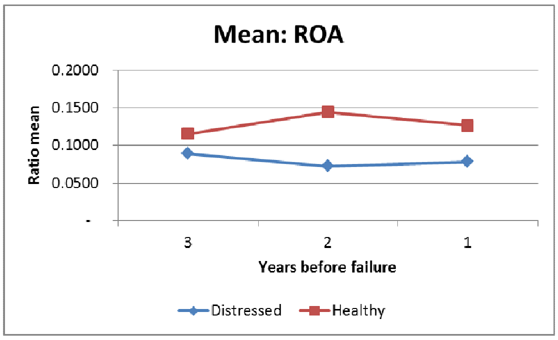


*Figure 31* Mean ROA

There is a clear visual difference between the means of H and D, D maintaining its position below that of H.

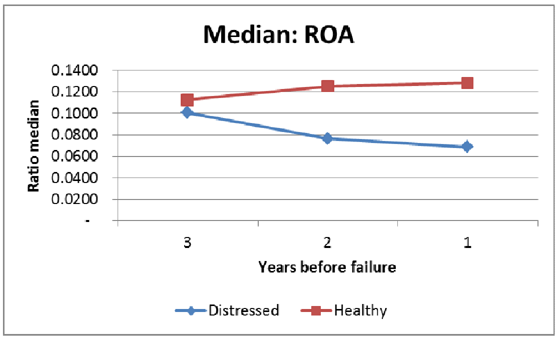


*Figure 32* Median ROA

Similar to the profile of the mean, there appears to be a difference between the medians of H and D organisations, which increases as distress approaches, starting off at a similar point in year three.

***Return on Equity (ROE)***

*Descriptive statistics*

The ROE variable had two outliers (MP14 year one, MP18 year one) influencing its mean (0.424), which resulted in an 80% difference in the 5% trimmed mean 0.236. These two values were excluded from the study, which resulted in a revised mean of 0.243 and a difference of 3% when compared to the trimmed mean (0.236). The data are not normally distributed, with kurtosis of 38.772 and are positively skewed (3.158)

*Hypothesis 17 ROE*

The results of the Mann-Whitney-*U* test concluded that the variable does not have a statistically significant (p= 0.407)difference between those of H (Md= 0.240, n=82) and D (Md= 0.181, n =82) organisations, U= 3 110, z= -0.829 and r= 0.157. Based on these findings, the null hypothesis is accepted and the variable not included in further analysis.

*Portfolio analysis*

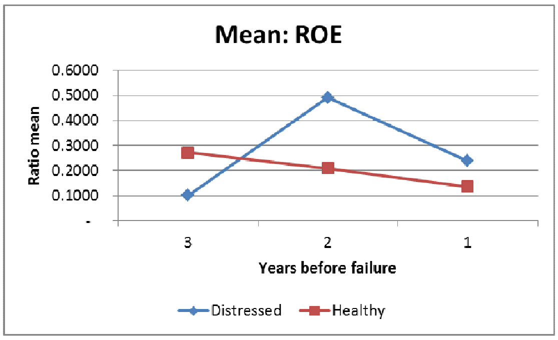


*Figure 33* Mean ROE

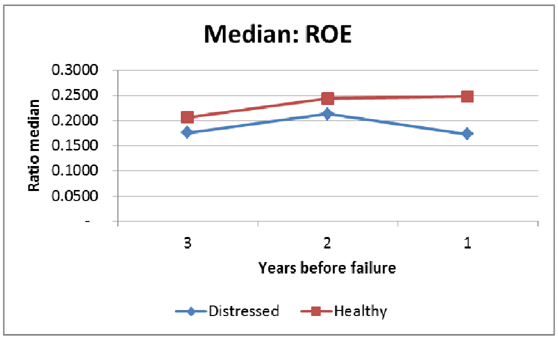


*Figure 34* Median ROE

The ROE for D organisations unexpectatly increases as distress approaches (potentially owing to the age of organisations) while that of H organisations remains fairly stable during the period under review.

The median for H organisations increases as distress approaches, while that of D organisations initially increases, whereafter it decreases.

### 6.3.1.6 Market-related ratios

#### *Market value of Equity to Total liabilities (MVE:TL)*

*Descriptive statistics*

The distribution of MVE:TL is not normal owing to skewness of 1.413and kurtosis of 2.076. The data set suffered from the influence of outliers: the five major influencing outliers (MP17 years three and two, MP1 years three and two, MP27 year one, MP16 years three and one) were identified and a revised mean (2.167) and 5% trimmed mean (1.981) calculated. The difference between the two points (9%) was below the predetermined threshold of 10.1%.

*Hypothesis 18 MVE :TL*

The Mann-Whitney *U* test results (U= 2 341) indicated that there is a statistically significant (p=0.044) difference with low importance (r= -0.163) between the median values of H (Md= 1.940, n= 76) and D (Md= 1.519, n= 76) organisations, z= -2.016. Based on these findings, the null hypothesis is rejected in favour of the alternative and the variable will be included in further statistical tests associated with this study.

### Portfolio analysis

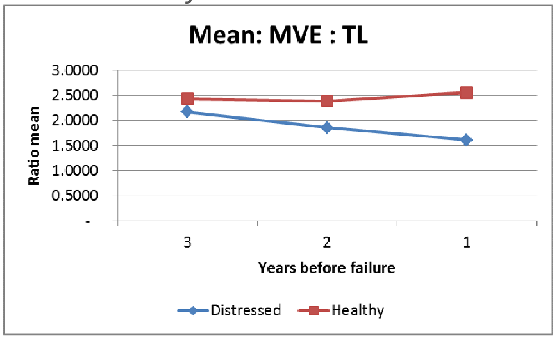


*Figure 35* Mean MVE:TL

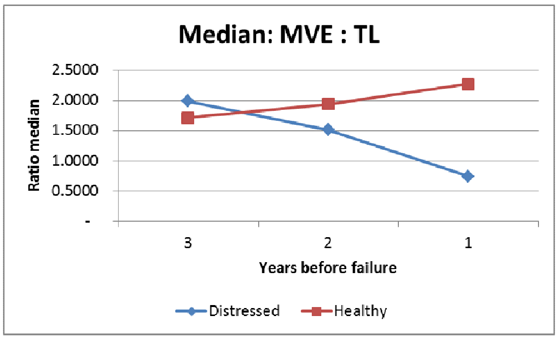


*Figure 36* Median MVE:TL

The mean value of the two dycohotomous groups does appear to differ visually: D organisations mean reflect a downward slope as the time before distress decreases, whereas H organisations results tend to remain fairly consistent during the period under review.

The median value of D and H organisations appears to react inversely as distress approaches: D organisations mediandecrease, while H organisations increase as time running up to distress decreases.

## *Price earnings ratio (PE)*

### *Descriptive statistics*

The PE variable was strongly influenced by outliers: a total of eight outliers (MP14 year one, MP20 year one, MP15 years three and two, MP24 year three, MP11 year two, MP22 year three and MP19 year two) which were excluded from further analysis in order to reduce the influence on the mean value. This resulted in a revised mean value of 9.313 and a trimmed mean value of 9.311, a difference of 0%, falling below the threshold. In addition to this, the data also had one missing value, MP19 year three. The data set is not normally distributed, showing skewness of -0.162 and kurtosis of 3.505 post the adjustment of outliers.

### *Hypothesis 19 PE*

The Mann-Whitney *U* results for PE concluded that there is no statistically significant (p= 0.360) difference in the median values of H (Md= 8.83, n= 67) and D organisations (Md= 9.77, n=67), the results of the test being U= 2 569, z= -0.915, r= -0.75. Based on these findings, the null hypothesis is accepted and the variable excluded from further analysis.

*Portfolio analysis*

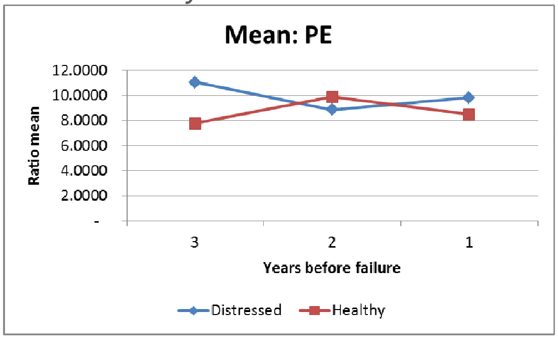


*Figure 37* Mean PE

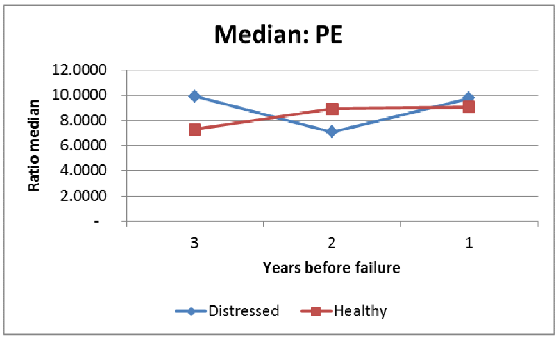


*Figure 38* Median PE

The mean values of D and H organisations for PE appear to have an inverse relationship, with H organisations ending below those of D.

D median PE ratio undulates from a high position in year three to a decrease in year two, increasing again in year one. The H position shows slightly less movement from years three to one, improving slightly between years three and two.

### 6.3.1.7 Summary

This section reviewed the descriptive statistics of the variables concluding as to whether the data were normally distributed or not, the results of the Mann-Whitney- *U* test concluding as to whether the null hypothesis was rejected or not and, finally, provided a short portfolio summary illustrating the movement of the mean and median of the ratios over the period preceding distress.

### 6.3.2 Correlation

This section will review the result of the Spearman rho test conducted to determine collinearity of those variables which have been identified as having a statistically significant difference between healthy and distressed organisations, in the results of their Mann-Whitney-*U* test. As indicated earlier, correlation between independent variables should be minimised to limit the impact on the overall regression model (Pallant, 2011). A total of 10 variables were found to be statistically significant in this regard. Their multi-correlation results are reflected in Table 14 Spearman rho results.

Highly correlated variables rho >0.5 were investigated and, based on logic and their relationship with other variables, the variable was either included or excluded.

The WC:TA which appeared to be the most meaningful ratio in the study, based on the Mann-Whitney-*U* test ($p=0.000$ and $r=-0.558$), displayed high levels of positive correlation with WC:S (rho=0.948), AR:S (rho=0.506) and INV:S (rho=0.669) all of which are shown to be statistically significant with $p= 0.000$, based on their relationship to WC:TA. The correlated variables are excluded from formulating the LR. In support of the variables selection, Wu et all. (2010) noted that WC:TA is one of the most widely used measures of liquidity (categorised as an activity-based ratio in this study) and its explanatory powers are evident in previous studies.

Third ranked CA:TA is highly positively correlated with INV:S (rho = 0.533), which is already excluded from further analysis due to its relationship to WC:TA.

TL:TA has a medium to high negative correlation with WC:TA (rho =0.418, $p<0.05$), WC:S (rho = 0.495) and high levels of positive correlation with TL:E (rho= 0.684, $p <0.05$) and CFO3: TL (rho = 0.543, $p<0.05$). TL:TA has a strong relationship with the definition of technical bankruptcy, where TA<TL; logically the variable is therefore the next step to distress as defined in this study (current assets < current liabilities). Based on this thinking and owing to its strong correlations with the mentioned four variables, of which WC:TA, is already being included in further analysis, TL:TA is excluded from further statistical steps, while TL:E and CFO3:TL will be included in following analysis.

TL:E has a mid-level strength negative correlation with WC:TA (rho=-0.270, $p= 0.022$) and a positive correlation with CA:TA (rho=0.308, $p =0.008$). CFO3:TL is negatively correlated with both of the already included variables albeit not strongly so (WC:TA rho=-0.087, $p>0.05$, CA:TA rho=-0.368, $p= 0.001$).

ROA as variable is included in further statistical steps due to its low-level correlations with the currently included variables. The final variable up for consideration is MV:TL. The variable displayed medium to high levels of correlation with ROA (rho =0.496, $p <0.05$) and CFO3:TL (rho=0.478, $p <0.05$). Since the correlation is below the rho < 0.5 threshold, the ratio will be included in the development of the LR function.

### 6.3.3 Variable summary

Accounting ratio-based models are typically built by data mining large numbers of ratios and assigning weightings to them, based on a sample of failed and non-failed firms. The selection of variables for the final model is based on their statistical significance and on improving the model. While the process which was employed to identify those significant variables – excluded as an example, OP:S and PAT1:PAT2 in this study – which have been found to be "powerful measures that capture the static and dynamic conditions of a firms [sic] profitability position" (Wu et al., 2010, p.27) does illustrate and support the sample-specific nature and limitations of generalisability referred to by Grice & Ingram, 2001; Grice & Dugan, 2001, Mensah (1984) explained this as follows: no two models are the same because different sets of financial ratios are used – hence the importance of the coefficients of each of these model variables being different.

Both Beaver et al. (2005) and Altman (2000) pointed out that, due to the nature of financial information, the variables used are of little consequence for the predictive capabilities of a model. Despite this, the variables in this study are deemed representative of all the categories which have been used in past studies and literature. Table 20 provides a summary of the final list of variables which was used in determining the LR model. Table 21 provides a list of the variables which were excluded on the basis of inter-correlations and logic. Table 22 provides a summary of those variables excluded from the study since their null hypothesis were accepted and there were no statistically significant difference between the medians of H and D firms.

Table 20
*Variables included in the LR*

| | Shape of distribution | Mann-Whitney-*U* | Z | Asymp. Sig. (2-tailed) | r |
|---|---|---|---|---|---|
| WC:TA | Normal | 1250.000 | -7.226 | .000 | -.558 |
| CA:TA | Normal | 1897.500 | -5.172 | .000 | -.399 |
| TL:E | Not normal | 2382.000 | -3.223 | .001 | -.249 |
| ROA | Not normal | 2544.000 | -3.122 | .002 | -.241 |
| CFO3:TL | Not normal | 2691.000 | -2.655 | .008 | -.205 |
| MVE:TL | Not normal | 2341.000 | -2.016 | .044 | -.156 |

Table 21
*Variables excluded from LR due to correlation*

| | Shape of distribution | Mann-Whitney-*U* | Z | Asymp. Sig. (2-tailed) | R |
|---|---|---|---|---|---|
| INV:S | Not normal | 1536.000 | -4.798 | .000 | -.370 |
| TL:TA | Normal | 2149.000 | -4.375 | .000 | -.338 |
| AR:S | Not normal | 2344.500 | -2.003 | .045 | -.155 |

Table 22
*Variables excluded from the study based on the results of Mann-Whitney-U*

| | Shape of distribution | Mann-Whitney-*U* | Z | Asymp. Sig. (2-tailed) | R |
|---|---|---|---|---|---|
| CFO:TL | Not normal | 3178.000 | -1.110 | .267 | -.086 |
| PE | Not normal | 2569.000 | -0.915 | .360 | -.071 |
| CFO : S | Not normal | 3024.500 | -.858 | .391 | -.066 |
| ROE | Not normal | 3110.000 | -.829 | .407 | -.064 |
| OP : S | Not normal | 3164.000 | -.390 | .696 | -.030 |
| CFO3:S3 | Not normal | 3351.500 | -.300 | .764 | -.023 |
| PAT1 : PAT2 | Not normal | 2725.000 | -.190 | .849 | -.015 |

This section presented the results discussion on the variables and the process of elimination to finalising those variables to be included in the logistic regression. The descriptive statistics, the results of the Mann-Whitney-*U* tests and the Spearman rho were presented and discussed in terms of their results. The section concluded with identifying six variables which will be included in the LR to determine the probability of an organisation's default.

## *6.4 Probability function*

### 6.4.1 Introduction

This section will discuss the results of the probability function which was derived from the LR and the preceding variables selected. It is a review of the model and the model classification results, drawing on the literature in chapter two for discussion purposes and concluding with the proposal.

### 6.4.2 Logistic regression function

As proposed in chapter three, LR is a classic statistical approach, in that it was used to determine a model function in order to predict the probability of distress. The LR approach was used because it is less restrictive than that of MDA and easier to interpret.

The model contains six independent variables, falling into the categories of liquidity, profitability, leverage as well as the less-used activity and market-related ratios. Beaver et al. (2005) found that the most common financial ratios used in distress prediction models focus on profitability, cash flow generation and leverage. While market-related ratios have also been included in some (Altman, 1968; Altman, 2000; T. Lin, 2009; Maricica & Georgeta, 2012), the exact combination of variables ranged between studies and samples, resulting in differing levels of importance and coefficients for each variable in different studies (Mensah, 1984). The six variables selected also fall within these categories, which is an obvious result since the initial group of variables were selected from these studies. The LR function is expressed as follows:

P(x)= 1 / [1+e – (b0 + b1 x X1 + b2 x X2+……bn x Xn) ]
where: P(x) is the probability of distress for a firm
bi is the coefficient for each independent variable

The full model was found to be statistically significant $x^2$ (6, n= 148) 88.99, p = 0.000, indicating that the model is able to distinguish between distressed and healthy organisations. The n =148 relates to the total number of firm years for the combined sample of 28 H and D organisations. At this point, the sample should be highlighted as a limitation. As with studies conducted in the past, the sample size is not seen as being representative of the entire population, 28 organisations falling below the 30 threshold commonly used. Furthermore the variables selected have the potential to be sample specific as indicated by (Laitinen, 1991)

Keeping the above in mind, the model is able to explain between 45.2% (Cox and Snell R Square) and 60.3% (Nagelkerke R square) of the variance in organisations experiencing distress, while correctly classifying 85.1% of the cases. Only three of the independent variables make a statistically significant contribution to the model WC:TA (p =0.000), CA:TA (p= 0.005), CFO3:TL (p=0.000). This is based on the Wald test statistic as reported.

The LR function which was derived from the variables is stated as:

$P(x)=1/[1+ e – (6.363 – 7.221 X_1 - 5.107 X_2 + 0.002 X_3 – 1.817 X_4 - 2.987 X_5 - 0.247 X_6 )$

| | |
|---|---|
| $X_1$ | = WC:TA |
| $X_2$ | = CA:TA |
| $X_3$ | = TL:E |
| $X_4$ | = ROA |
| $X_5$ | = CFO3:TL |
| $X_6$ | = MVE:TL |

It is important to understand the sign in front of the coefficient because this determines the direction of the relationship between the variable and the independent variable. Mensah (1984) contended that, owing to the combination of ratios used, studies would show differences relating to the size of the coefficient. In spite of this, the researcher finds it highly unlikely that the direction of the relationship between the dependent and independent variable would change on the basis of the combination of ratios used.

The coefficient values will influence the overall exponent value: the higher the exponential value, the greater the probability of distress. Higher liquidity (WC:TA, CA:TA, CFO3:TL), lower leverage (TL:E, MVE:TL), and higher profitability (ROA) are all associated variables with decreased probability of default, regardless of the age of a organisation. If a firm has the ability to quickly convert assets into cash, if it is profitable and if it does not rely heavily on debt, its chances of survival are far greater (Wiklund, Baker, & Shepherd, 2010).

***WC:TA***

WC:TA has a negative relationship with the dependent, meaning that, if WC:TA increases, there would be a decrease in the probability of distress – the negative relationship also being reflected in the Z-score (Altman, 1968). The ratio is a measure of the net liquidity position of an entity relative to its total capitalisation. Working capital is defined as trade receivables, inventory and trade payables, while total assets refer to the cumulative total of current and non-current assets. Altman in 1968 added this ratio explicitly for consideration of liquidity and size characteristics, while Wu et all. (2010) indicated that it is the most widely used measure of liquidity in literature and its explanatory power is evident: the ratio is classified as an activity-based ratio in this study. This is supported by a high and statistically significant Wald statistic in studies conducted by Wu et al. (2010), the ratio was also favoured by Beaver (1966), Deakin (1972) and Ohlson (1980).

Assuming that the main asset-based components of working capital increase, these being inventory and trade receivables, and the liability component decreases, the overall working capital position would increase, meaning that there are adequate assets to repay the looming short-term debt obligation. Therefore the asset related working capital items which are easily converted into cash to the proportion of total assets, would indicate an overall improvement in the liquidity of the organisation, ultimately decreasing the possibility of distress. The odds ratio reported for WC:TA was 0.001, indicating that, with every unit increase in WC:TA, organisations were 0.001 less likely to fall into distress.

### *CA:TA*

As reported by Deakin (1972), WC:TA and CA:TA measures were both selected to form part of his discrimination function, both of these showing negative coefficient values in the study for the two years prior to failure. Attached to CA:TA is the second largest coefficient in absolute terms, -5.197. The ratio provides insight into the composition of total assets, the proportion of which is ‘short term in nature, relevant to the total asset component. The sample data showed a decline of 24% in the median value from year three to year one in the D sample, whereas the H sample showed only small fluctuations, maintaining its level, which illustrates that there is a potential decrease in the value of liquid assets, for example, cash in the D organisations. This also illustrates the relationship to the dependent variable: a lower CA:TA would increase the probability of distress. The odds ratio reported for the variable was 0.006, meaning that, with every unit increase in WC:TA, an organisation is 0.006 less likely to fall into distress.

### *TL: E*

TL:E measures the proportion of debt to equity which an organisation uses to finance its assets. A high value for this ratio would mean that an organisation is aggressive in its financing of assets; interest payments decreasing profitability and potentially placing pressure on the cash flow. The variable was included in more recent studies and models developed by Muller et al. (2009), T. Lin (2009), Alireza et al. (2012) and Maricica & Georgeta (2012).

Both the means and medians of the healthy organisations showed a decrease in the variable as the years to distress decreased, while the opposite is evident for D organisations. Based on this, one can expect that a higher value of the variable would indicate a higher likelihood of distress. The variable has a small coefficient (b= 0.002) and is not deemed statistically significant (p= 0.983), its role in determining the probability function result being lower than all other variables. It has a positive coefficient in the function, indicating that a higher TL:E would result in a higher probability of distress. Odds for this variable are 1.002, indicating that a unit increase in TL:E would result in a 1.002 increase in the probability that an organisation will fall into distress.

The variable has a relatively low coefficient in this study and its exclusion would cause only marginal changes to the coefficients of the remaining variables and the overall model classification.

### *ROA*

This ratio is an indication of the true operating profitability of the entity in utilising its assets, which is regarded as a measure of size by (Maricica & Georgeta, 2012), and of the earnings power of its assets (Beaver et al., 2005). The ratio was also deemed to outperform other profitability measures including cash flows and is key to determining firm value (earnings power of assets) (Altman, 2000). The ratio or a variable thereof was used in 13 of the 19 studies which were reviewed as part of the literature study.

Profitability is deemed a key indicator of ability to repay debt obligations: distressed organisations are more likely to have lower ROA values (Beaver et al., 2005), since their assets should be used less efficiently. This is confirmed by the decreasing trend in median value of D organisations as distress approaches. As is the case with the previously mentioned coefficients, ROA also relates negatively to the dependent variable, meaning a lower ROA increases the probability of distress. The ROA odds at the 95% confidence level showed a wide range with an upper and lower limit of 0.002 and 10.772 respectively. This means that we can be 95% confident that the OR of ROA lies somewhere between these two values.

### *CFO:TL*

Logically, CFO3:TL of D organisations would be more likely to have a lower cash flow to liabilities ratio than would H organisations, which was confirmed in the earlier hypothesis. The ratio was found to be a significant contributor to the probability function. This finding contradicts those of Maricica & Georgeta, (2012), who found that there is no significant difference in loan repayment capabilities of the two groups in their study, further highlighting the potential of sample specific ratio selection. The ratio or a variable thereof was favoured in the earlier studies conducted by Beaver (1966), Deakin (1972), Ohlson (1980) and more recently Muller et al. (2009)

Again the coefficient to the variable is negative, meaning that a higher variable would result in a decrease in the probability of distress. The ratio plays an important role in determining the probability of distress in the function as it has the third highest coefficient. The OR ratio for this variable was 0.5, meaning that an increase in CFO3:TL indicates that the odds are 0.5 that the organisation would not become distressed.

### *MVE:TL*

The final variable is MVE:TL: this variable provides insight into the market dimension as a financial stress predictor (Altman, 2000), through incorporation of share price information. In addition to this, market capitalisation is viewed as a firm size indicator (Wiklund et al., 2010). The ratio was included in the discriminant functions developed my Altman (1968), T. Lin (2009) and Wu et al (2010). A D organisation variable is expected to decrease as distress approaches, due to the market incorporating the signals in the share price. This is clear in both the mean and median values of the variable. The variable has a negative coefficient, indicating that a higher value would result in a lower probability of distress. The MVE:TL variable is not deemed statistically significant (p =

0.75) while the reported OR is 0.781, indicating that a unit increase in MVE:TL would result in a 0.781 decrease in the odds that an organisation would become distressed.

### 6.4.3 Model classification results

Distress prediction is a sensitive topic and, as a result, very few users are in a position to tolerate a low accuracy or classification rate. The following section reviews the overall accuracy of the model by focusing on the sensitivity and specificity.

### 6.4.4 Sensitivity and specificity

The sensitivity of the model relates to the ‘true positive’, those organisations which are correctly classified as H in a specific year, being 63 in total (85.1%), while the specificity relates to the ‘true negative’, those organisations which are correctly classified as D (85,1% n= 63) in a specific year. The cut-off point between being healthy and distressed in terms of the function being 0.5, means that an H organisation with a function result of 0.51 would be classified as D in that year.

The positive and negative predictive value relates to the percentage of cases that the model classifies as having the characteristics which are observed in the population (Pallant, 2011).The predictive value of the model for both D and H organisations is 85.1%, meaning that, of the organisations which were predicted to be distressed or healthy, 85.1% were correctly classified.

The likelihood ratios of a positive test indicate that it is 5.73 times more likely for an organisation to be classified as H when it should in fact be classified as D, while it is 0.17 more likely for a D organisation to be classified as H.

It should be noted that common practice in developing prediction models is to pool the ratios across various years, which is the case in this study. Mensah (1984) argues that this is done without considering the impact of the underlying economic environment which affects the accuracy of the models based on the findings from his study. In contrast to this, a more recent study conducted in South Africa found that subdividing data in terms of economic cycles did not truly increase the predictive accuracy of the distress models (Muller et al., 2009).

Figure 39 clearly illustrates the increase in probability over the period of three years prior to distress of organisations classified as D, as it approaches the definition of being in distress. The probability of an H organisation falling into distress is clearly far less likely than that of the D sample, which increases gradually. Compared to a stable probability experienced by H organisations, this is as expected from the sample and in line with the results of Ohlson (1966) and Zmijewski (1984).

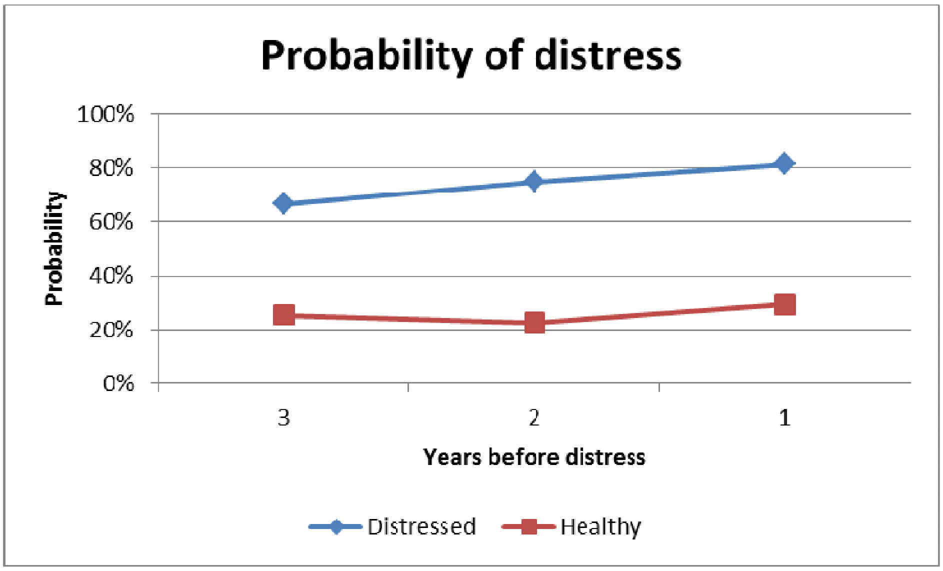


*Figure 39* Illustration of the sample probability of distress over time

Table 23 provides insight into the model accuracies during the three years preceding distress. The correct probability classification peaking in year one as distressed firms is correctly predicted by 91.7%. Misclassifying a distressed organisation as a healthy one would have a far greater financial impact on stakeholders than misclassification of a healthy organisation, the former representing a greater number of misclassifications in this model.

Table 23
*Model probability accuracy classification results across years*

| | Year 3 | | Year 2 | | Year 1 | |
|---|---|---|---|---|---|---|
| | **Healthy** | **Distressed** | **Healthy** | **Distressed** | **Healthy** | **Distressed** |
| Healthy | 21 | 6 | 23 | 3 | 19 | 2 |
| Distressed | 3 | 18 | 3 | 23 | 5 | 22 |
| Correctness | 87.5% | 75.0% | 88.5% | 88.5% | 79.2% | 91.7% |

### 6.4.5 Out-of-sample test results

In most model studies, out-of-sample test data are used to determine the accuracy and generalisability of the model. Due to limitations on information, the model was not tested on out-of-sample data which, is also mentioned as a limitation to the study.

## *6.5 Summary*

The chapter focused on the discussion of the results which were documented in chapter five. At the start of this chapter the 19 variables which were being considered for inclusion in the LR were discussed in terms of their descriptive statistics, from which it was concluded that the majority of the data were not normally distributed. Following these results, the results of the hypothesis and Mann-Whitney-U test were discussed and concluded and, finally, a portfolio analysis was done, which illustrated the ratio behaviour of organisations in distress when compared to those in healthy situations. The chapter concluded with a discussion of the LR that was developed and its results.

# 7 Conclusion

By way of introduction we will summarise the results achieved so far in this research report. Chapter two provided an overview of the literature relating to financial ratio prediction models, the criticism imposed against these models and their use, and a review of a number of previous studies' model functions. Chapter three presented the proposal to develop a distress prediction model using a classic statistical approach and the hypothesis for selecting variables. Chapter four discussed the methodology to be used in preparation for developing the model, while chapter five provided the results of the methodology implemented, highlighting descriptive statistics on the variables, variable selection as well as the LR model. Chapter six discussed the descriptive statistics associated with the variables and the LR model, linking the model with previous literature.

Financial prediction models, specifically those which are accounting based, are widely used for distress prediction as discussed in chapter two. Frequent criticism against their use as prediction models is that their primary source of information is financial statements. However, financial statement information is the primary source of information in most of these distress prediction models since it reflects the most important aspects of an organisation's financial health (Maricica & Georgeta, 2012).

Accounting ratio-based models are typically built by data mining large numbers of ratios and assigning weightings to them, with reference to a sample of failed and non-failed firms. The hypothesis and proposal made in chapter three are not very different from this. In their studies of distress prediction, Altman (2000) and Beaver et al. (2005) contended that the financial ratios used are of little consequence since there are high levels of correlation amongst them. However, instead, the *level* of the ratio should be regarded as providing more relevant information. Based on this, 19 variables were included in the original list. Included in the list were ROA, CFO3:TL and TL:TA – variables which were found to capture all the explanatory power of financial statements and used in the Ohlson, Zmijewski, and Shumway models (Beaver et al., 2005). It should be noted that the current ratio which features prominently in the literature reviewed, was not included as a variable because it is the definition criterion used for distress. On the basis of the results of the hypothesis testing and logic, six variables were selected for inclusion in the final LR model.

The primary purpose of this research was to add to the body of knowledge of distress prediction by developing a model using locally listed firms. The model showed success in accurately classifying 85.1% of H and D organisations. While the proposal was completed and a model has been developed, it does have significant limitations which should be highlighted at this juncture. The model is based on a sample of 28 distressed and healthy organisations, a small matched pairs sample; while the matched pairs approach has been criticised and has limitations of its own, the sample size should also be mentioned as a limitation. In addition to this, the study assumed that a common distress process was experienced by all firms in the sample. Despite there being at least three different processes, this assumption would influence both the ratios selected and the coefficients used in the model (Laitinen, 1991) and ultimately the model could be viewed sample specific. Due to data constraints, no out-of-sample testing was conducted and therefore the out-of-sample accuracy of probability rates is unknown. In the light of the preceding information, caution should be exercised if the model is used.

## *7.1 Future research topics*

In many cases, limitations of one study can be viewed as future research topics.

This study has based its definition on the financial characteristics of an organisation that the researcher considers to be in line with the Companies Act 71 of 2008. However there is no definitive definition and each study places its focus on its own definition. Providing a definitive definition of what would constitute financial distress and failure is a vital future point of research.

As with the definition of distress, there are no clear guidelines on the variables which provide the best predictive value when associated with distress. Although this study confines itself to financial variables, this restriction is viewed by some as a limitation of prediction models since organisations are not islands and, therefore, variables relating to operations, markets and economics should also be included in these types of studies. With this in mind, the following variables are suggested for inclusion in future research: corporate diversification and firms size – which have been highlighted by both Beaver et al. (2005), Wu et al. (2010) – as potentially having an impact on distress and are possible areas requiring further research for inclusion in distress prediction. Another non-financial indicator which should be considered for inclusion is management effectiveness since poor management has long been a cause of financial failure (Xu & Wang, 2009).

Findings additional to the above indicate that greater success in predictive capabilities would be obtained from relying less on generally independent variables, and concentrating rather on industry relevant ratios, which would make a model less generalised but potentially more accurate (Mc Gurr & De Vaney, 1998)

A topic for future research which might prove more valuable than research to date would be that of the evolution of an organisation's prediction scores over a period of time – to determine its health – rather than focusing on a single point in time. Also, research could be conducted into how long organisations survive post the initial signals of distress and the determinants of this time: distress as defined in this study.

The generalisability of these studies is questioned (Dimitras, Zanakis, & Zopounidis, 1996) in many instances for reasons of sample bias. It is well understood that the financial characteristics of a privately owned enterprise differ from those of a publicly listed entity which, owing to information available, is usually the focus point of these studies (Agarwal & Taffler, 2008) – hence the development models with predictive capabilities focusing on other business forms (Mateos-Ronco & Lopez Mas, 2011) and sizes such as co-operatives, privately owned organisations. Alternatively, a small or medium enterprise failure prediction model would be beneficial to stakeholders in future.

## *7.2 Closing remarks*

Failure prediction models endeavour to show that healthy and distressed organisations have dissimilar financial characteristics over a period of time. Using a classic statistical method, this study endeavoured to develop a failure prediction tool, the method applied being LR, due to its easy interpretation, the dichotomous nature of the study and the distribution of data.

Variables relating to profitability, leverage and liquidity are widely regarded as the more important variables for inclusion in a distress model (Wu et al., 2010). However in addition this model included both market-related and activity-related variables as explanatory variables.

The model showed overall success in correctly classifying 85.1% of both D and H organisations, while the highest overall accuracy was obtained in year one at 91.7%. Organisations will find these results promising since they provide an opportunity for corrective action. As mentioned in the literature and findings, the model is sample biased and, although findings show that sampling bias does not influence model accuracy significantly (Zmijewski, 1984), the exercise of care is still recommended. The additional point that the generalisability of the prediction models has long been criticised, is made by the researcher as a potential limitation of the model.

The review of literature suggested that, while there is a growing body of knowledge on prediction tools, the definition and reasons behind failure and distress are not well understood. The proposed model adds to the growing body of tools aimed at providing a thermometer of potential distress, but does not provide further insight into the reasons for failure

# 8 Annexure 1 References

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