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A comparative study between Altman Z-Score and verifier determinants theory as early warning indicators of business failure in South African public listed companies

By

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ABSTRACT

The identification of reliable early warnings signs which encompass qualitative and quantitate inputs to business distress and failure prediction could reduce the incidence of business failure if companies take corrective action early enough as the signals of distress emerge.

The concept of verifier determinants as early warning signs of business failure and distress as introduced by Holtzhauzen & Pretorius (2013) has largely been theoretical and unexamined in terms of the methodology's ability to identify business distress. The performance of the model is tested against the well-established Altman Z-Score model of prediction.

This study tests the consistency of the classification of companies as falling, grey and non-failing by applying the Altman Z-Score model and the verifier determinants theory to a sample 38 JSE listed companies. 19 Suspended companies were selected and matched with another 19 companies of similar size and operating in the same industries.

The consistency of the classifications was tested via a simple measure of percentage agreement using a cross tabulation, then a Cohen Kappa coefficient was applied to test for agreement over and above agreement by chance. The study further applied a Spearman correlation coefficient to determine the level of association between the results produced by the two models.

The findings of the study indicate a statistically significant association between the Altman Z-Score and the aggregate score of default as calculated through the application of verifier determinants theory. The study further identifies two verifier determinants (i) Late submission of financial information and (ii) Underutilisation of assets which have the strongest association with the Altman model and overall aggregate score of default. We argue that these individual verifier determinants could be used as a proxy for the overall model to monitor the risk of company distress.

KEYWORDS: Business failure, early warning signs, verifier determinants, z-score

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.

Mabule Lucas Setoaba **Date: 07 November 2016**

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1.1 Introduction

There has been 690 company liquidations and 605 close corporation liquidations in the first eight months of 2016 amongst South African corporates (Stats SA, 2016). That is 1, 295 incidents of corporate failure in the first eight months of 2016 and a cumulative 17 962 incidents of corporate failure in South Africa between January 2010 and August 2016(Stats SA, 2016). This failure is at great cost to investors, creditors, employees and other stakeholders.

Although business failure prediction has been extensively researched, the scope of stakeholders impacted by business failure and the large costs associated with it have continued to provide stimulation for further research and development of predictive models in order to take preventative or corrective actions to avoid complete failure (Balcaen & Ooghe, 2004) (Deaking, 1972).

The efforts to develop models to predict bank and corporate failure were reignited following the 2008 financial crisis and have been of increasing interest to investors, creditors, borrowing organisations and governments alike (Rankov & Kotlica, 2013). Avoidance of business failure is also a key goal for management and keeping with their fiduciary duties to towards their stakeholders (Rankov & Kotlica, 2013).

1.2 Problem definition and purpose

According to Edward Altman (Altman, 1968), “Signs of potential financial distress are evident long before bankruptcy occurs”. Research to identify early warning signs of business failure seeks to identify and verify the key factors to be considered in order to identify the early warning signs of business failure or distress. According to Ranlov and Kotlica (2013), financial distress begins when an organisation is unable to meet its scheduled payments or when the projection of future cash flows points to an inability to do so in near future. It could, however, be argued that an inability to meet financial obligations is a manifestation of financial distress and not a predictor thereof.

While few models have been developed in a South African context, Pretorius and Holtzhauzen (2013) introduce the concept of verifier determinants of early warning signs as a tool to confirm the causes of decline in order to direct rescue strategies. Their study uses early warning sign theory to establish the verifier determinants that can guide entrepreneurs and turnaround practitioners in the timely planning for the current rescue and future sustainability of an enterprise (Holtzhauzen, 2011). Although the concept of a verifier determinant will be explained in detail in this study ,Holtzhauzen (2011) also describes a verifier determinant as a Factor confirming the existence of an early warning sign.

The ability to detect the existence of early warning signs of distress will enhance the ability of management, shareholders, creditors and other stakeholders to take corrective action sooner rather than . Proponents of corporate failure prediction techniques urge for an accurate failure prediction model so as to be able to take preventive or corrective actions in companies that are predicted to fail in the future (Rankov & Kotlica, 2013). Evidence shows that the market value of a distressed firm declines substantially, which may severely affect different stakeholders of the firm (Rankov & Kotlica, 2013)

Rankov and Kotlica's (2013) observations are consistent with Pretorius and Holtzhauzen (2013) assertion that prediction and early intervention by turnaround strategists in situations where businesses could go into decline has the potential of reducing the incidents of failure and consequently the costs associated with business failure (Pretorius & Holtzhauzen, 2013). Early warning signs theory serves as the main base on which verifier determinant theory is built (Pretorius & Holtzhauzen, 2013).

Most models seeking to forecast business distress and failure are quantitative in nature and there is minimal input of qualitative factors. Despite the theoretical appeal of the recent prediction models which have adopted alternative hybrid approaches which are not purely quantitative in nature, there is limited evidence in literature to support their performance compared with traditional simple accounting-ratio-based approaches (Agarwal & Taffler, 2006). Empirical tests to of the relative power of the different approaches is yet to be conducted.

Rankov and Kotlica (2013) assert that there are over 150 business failure or bankruptcy models that currently exist. The existing models span a varying array of techniques including qualitative, univariate (accounting and market measures), multivariate (accounting and market measures), discriminant and logit models, probit models, artificial intelligence models (expert systems, neural network). Rankov and Kotlica (2013) argue that future research should be focused on how these models can be applied: as opposed to the development of new models (Rankov & Kotlica, 2013) .

The main aim of this study was to test the relevance and applicability of Pretorius and Holtzhaulzen's (2013) verifier determinants theory as an indicator of early warning signs of business distress. This was achieved by testing the performance of the verifier determinants theory against the predictive ability of the Altman Z-Score (Altman, 1968) model of prediction of corporate bankruptcy.

Knowing the verifier determinants could assist decision making and improve the effectiveness of turnaround strategies. Business rescue practitioners can improve their 'investigation of the affairs' activity by using such verifier determinants. (Pretorius & Holtzhauzen, 2013)

1.3 Research Motivation

The South African National Development Plan places great emphasis on small business development as a tool for economic development and economic growth (NationalPlanningComission, 2011). South Africa experienced an average growth rate of approximately 5 percent in real terms between 2004 and 2007. However, the period 2008 to 2012 only recorded average growth just above 2 per cent; largely a result of the global economic recession. (Stats SA, 2016).

Statistics South Africa reports that 2,064 businesses were liquidated in 2015 (Stats SA, 2015) significantly down from the 4133 liquidations reported in 2008 following the 2007/8 global financial crisis. The rate of failure for small businesses is reported to be as high as 63% in the first two years of trading" (FIN24, 2016). The GDP growth rate for 2015 was recorded at 0.6% (Stats SA, 2016) and the forecast for 2016 is approximately 1% (Stats SA, 2016).

As evidenced post the 2007/8 financial crisis, the slowdown and possible contraction in the South African economy can result in an increasing number of businesses going into distress with the possibility of failure. This makes this study considering techniques to develop early warning signal particularly relevant at this stage.

The cost of corporate failure, particularly in an emerging economy such as South Africa, has far-reaching effects on the development of the country as a whole. Corporate failure results in job losses which in turn stifle the overall economic growth.

Company failure is not an isolated and self-contained event and the failure may trigger negative shocks for the internal and external stakeholders. The total economic and social cost of business failure may be large and beyond the direct financial loss computed from the winding up of the company. Company failure generates various types of costs not only for the direct (internal) stakeholders of the company the entrepreneur, management and employees, but also for the direct environment of the firm. Shareholders and providers, clients and suppliers, the Government – and the economy as a whole will all stand to lose as a result of corporate failure (Balchaen & Ooghe, 2004). Such failure in a South African context adds additional pressure on an already fragile economy.

Balcaen and Ooghe (2004) note that the failure of a well-connected company in the economy can have a contagion effect that could cause a downward spiral for the economy as a whole. A clear example of this was is the case of Finland, where Nokia accounted for up to 4% of the country's GDP. Nokia was the driving force behind Finland's export dependent economy and the collapse of the company resulted in severe economic pressure for the country as a whole (Mehta, 2016). The Finnish case study clearly illustrates that that prediction of company failure is important not only from the 'individual' point of view, but also for the 'society as a whole.

Balcaen and Ooghe (2004) noted that the lack of a stable theoretical framework was one of the contributors to the difficulty in construction a viable model for distress and failure prediction (Balcaen & Ooghe, 2004). However as noted by Rankov and Kotlica (2013) there are is a large number of business failure or bankruptcy models that currently exist and this study seeks to test the validity of the new approach introduced by Pretorius and Holtzhauzen's (2013).

This study could contribute to the academic acceptance and validity of verifier determinants as reliable tools for the identification of early warning signals consistent with the possibility of distress and failure. The verifier determinant theory introduced by Pretorius and Holtzhauzen's (2013) has not been tested against other business failure prediction models since its introduction in their study.

1.4 Research scope and objective

The research focused on testing the validity of the of the verifier determinants theory as a tool for identification of early warning sign of business distress or failure. The verifier determinants method of company evaluation will therefore be applied to a sample of companies in order to classify the failing or non-failing. The Altman Z-Score Model will then be applied to the same sample of companies to classify them as failing or non-failing. The classification of the companies from the application of the two models will then be compared to determine the extent to which the models have classified the companies consistently.

This study therefore focuses on the classification and predictive ability of the following failure prediction Models:

i. Verifier determinants theory as proposed by Pretorius and Holtzhauzen's (2013) and,
ii. Altman Z-Score model as proposed by Edward Altman (1968)

The research is focused on the consistency of outcomes of the classification of the sample of companies when the two methodologies are applied. The Altman model (1968, 2006) is one of the most influential models in the area of bankruptcy prediction (Salimi, 2015). When the model was initially developed, the discriminant-ratio model proved to be extremely accurate and predicted bankruptcy correctly in 94 percent of the initial sample (Altman, 1968)

The Altman Z-Score (1968) has been widely applied and tested by researchers including (Salimi, 2015) and is generally accepted as a good predictor of failure and distress. Almamy, Aston and Ngwa (2016) state in their study that Altman (1968) model is considered by most researchers, practitioners and managers as an effective tool to predict the health of companies.

For this reason, the Altman Z-Score (1968) is used as the benchmark in the study and Pretorius and Holtzhauzen's (2013) verifier determinants theory is tested against this model.

1.5 Research Problem

This study seeks to test the validity of the verifier determinants as identified by Pretorius and Holtzhauzen (2013) as tools for the identification of early warning signals indicating the possibility of business distress and failure.

The key question the study seeks to answer is: "Does the application of the verifier determinants as identified by Pretorius and Holtzhauzen (2013) result in the same company classification decision as the application of Altman Z-Score (Altman, 1968) in determining the likelihood of a company going into distress?".

In order to understand this, the study seeks further academic research to support the importance of each of each of the verifier determinants as identified by Pretorius and Holtzhauzen (2013). The following questions are pertinent for each verifier determinant:

The research will examine the inputs into each of the models and seek to understand the cause of the differences in the outcomes of the model predictions especially in terms of which explanatory variables and methodologies are most effective.

2 Chapter 2: Theory and Literature Review

2.1 Introduction: Business failure Prediction

Extensive research has been done on business failure prediction techniques over the past half a century. The research paper and prediction model published by Beaver (Beaver, 1967a) is generally accepted as the genesis of business distress and failure prediction. Beaver introduced the use of financial ratios as a means of predicting business failure. The analysis was univariate in nature, meaning that Beaver's method only examined a single ratio at a time and at a particular point in time (e.g. financial year end) to determine the like hood of business failure and distress(Beaver, 1966). This approach is simple to apply however it is not suitable for the multifaceted nature of business applicable today. In his own recommendations, Beaver suggests that using several different ratios and/or rates of change in ratios over time, would have higher predictive ability than the single ratios (Beaver, 1967a).

Following Beaver's (1966) a univariate model, Altman (1968) introduced the use of multiple discriminant analysis models. The Altman model remains largely applicable to date however in 1972 Deakin (Deakin, 1972) challenged the assumption that Altman (1968) had used a random sampling. Altman had in fact used paired sampling in his study and therefore Deakin sought to introduce a random sample to the multiple discriminant analysis model. In 1980 Ohlson (1980) further enhanced the business failure prediction techniques by introducing the use of a conditional logit analysis (LA) for predicting business failure. This advancement by Ohlson was significant as a logit analysis does not have the underlying assumption of normality or equal covariance which are prerequisites for MDA (Gepp, Kumar, & Bhattacharya, 2010).

A number of different business failure prediction techniques have been developed over the years from 1968 to date. Below we summarise some of the key studies and their findings and analyse their impact of business failure predictor in its current form today.

2.2 Overview of business failure prediction theories

2.2.1 Beaver 1966

Beaver's (Beaver, 1966) study consisted of 79 listed firms which had failed over the period spanning 1954-1964. He applied matched sampling in the study whereby each failed firm was matched with a non-failed firm from the same industry and with similar asset size.

This study identified cash flow to total debt as the best discriminator between failed and non-failed companies. Cash flow was determined as net income with non-cash items such a depreciation and amortisation added back to the figure. (Rankov & Kotlica, 2013). The model had a classification accuracy of 87% one year before failure to 78% five years before failure (Beaver, 1966). Beaver's study therefore focused on the ability to generate cash (liquidity) and debt (leverage) as the key determinants of the likelihood of company success or failure.

2.2.2 Altman Z-Score

Altman (Altman, 1968) challenged the use of one variable at a time as a method of failure prediction and he suggested that a multivariate technique would be more appropriate. He therefore developed a model which used 22 financial ratios, but eventually found that only five ratios (working capital/assets, retained earnings/assets, EBIT/assets, market value of equity/ book value of equity and sales/assets) were statistically significant factors in predicting business failure.

Similar to Beaver (1966) Altman had used paired sampling whereby 33 listed failing firms were matched with non-failing firms. The sample of non-failing was matched by industry, size and year. The model was found to be accurate in predicting failure for 95% of the companies one year before actual failure. (Rankov & Kotlica, 2013). The Altman model has been regarded as one of the best predictors of failure over the past 50 years.

2.2.3 Deakin *(1972)*

The sampling techniques used by Beaver (1966) and Altman (1968) was problematic in that the number of failing firms were presented as equal to the number of non-failing firms. This is not representative of the real world and in essence creates a problem of oversampling of failing firms. Deakin (1972) challenged Altman's assertion that he had used random sampling in his study where in fact paired samples had been used. Deakin (1972) therefore a randomly selected sample of 11 failed and 23 non-failed firms to develop his failure prediction model. The model was able to predict failure with 96% accuracy a year before failure and with 79% accuracy five years before (Rankov & Kotlica, 2013). The key insight from Deakin's study was the impact of sampling on the effectiveness of the failure prediction model. By improving the sampling techniques, Deakin had expected to develop a model which had reliable failure prediction accuracy.

2.2.4 Ohlson (Ohlson, 1980)

The statistical logistic regression model was first introduced by Ohlson (Ohlson, 1980) and this was intended to improve upon the multivariate discriminate technique introduced by Altman (1968). To overcome the problem with oversampling as identified by Deakin (1972), Ohlson used a random sample which comprised of 105 listed failed companies and 2,058 listed non-failed companies. Ohlson applied nine ratios in the model but concluded that only four of them size, financial structure, performance and current liquidity (Ohlson, 1980) were significant in predicting failure. The model had a predictive accuracy of 96.3% one year prior to default (Rankov & Kotlica, 2013) .

2.2.5 Hazard model

A significant criticism of the failure prediction models which had been used in the 1960's to 1990's was that the models relied on a single period of accounting data. In response to this Shumway (2001) proposed the hazard model which was is a multi-period logit model which incorporated accounting and market driven data including company size and share returns. This inclusion of multiple variables over multiple time periods was expected to lead to greater levels of failure prediction (ANDREICA, 2013). The hazard model therefore represented a significant advancement in the theory of business failure prediction at the time.

2.2.6 Neural computing

The advent of technological advances artificial neural computing has been applied to various fields including business failure prediction. Neural computing comprises a network of interconnected called artificial neurones (AN) which aggregate and model large volumes of data. The data enable the system to develop predictive abilities which are responsive to change in real world information flows. The Altman (1968) model was applied to a sample of 65 failing and 64 non-failing companies overlaid with artificial neural techniques. According to Durham (1992), the model correctly identified all failed and non-failed firms compared to 86.8% accuracy by MDA (Ko et al., 1992).

2.2.7 The instability value at risk

Following the 2008 financial crisis, market risk evaluation was again at the forefront of risk analysis and Satchkov (Satchkov, 2010) proposed the use of instability value at risk as a method of business failure prediction. The study applied value at risk methodology to companies listed on the S&P 500's using their historical data from 1989 to 2010 as seeks to evaluate company earnings relative to the value at risk. In essence, the model identifies instances where a company yields returns which are significantly different to the risk profile of the company, therefore, violating then expected risk-return relationship. These occurrences are noted as periods of instability of value at risk (Satchkov, 2010). Satchkov' s model indicated a period of the highest instability value at risk over the period 31st December 2006 to 31st December 2008 which coincided with the period of the 2008 global financial crisis. Satchkov asserts that the new measure, called the instability VaR, is shown to dominate all traditional methods of calculation (Satchkov, 2010).

2.2.8 Credit default scores

Credit ratings and credit default scores are a common measure of risk used by credit providers to evaluate their counterparties. The probability of default of company is a like hood of the company failing to meet its financial obligations. The probability of default is typically calculated taking the following factors into account: (i) cash flow, (ii) profitability, (iii) leverage, (iv) size, (v) liquid asset, (vi) short-term solvency, and (vii) activity. (Rankov & Kotlica, 2013)

It is interesting to note that these factors are similar to those applied in the Altman Z-Score model which will be used in the assessment of the sample of companies in this study. The use of credit default scores has a limitation in that it focuses on credit risk factors at the exclusion other factors such as reputational risk and market which themselves could be triggers of business distress.

2.2.9 Recursive partitioning and decision Trees

Recursive partitioning and decision trees are non-parametric methods of classification of constituents of a population into separate discrete non-overlapping categories (Gepp et al., 2010). The process in iterative in that a sequence of related inquiries may follow one another with each outcome providing evidence of the classification of the company. Gepp (Gepp et al., 2010) suggest that decision trees may be superior classifiers and predictors of business failure (Gepp et al., 2010).

2.3 Classic cross-sectional statistical methods

Different methodologies of business failure prediction have been developed over the years as illustrated in this study. However, the commonly applied methods of business failure prediction are largely the classic cross-sectional statistical methods (Balcaen & Ooghe, 2004). As new techniques were developed over the years the incremental accuracy of the models was shown to be minimal. Beaver (Beaver, 1966) had a prediction accuracy ratio of 87% one year ahead of default compared to 95% prediction accuracy achieved by Altman (1968); 96% achieved by

Deakin (1972) and 96,3% achieved by Ohlson (1980).This study has therefore sought to further analyse the different cross-sectional statistical techniques.

The dominant business failure prediction techniques introduced over the years include the application of (1) univariate analysis, (2) risk index models, (3) multivariate discriminant analysis, and (4) conditional probability models, such as logit, probit and linear probability models (Balcaen & Ooghe, 2004).

2.3.1 Univariate failure prediction models:

The univariate failure prediction models, the focuses on individual signs or ratios which can be used to determine if there is a risk of failure. A single financial ratio or a series of other comparable measures are calculated for each company being evaluated and a classification procedure is then carried out separately for each measure or ratio in the model. As a result, each variable reflects its own classification outcome for the company as a whole. In order to classify the company as a whole, the value for each measure or ratio is analysed and evaluated separately and based on a predetermined cut-off point which is considered the optimal measure at which the percentage of misclassifications is kept as low as possible, the company is classified as failing or non-failing. (Balcaen & Ooghe, 2004).

Most classification models are designed such that a firm ratio that if a firm's ratio value is below the cut-off point, it is classified as failing and, if the firm's ratio is above the cut- off point, it is classified as non-failing (Balcaen & Ooghe, 2004).

2.3.2 Risk Index Models

A risk index is a simple point system which uses different t financial ratios which are commonly regarded as good measures of financial health. Each financial ratio and evaluated and allocated a certain number of points ranging from 0 to 100 according to the values of the ratios for the firm. The models are generally designed such that a high reflects good financial whereas a low score indicates poor health. The risk index takes account of the fact that some ratios are more important than others and therefore points are allocated in a way that the most important ratios have higher weights (i.e. correspond to a higher maximum of points) (Balcaen & Ooghe, 2004). The model is in essence risk weighted for each factor that is taken into account and the all the variables are scored based on the aggregate score.

2.3.3 Multiple discriminant analysis

A multiple discriminant analysis model is made up of a linear combination of variables, which when evaluated simultaneous through the equation offer the best discrimination between the group of failing and non-failing firms (Balcaen & Ooghe, 2004).

In an MDA model a number of financial equations, ratios or attributes of a company are combined into one single multivariate discriminant score. The discriminant score is a one-dimensional measure which has a value between $-\infty$ and $+\infty$ and gives an indication of the financial health of the firm (Balcaen & Ooghe, 2004). MDA are generally called continuous scoring system as a result of the scoring methodology applied to evaluate the firms. In most studies, a low discriminant score indicates a poor financial health while a high score would indicate good company health(Balcaen & Ooghe, 2004)

The MDA is a statistical technique that can be used to classify an observation into one of several groups dependent upon the observation’s individual characteristics. The model seeks to derive a linear [or quadratic] combination of these characteristics which ‘best’ discriminates between the failing and non-failing groups (Balcaen & Ooghe, 2004)

After the 1980s, the use of MDA had decreased but the MDA method is frequently used as a ‘baseline’ method for comparative studies (Altman & Narayanan, 1997). In other words, MDA seems to be the generally accepted ‘standard method’ (Balcaen & Ooghe, 2004).

2.3.4 Conditional probability models

A conditional probability model calculates the likelihood of company failure based on a number of a characteristics of the company using a by a non-linear maximum likelihood estimation. The models are statistical in nature and have inherent limitations relating to the assumptions of a normal distribution in the sample being evaluated using this model. The logit models assume a logistic distribution while the probit models assume a cumulative normal distribution. A assumption of a linear relationship between the variable (model inputs) and the likelihood of failure is a key limitation of the linear probability models. The logit analysis is the most popular conditional probability method in corporate failure prediction literature. (Balcaen & Ooghe, 2004).

2.4 *Short*comings of classical statistical failure prediction methods

2.4.1 Lack of objectivity in the selection of independent variables

Bruwer and Hamman (2006) evaluated a number of South African studies done into business failure and distress. They concluded that the main limitation of prior studies was the arbitrary selection of the independent variables; no rational or objective basis of selection was necessarily applied (Bruwer & Hamman, 2006). This is aligned with the limitations of predictive models as identified by Balcaen and Ooghe (2004) who noted that the selection of independent variables was often arbitrary and irrational. Balcaen and Ooghe (2004) noted that an empirical selection of the independent variable also had the potential of resulting in a model that was tailored to the sample and as a result could not be reliably generalised to a wider population.

2.4.2 The definition of business failure

The definition of failure of failure is often inconsistent between various studies which have been performed into corporate failure. Amongst the nine South African company failure prediction research studies evaluated by Bruwer and Hamman (2006) five different definitions of failure were applied (Bruwer & Hamman, 2006). “The terms bankruptcy, failure, insolvency, liquidation, default and delisting are often used and sometimes refer to the same failure concept” (Balcaen & Ooghe, 2004). This creates a limitation in the interpretation of results and could have a material impact on whether a company is classified as failing or not. Court and Radloff (1993) defined business failure with reference to delisting and liquidation while Arron and Sandler (1994) refer to liquidation due to bankruptcy.

The field of business failure prediction has many aliases, such as bankruptcy prediction, firm failure prediction and financial distress prediction. Hereafter it will be referred to as business failure prediction (BFP) (Gepp et al., 2010). Beaver defines failure as the inability of a firm to pay its financial obligations.(Beaver, 1966)

2.4.3 Impact of time and economic cycles

Most failure or distress prediction models consider failure at a point in time however in reality business decline happens over a period of time and is more likely triggered by different events and circumstances (Balcaen & Ooghe, 2004). Failure can also be influenced by economic conditions and market conditions which are exogenous to the company (Bruwer & Hamman, 2006). Most business failure prediction models do not cater for these factors including industry specific sensitivities to various cycles which some sectors are more resilient to overcome than others. Altman (2000) notes that a more robust prediction technique could be developed if financial data could be examined for a period of (t+1) however this is not possible due to data limitations.

2.4.4 The effects of sampling on models

If the results of a sampling technique are to be generalised to a wider population, the sample selected must be statistically representative (Wegner, 2012). According to Balcaen and Ooghe (2004) a large number of studies applied matched sampling and other non-statistical techniques and are therefore not representative, limiting their applicability to generalised populations (Balcaen & Ooghe, 2004).

Matched sampling results in oversampling of the failing companies as there are generally lower observations of failing companies in the general economy. The statistical techniques applied to the sample data generally assumes random sampling and therefore the test results are subject to a choice-based sample bias (Platt & Platt, 2002).

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2.4.5 Instability of predictive models over time

Statistical predictive models assume a stable relationship between the independent (predicting) variable and the dependent variable. Due to changes in accounting policies and reporting methodologies, changes in interest rates, inflation and other exogenous factors, the relationship between elements reported in a company's financial statements change over time. A qualitative statistical model is not dynamic to take into account the changing relationship between the factors and therefore the model can prove to be unreliable over time (Richardson & Davidson, 1983).

According to Taffler and Agarwal (2003) most classical models only serve to classify companies as failing and non-failing companies based whether the company's profile most resembles the sample on companies which have been classified as failing or non-failing in the context. Keasey and Watson (1991) describe this problem as pattern recognition in the models (Keasey & Watson, 1991)

2.4.6 Risk of misclassification by failure prediction models

All forecasting models have a degree of error associated with their predictive and classification ability. In the case of business failure prediction, it is a more critical error to classify a failing business as successful (Type I error) than to classify a successful business as failing (Type II error). The reason for this is that a Type II error only creates a lost opportunity cost from not dealing with a successful business (Gepp et al., 2010).

2.5 Failure prediction and early warning signs

Business failure prediction methodologies are typically rooted in early warning signs theory. It is the principle and belief that failure does not occur as a sudden event but is progressive that suggest that failure can be predicted. Ansoff (Ansoff, 1975) introduced the concept of early warning sign as an academic theory when he made the assertion that weak signals consist of which imprecise symptoms of impending future problems could be noted in systems before such failure materialises (Ansoff, 1975).

Early warning signals are simple properties that change in characteristic ways prior to a critical transition and as such prior to a business transitioning from a performing (non-failing enterprise) to a failing (distressed or nonperforming company), there are properties within the enterprise that change in prior to this critical transition.

Early warning systems which are similar in their objectives to business failure prediction models described in this paper gained traction following the 2008 financial crisis. As part of the increasing research developed following the 2008 financial crisis, Borio & Lowe (Borio & Lowe, 2002) developed an early warning system specifically banking institutions. Their system identified three main factors which are critical warning indicators: Credit risk, asset prices and real exchange rate. They developed thresholds for these factors and if the thresholds were breached they found that this could a good indicator that a financial crisis might occur. Using this method Brio and Lowe (2002) were able to predict financial crisis with up to 60% accuracy.

Bussière & Fratzscher (Bussiere & Fratzscher, 2002) developed an early-warning system model applying a multinomial logit model. Their model showed that they could predict a macro-economic financial crisis in 32 open emerging market economies over the period from 1993-2001. These models could be applied to corporate failure prediction if adapted for the use of appropriate independent variables.

2.6 Altman (1968) Z-Score Model

The Altman (1968)Z-Score model is a linear analysis in that five measures are objectively weighted and summed up to arrive at an overall score that then becomes the basis for classification of firms into one of the a priori groupings (distressed; grey area and non-distressed). The discriminant-ratio model has proved to be extremely accurate in predicting bankruptcy with 94% accuracy in the initial study (Altman, 1968).

The Z-Score formula is a follows:

$Z = 0.012 X_1 + 0.14X2 + 0.33X3 + 0.006X4 + 0.999X5$

Where:

X1 : Working Capital/Total Assets

X2 : Retained Earnings/Total Assets

X3 : Earnings before interest and taxes/Total Assets

X4 : Market value equity/Book value of total debt

X5 : Sales/Total assets

Z : Overall Index

X_1: Working capital refers to the quantum of funds required to maintain day-to-day expenditure on operational activities of a business. Şamiloğlu & Akgün (2016) confirm that there is a significant and negative relationship between account receivable period and return on asset, return on equity, operating profit margin and net profit margin. Managers can create value for shareholders by reducing effectively managing working capital.

X_2: Retained Earnings/Total Assets. Retained earnings measures the cumulative profitability over time which has not been withdrawn from the company. This therefore represents reserves act as a buffer for a business in periods where the company experiences financial losses.

X_3: Earnings before Interest and Taxes/Total Assets. This measures the earnings from assets before financing costs and statutory obligations. This gives an indication of the operation efficiency of the of the business assets.

X_4: Market Value of Equity/Book Value of Total Debt. This measures the funding mix of the business and explains to which the company's assets are funded by equity.

X_5: Sales/Total Assets. Capital-turnover indicates the extent to which assets are used to generate sales.

2.7 Verifier determinants: Key Components

Pretorius and Holtzhauzen (2013) introduce the concept of verifier determinants of early warning signs as a tool to confirm the causes of decline in order to direct rescue strategies and reduce the time between the first observation and the implementation of turnaround strategies. The verifier determinant can further be used to isolate the cause of the causes of decline. (Pretorius & Holtzhauzen, 2013)

A verifier points to some factor or element that confirms, validates and ensures firstly that the cause of decline exists and secondly that the early warning sign used to identify it is in fact present. The term determinant therefore mainly reflects the agreement or consensus between the cause and the apparent warning sign verifier (Pretorius & Holtzhauzen, 2013)

Until the publication of Pretorius and Holtzhauzen's (2013) theory on verifier determinants, literature had been silent on the subject. Most studies cluster concepts such as signs, signals, causes and indicators under the general collective of 'early warning signs' (EWS). Early warning signs theory serves as the main base on which verifier determinant theory is built. Early warning signs are defined as an internal or external extension of an event or factor or a combination of all, which may directly or indirectly highlight the pending demise of a business or business unit if not addressed and rectified in the course of business (Pretorius & Holtzhauzen, 2013).

Balcaen and Ooghe (2004) point out that the there are many different phases and paths to failure that exist. These include diminishing resources, poor leadership, strategic issues, operational issues and combinations thereof. This is consistent with the elements of the verifier determinants as identified by Pretorius and Holtzhauzen (2013) which are:

i. Management verifier determinants
ii. Financial verifier determinants
iii. Strategic verifier determinants
iv. Operational and marketing verifier determinants
v. Banking verifier determinants

The element components constituting each verifier determinant are listed in Appendix A.

2.7.1 Management verifier determinants

Pretorius and Holtzhauzen (2013) identify twelve managerial verifier determinants which focus on deficiencies in management. This encompasses systems to aid decision making, the level of education, experience and skill of the management team relative to the nature of the business they are running. (Pretorius & Holtzhauzen, 2013).

2.7.2 Financial verifier determinants

Twelve financial verifier determinants were identified focusing on fiscal discipline and accounting management and an emphasis is placed on cost control and budgeting (Pretorius & Holtzhauzen, 2013).

2.7.3 Strategic verifier determinants

Ten strategic verifiers focused on the ability of business to adapt to changing market conditions, driving growth in a controlled and disciplined pace and operational strategies are of importance (Pretorius & Holtzhauzen, 2013).

2.7.4 Operational and marketing verifier determinants

Ten operational and market verifier determinants emphasise the importance of operational efficiencies through advanced production techniques, a customer-centric service focus with an understanding of evolving market demand and appropriate distribution channels (Pretorius & Holtzhauzen, 2013).

2.7.5 Banking verifier determinants

The six banking verifier determinants highlight the importance of the management of funding facilities and payment of creditors. These verifiers are cash flow focused and emphasise fiscal discipline (Pretorius & Holtzhauzen, 2013).

2.8 Rationale for focus in Pretorius and Holtzhauzen (2013) verifier determinants and Altman

Altman (1968) has proven to be highly reliable and correctly predicted bankruptcy in 94% of the initial sample tested in the study. Reisz and Perlich (2004) found that that Altman's (1968) z-score was better at predicting failure over a 1-year period than both their KMV-type and down-and-out barrier option models. Their market-based models were however better over longer horizons (3 to 10 years) (Reisz & Perlich, 2007).

The robustness of the Altman (1968) model was again confirmed by Agarwal & Taffler, (2008) in their study which sought to compare the predictive performance of market based models relative to the traditional accounting based methodologies where they found that the Altman (1968) Z-score model was marginally more accurate although the difference was not statistically significant (Agarwal & Taffler, 2008).

The proven reliability of the Altman Z-Score (1968) model therefore makes it a good benchmark against which to evaluate the performance of the relatively new and largely untested theory of verifier determinants as proposed by Pretorius and Holtzhauzen's (2013).

Pretorius and Holtzhauzen (2013) have introduced a qualitative methodology which remains largely untested. This study aims to evaluate the reliability of the model.

2.9 Conclusion to literature review

The impact of business failure is far reaching and affects multiple stakeholders including investors, employees, suppliers, customers and can have an impact on the general economic environment. The significance of business failure has therefore motivated the continued investigation into business failure techniques and the 2008/9 brought the subject back into sharp focus.

Business failure prediction theory has evolved from the use of single ratios for prediction, as proposed by Beaver (1966) which showed an 87% prediction ability one year prior failure. Altman recognised that the use of multiple ratio analysis could improve the predictive power of the model and therefore Altman (1968) introduced the multiple discriminant analysis model. The Altman model has a failure prediction accuracy ratio of 95% one year prior to actual failure, therefore showing a significant improvement on the model developed by Beaver (1966).

The model developed by Deakin (Deakin, 1972) highlighted the deficiency in the paired sampling methodology which had been used by Beaver and Altman in their respective studies. The results of Deakin's study however resulted in a 96% failure prediction accuracy one year prior to failure. This was therefore a very small improvement in the accuracy of the model over the Altman model. This result in a sense highlighted that the use of paired sampling was not as detrimental to the resultant model as Deakin had argued it would be.

The statistical logistic regression model was then introduced by Ohlson (Ohlson, 1980) and this model had a predictive accuracy of 96.3% one year prior to default. The hazard model, neural computing and market risk based model were also developed with a hope to improving the predictive ability of existing models. The 2008/9 financial crisis resulted in even more model of financial distress prediction, particularly in the banking sector have been developed (Opoku, Chizema, Arthur, Appiah, & Chizema, 2015). The minimal improvement in the accuracy of business failure prediction therefore saw the multiple discriminant analysis model continue to dominate business failure prediction. This study used the Altman Z-Score as the benchmark model due to its consistent failure prediction ability proven in numerous studies.

Literature shows that the classical statistical model such as the Altman is susceptible to numerous limitations. The selection of independent variables (predictor variables) used in the studies is generally arbitrarily chosen by the researchers (Balcaen & Ooghe, 2004). The use of accounting data means that the models rely on historical information which limits the model's predictive ability and can be impacted by the accuracy and timing of the accounting data (Balcaen & Ooghe, 2004). The models also do not take into account the impact of exogenous factors such as economic cycles into account when evaluating the performance of the company (Balcaen & Ooghe, 2004). The use of models such as Neural computing seeks to overcome some of these limitations as neural networks can adjust for changes in real time data, such models are however more complicated to implement (Satchkov, 2010) .

The majority of failure prediction models are quantitative in nature and do not take qualitative factors which could be key indicators of the risk of failure. Ansoff (Ansoff, 1975) introduced the concept of early warning sign as academic theory when he made the assertion that weak signals consist of which imprecise symptoms of impending future problems could be noted in systems before such failure materialises (Ansoff, 1975).

The study by Holtzhauzen and Pretorius (2013) sought to integrate both qualitative and quantitative factors as early warning signs of business failure and distress. Holtzhauzen and Pretorius (2013) introduce the concept of verifier determinants as early warning signs of failure and the main categories of verifier determinants span across Management, Financial, Strategic, Operation and Marketing and Banking verifiers (Gert Holtzhauzen & Pretorius, 2013).

A large number of failure prediction methods have been developed over the years and a focus on qualitative consideration as proposed by Holtzhauzen and Pretorius (2013) is significant to the existing body of knowledge and literature. Rather than seeking to develop further business failure prediction techniques, this study seeks to test the validity of the verifier determinants theory relative the robust and well established Altman Z-Score model.

3 Research Questions

The theory of verifier determinants as early warning signs of business distress was introduced by Holtzhauzen and Pretorius (2013). This study seeks to evaluate the ability of this new method of business distress prediction and company classification which was developed in a South African context against the performance of the well-established Altman Z Score (1968). This will be achieved by testing the consistency of outcomes between the results obtained from the application of verifier determinants theory and the results achieved from the application off the Altman Z-Score (Altman, 1968) to a sample of companies.

3.1 Hypothesis 1

The consistency of the classification of companies as failing, grey area and non-failing which is achieved from the application of the two models will be tested through the following hypothesis:

H_0 = The null hypothesis states that the aggregate score of default ("ASD") as derived from the application of verifier determinants theory and the Z-Scores as derived from the application of the Altman Z-Score model to a sample of companies ***will not*** lead to any observed agreement in the classification of the companies by the two models as failing, grey area or non-failing.

H_1 = The alternate hypothesis states that the aggregate score of default ("ASD") as derived from the application of verifier determinants theory and the Z-Scores as derived from the application of the Altman Z-Score model to a sample of companies ***will*** lead to observations of agreement in the classification of the companies by the two models as failing, grey area or non-failing

$H1_0$: % of observed agreement = 0

$H1_1$: % of observed agreement > 0

3.2 Hypothesis 2

The classification of companies as failing, grey area and non-failing could be attributable to chance. Cohen's kappa (κ) tests for the agreement between two raters over and above chance agreement. This is tested through the following hypothesis:

H_0 = The null hypothesis states that the percentage of observed agreement in the classification of companies as failing, grey area or non-failing as achieved through the application of the aggregate score of default ("ASD") as derived from the verifier determinants theory and the Z-

Scores as derived from the application of the Altman Z-Score model to a sample of companies ***is no different*** to agreement achieved by chance, and therefore $\kappa = 0$.

H_1 = The alternate hypothesis states that the percentage of observed agreement in the classification of companies as failing, grey area or non-failing as achieved through the application of the aggregate score of default ("ASD") as derived from the verifier determinants theory and the Z-Scores as derived from the application of the Altman Z-Score model to a sample of companies ***is different*** to agreement achieved by chance, and therefore $\kappa > 0$.

$H2_0$: (κ) = 0, the kappa (κ) coefficient of agreement over chance agreement equals zero.

$H2_1$: (κ) > 0, the kappa (κ) coefficient of agreement over chance agreement is greater than zero.

3.3 Hypothesis 3

The Z-Score and Aggregate scores of default calculated for each company can be used to rank the companies in order of their likelihood to experience failure or distress. If the application of the verifier determinants theory results in the same company rankings as the application of the Altman Z-Score, this would be indicative of a degree of consistency between the models. The consistency rankings of the companies through the application of the two models will be tested via the hypothesis:

H_0 = The null hypothesis states that there is *no statistically significant rank order relationship* between the company rankings as achieved through the application of the Altman Z-Score and the aggregate score of default determined through verifier determinants theory.

H_1 = The alternate hypothesis states *is a statistically significant rank order relationship* between the company rankings as achieved through the application of the Altman Z-Score and the aggregate score of default determined through verifier determinants theory.

$H3_0$: $\rho = 0$, the correlation coefficient between the ranking per the z-scores and aggregate scores of default is equal to zero in the population.

$H3_0$: $\rho \neq 0$, the correlation coefficient between the ranking per the z-scores and aggregate scores of default is not equal to zero in the population

3.4 Hypothesis 4

The study seeks to determine if there is a statistically significant relationship between the twelve financial verifier determinants .i.e. do the individual financial verifier determinants show a statistically significant relationship between each other?

H_0 = the null hypothesis states that there is no statistically significant association between the individual financial verifier determinants.

H_1 = the alternate hypothesis states that there is a statistically significant association between the individual financial verifier determinants

For each of the twelve verifier determinants:

$H3_0$: $\rho = 0$

$H3_0$: $\rho \neq 0$

3.5 Hypothesis 5

The study further seeks to determine if there is a statistically significant relationship between the individual financial verifier determinants and the outcomes achieved through the application of the Altman Z-Score.

H_0 = the null hypothesis states that the correlation coefficient between the individual financial verifier determinants and the calculated Z-Scores is zero.

H_1 = the alternate hypothesis states that the correlation coefficient between the individual financial verifier determinants and the calculated Z-Scores is not zero.

For each of the twelve verifier determinants:

$H3_0$: $\rho = 0$

$H3_0$: $\rho \neq 0$

4 Research Methodology

4.1 Introduction

This study tested the validity of the verifier determinants theory as introduced by Pretorius and Holtzhauzen (2013) as tools for the identification of early warning signals indicating the possibility of business distress and failure. The concept of verifier determinants aims to confirm the existence of problems within a business or the business environment which could result in the business going into distress (Holtzhauzen, 2011).

In contrast to the relatively new business distress warning approach introduced by Pretorius and Holtzhauzen (2013) the Altman Z-Score model (1968) of business failure has been in use since its introduction five decades ago.

The reliability of the verifier determinants has been tested relative to the performance of the Z-Score model (Altman, 1968). This was achieved by testing the consistency of outcomes between the results obtained from the application of verifier determinants theory and the results achieved from the application of the Altman Z-Score model (Altman, 1968)

The main question the study sought to answer was to determine whether or not the verifier determinants theory can be used as a reliable method of predicting business failure and distress.

4.2 Proposed Research Design

The research adopted a pure quantitative approach, based on secondary publicly available market data. The main source of information was company financial data obtained from the company's annual financial statements as aggregated via Bloomberg, Share Data, JSE News Service (Sens) and public company websites.

4.3 Population

The population in this study comprises all public listed companies in South Africa. The JSE is the only listing exchange in South Africa but comprises two separate listing boards, the main board and the Altx exchange (JSE Limited, 2016). The population is defined as companies listed on either the JSE or the Altx board.

4.3.1 Company selection criteria:

i. Companies listed on the Johannesburg Stock Exchange

ii. The company must be a trading company or parent company with trading subsidiaries. i.e. exclude hybrid equity instruments.

iii. Exclude companies in the financial sector

iv. Select suspended companies

v. Select a paired sample

4.3.2 First filter: Company listed on the Johannesburg Stock Exchange

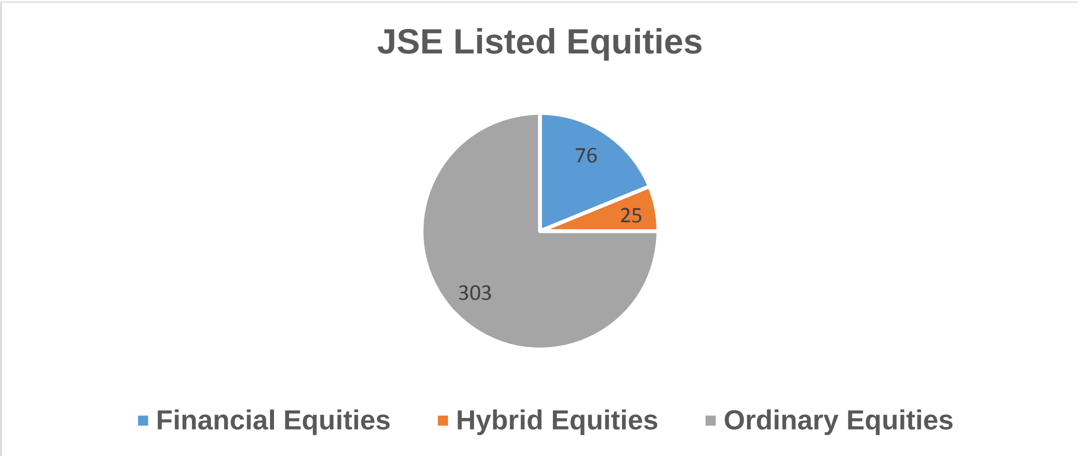
The total listed equities population on the JSE including the main board and the alternative exchange comprises 404 members or listed instruments.

4.3.3 Exclude Hybrid Equity Instruments

The total however includes hybrid equity instruments such as preference shares and some equity listed funds, which are not themselves trading companies (JSE Limited, 2016).

4.3.4 Exclude companies in the financial sector

The application of the Altman Z-Score model is however not suitable for financial companies (Altman, 1968)



4.4 Sample Size and Nature of Sample

The population of the study comprises South African public listed companies. The complete list of companies listed on the both the main board and Altx exchange was obtained via

Bloomberg. The fact that a complete list of the population is available provides an opportunity to use statistical sampling techniques (Saunders & Lewis, 2012).

A non-statistical sampling technique, purposive sampling, was therefore applied. Purposive sampling is appropriate when a researcher uses their judgement to actively choose a sample that will best be able to answer the research question and meet the objectives (Saunders & Lewis, 2012).

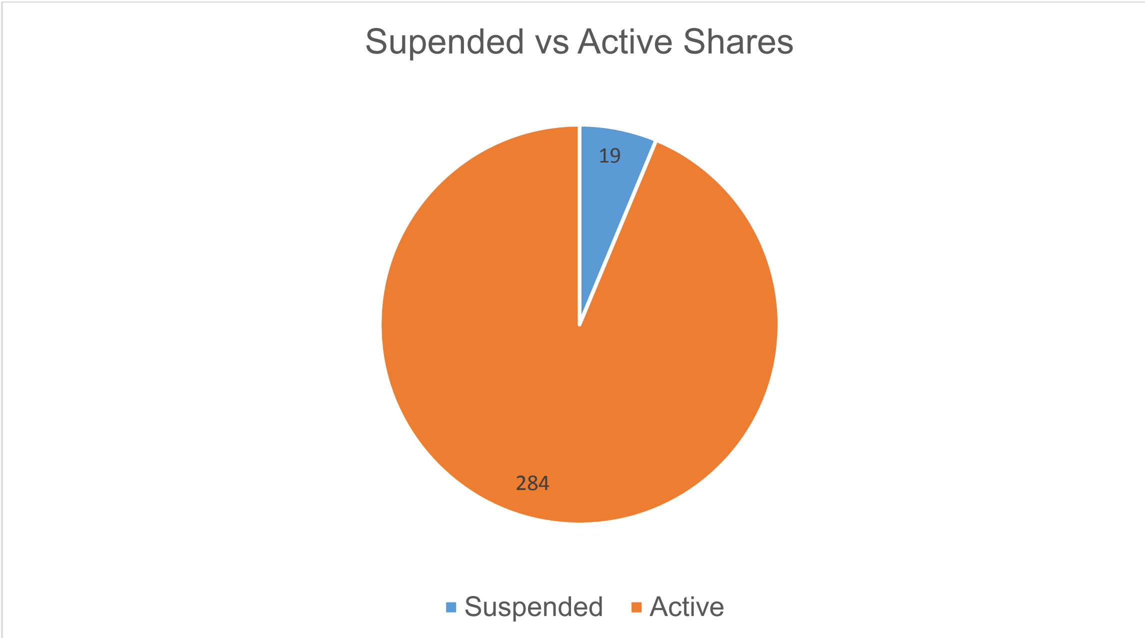
The application of the Altman Z-Score model is however not suitable for financial companies (Altman, 1968) and therefore financial sector companies were excluded from the study. Hybrid equity instruments, which are not themselves trading companies were also removed from the population. This left 303 ordinary equity instruments which were considered for inclusion in the final sample.

4.4.1 Identification of Suspended Companies

In line with the principle of purposive sampling, this study focused on the JSE listed companies whose shares have been suspended. These companies were identified through their trading status which indicated "S" for suspended. This was done to increase the likelihood of selecting companies which are likely to be in distress or experience failure.

While distress is not the only reason for the suspension of shares, the JSE may suspend a listing of shares if the company is placed under provisional liquidation; has adopted a special resolution to be wound up voluntarily; or the company is placed under business rescue (JSE Limited, 2016).

Listed companies whose shares have been suspended are identified by the code (s) on the listing boards (JSE Limited, 2016) and their trading status is classified as "Not active" on Bloomberg. At the time the data was extracted, there were 25 suspended companies on the JSE (Sharedata, 2016), however 6 of the suspended companies were in the financial sector and therefore only the remaining 19 were included in the sample.



4.4.2 Selection of Paired Samples

In their study evaluating 35 years of methodologies applied to business failure studies, Balcaen and Ooghe (2004) state that the majority of studies, researchers use matched samples of failed and non-failed companies. Paired samples were used by Beaver (1966) and by Altman (1968).

For each company in the failed sample, a similar paired non-failed company is selected or some multiple (Balchaen & Ooghe, 2004). They further state that the use of non-random paired samples may result in over-sampling as in the real world the number of failing firms does not match the number of non-failing firms (Balchaen & Ooghe, 2004). Beaver (Beaver, 1966) also designed his study such that each failed firm was matched with a non-failed firm from the same industry and with similar asset size (Beaver, 1966)

This study has used paired sampling, whereby an equivalent number of firms which have not been suspended from trading were included in the study. Firms of similar size with reference to revenues or total assets, operating in similar sectors to the suspended firms were included in the sample. The total sample size of firms examined was therefore 38. Paired samples were used to ensure that failing and non-failing firms are included in the sample.

The classification of the companies by the two models as failing and non-failing was evaluated using the paired samples.

4.5 Unit of Analysis

The unit of analysis for this study is the company under investigation. This includes both failed and non-failed firms.

4.6 Data Collection and Validity

The population of the study comprises South African public listed companies and therefore the primary source of data was the JSE Limited, Bloomberg and Share data. The data used in the study was in the form of company annual financial statements and stock exchange news service announcements.

4.6.1 Extraction of Annual Financial Statements

The annual financial statements of each company in the sample were downloaded in excel format from Bloomberg. The data downloaded comprised a 10-year history of the:

i. Balance sheet
ii. Income statement
iii. Cash flow statement
iv. Key financial ratios

In instances where the company had not been listed for 10 years, the maximum number of financial periods available was extracted.

4.6.2 History of SENS Announcements

The JSE listing requirements compel companies to release announcements to the public if there is information that is material to the performance, or evaluation of the future potential of the company which becomes evident (JSE Limited, 2016). Companies therefore release SENS (Stock exchange news service) announcements as a means of communicating to investors, shareholders and other stakeholders of the company. This information gathered through SENS announcements has been used in this study as a tool for evaluating certain factors relating to the existence of evidence of verifier determinants.

The Stock Exchange News Service (SENS) provided rich qualitative data especially in relation to profit warnings, dividend payments, suspension of trading, resignation of directors as the

JSE listing requirements require that companies make disclosure to the market if there is an expectation of a significant event taking place in the reporting period (JSE Limited, 2016).

The SENS announcements were gathered via Share data which aggregates the information directly from the JSE. Refer to Annexure D for an example of the SENS history aggregated.

4.6.3 Reliance on secondary data

As evidenced above, this study has therefore relied on secondary data which is available in the public domain. Schuster Anderson & Brodowsky (2014) note the disadvantages of using secondary data including questioning the accuracy and relevance of the data for the particular study where the data was not principally compiled for the purposes of the study (Schuster, Anderson, & Brodowsky, 2014).

This is true for this study as the data as compiled and aggregated by Bloomberg, Share Data and the JSE, would have been collated for the benefit of investors, shareholders and other market participants and not for the purposes of this research. Furthermore, the researcher has no control over the method used to collect and aggregate the data, who gathered the data, why it was gathered, and whether it is consistent with other related information. (Schuster, Anderson, & Brodowsky, 2014)

4.6.4 Data integrity

The concerns regarding the collection and integrity of data is mitigated by the quality of the sources from which the data will be obtained for the purposes of this study.

The Johannesburg Stock Exchanges

The JSE Limited is a globally recognised stock exchange used by local and international investors looking to gain exposure to the capital markets in South Africa. The exchange has safeguards and controls in place to ensure data and information integrity (JSE Limited, 2016).

Bloomberg

Bloomberg is a global financial news and company financial information aggregator which will be used to collect quantitative data including annual financial statements of the sample of companies which will be investigated in the study. The data collected by Bloomberg is sourced from the underlying companies themselves and company financial reports. Bloomberg also provides company analysis and performance projections which is available only to subscribed member of the Bloomberg platform. The focus of this study is on the publicly available financial information.

Share Data

Share Data Online is the companion website to Profile's Stock Exchange Handbook which collates information including company results and news, consensus forecast earnings, detailed factsheets updated daily, and with comprehensive archives and useful company analysis tools (Sharedata, 2016). Share data also provides company annual financial statement is a standardised Microsoft excel format.

4.7 Method of Analysis

The financial data retrieved from Bloomberg and Share Data comprised financial statements for the 38 companies included in the study and was retrieved in excel format.

4.7.1 Application of the Altman Z-Score

The Altman Z-Score (1968) is a statistical multivariate analysis which is quantitative in nature. The distress and failure prediction model has been applied to the financial data of the sample of companies selected to determine the classification of each company as failing or non-failing.

The Altman Z Score is determined by applying the following formula:

$$\mathbf{Z = 0.012\, X_1 + 0.14X2 + 0.33X3 + 0.006X4 + 0.999X5}$$

Where:

X1 : Working Capital/Total Assets

X2 : Retained Earnings/Total Assets

X3 : Earnings before interest and taxes/Total Assets

X4 : Market value equity/Book value of total debt

X5 : Sales/Total assets

Z : Overall Index

The company financial history as extracted from Bloomberg was applied to the Altman Z-Score formula as above to determine a score for each company in the sample.

In study Altman (1968) asserts that the best critical value for discrimination between failing and non-failing firms falls between 2.67-2.68 and therefore 2.675 is the midpoint chosen as the Z value that discriminates best between the bankrupt and non-bankrupt firms (Altman, 1968). This methodology of classification as articulated by Altman was therefore applied to the sample of companies to classify them between failing and non-failing.

Altman also concluded through his observations of firms which had been misclassified that companies with a Z score of greater than 2.99 clearly fall into the "non-bankrupt" sector, while those firms having a Z below 1.81 are all bankrupt (Altman, 1968). The area between 1.81 and 2.99 was classified as a grey area, however 45% of the companies in the grey area were in fact bankrupt within an average of 15 months from the time the prediction forecast was modelled (Altman, 1968).

The following matrix as developed in Altman's study can has been applied to classify the companies in the sample into the relevant categories based on the Z-Score calculations:

Table 4.1 Altman cut off thresholds

Calculated Z-Score	Interpretation	Classification
Z is >=3.0	Minimal risk of failure and the company is considered to be safe from bankruptcy	Non- Failing
Z is 2.7 to 3.0,	The company has a good probability of remaining safe from bankruptcy. The company is theoretically in the upper 55% of the grey, but this is in the grey area none the less.	Grey Area
Z is 1.8 to 2.7,	The company is in the bottom 45% of the grey area and statistically these companies are likely to experience bankruptcy within the next two years of the forecast being performed.	Grey Area
Z is <= 1.8,	The company is highly likely to be bankrupt; these entities are at the highest risk of failure.	Failing

Source: (Altman, 1968)

The Altman model (1968, 2006) is one of the most influential models in the area of bankruptcy prediction (Salimi, 2015). When the model was initially developed, the discriminant-ratio model proved to be extremely accurate and predicted bankruptcy correctly in 94 percent of the initial sample (Altman, 1968). Salimi (2015) concluded that the model remains robust but not 100% accurate in predicting bankruptcy. According to Salimi's study, the model's prediction accuracy over the three years prior to bankruptcy was 79.4% and 87.6% prediction accuracy one year before bankruptcy (Salimi, 2015).

The Altman Z-Score (1968) has been widely applied and tested by researchers including (Salimi, 2015) and is generally accepted as a good predictor of failure and distress. Almamy, Aston and Ngwa (2016) state in their study that Altman (1968) model is considered by most researchers, practitioners and managers as an effective tool to predict the health of companies. Altman has performed a number of iterative studies seeking to improve the accuracy of the Z-Score model however the original model still remains reliable and generally accepted by as a good benchmark (Rankov & Kotlica, 2013).

For this reason, the Altman Z-Score (1968) is used as the benchmark in the study and Pretorius and Holtzhauzen' s (2013) verifier determinants theory is tested against the Altman model. For the purposes of the calculation of the Altman Z-Scores for each of the companies in the sample, the relevant line items from the financial statements will be imputed into the formula to determine the final Z-Score of the company. Based on the Z score calculated, the companies will be classified into the relevant categories, Failing Non-Failing or Grey areas as prescribed by Altman (1968) and illustrated in table 4.1.

4.7.2 Evaluation based on Verifier determinants

The study by Pretorius and Holtzhauzen (2011) is based on early warning signs theory and seeks to identify factors that are used by business turnaround practitioners to identify the underlying causes of business failure and distress. Pretorius and Holtzhauzen (2013) introduce the concept of verifier determinants of early warning signs as a tool to confirm the causes of decline in order to direct rescue strategies and reduce the time between the first observation and the implementation of turnaround strategies. The verifier determinant can further be used to isolate the cause of the causes of decline. (Pretorius & Holtzhauzen, 2013)

A verifier points to some factor or element that confirms, validates and ensures firstly that the cause of decline exists and secondly that the early warning sign used to identify it is in fact present. The term determinant therefore mainly reflects the agreement or consensus between the cause and the apparent warning sign verifier (Pretorius & Holtzhauzen, 2013)

Pretorius and Holtzhauzen' s (2013) verifier determinants theory is a qualitative approach based on an experimental qualitative research design. In their study, the research respondents were given three comprehensive case studies to evaluate in their own time as preparation for the interviews (to later determine how verifier determinants were applied in their evaluation process) (Pretorius & Holtzhauzen, 2013). Once verifier determinants had been identified, the subjects were asked to compare the cases and identify the verifier determinants for each case (Pretorius & Holtzhauzen, 2013).

The five categories of verifier determinants each comprises a number constituents elements which can be evaluated to determine if there is evidence of the existence of an early warning sign which indicates the risk of decline. The constituent element for each verifier determinant are detailed in Annexure A. The verifier determinants and their use depends on exposure and access to information and can be influenced by the evaluators past experiences and judgement (non-factual) rendering them ‘irrational’ in modern management perspectives.

The research approach adopted by Pretorius and Holtzhauzen (2013) was exploratory and qualitative in nature. The research respondents were given three comprehensive case studies to evaluate in their own time as preparation for the interviews (to later determine how verifier determinants were applied in their evaluation process). Once verifier determinants had been identified, the subjects were asked to compare the cases and identify the verifier determinants for each case (Pretorius & Holtzhauzen, 2013).

Pretorius and Holtzhauzen (2013) used case information in their study to confirm the existence and application of verifier determinants. There were no interviews with management or company insiders performed to evaluate the performance of the companies or to confirm the existence of the verifier determinants. Similarly, to be consistent with the study by Pretorius and Holtzhauzen (2013) this study evaluated the existence of the components of the verifier determinants based on publicly available company information. A qualitative analysis of secondary data based on SENS (Stock Exchange News Service Announcements) was be performed.

The study’s main finding is the confirmation of the existence and use of verifier determinants as factors to consider when identifying causes of business decline, resulting in distress and failure (Pretorius & Holtzhauzen, 2013).

The verifier determinants were classified into five categories being:

- (i) Managerial verifier determinants;
- (ii) Financial verifier determinants;
- (iii) Strategic verifier determinants;
- (iv) Operational verifier determinants;
- (v) Banking verifier determinants.

The five categories of verifier determinants each comprise a number constituents elements which can be evaluated to determine if there is evidence of the existence of an early warning sign which indicates the risk of decline. The constituent elements for each verifier determinant are detailed in Annexure A.

The findings of the study by Holtzhauzen (2011) concluded that financial verifier determinants were of high importance as early warning indicators of business decline or distress. Refer to annexure C for the rankings of the verifier determinants. The financial verifier determinants are also largely measurable (Holtzhauzen, 2011). The study also found that the all five categories of verifier determinants were highly correlated with each other and the hypothesis that the verifier determinant categories were not correlated was therefore rejected (Holtzhauzen, 2011).

Based on the findings as outlined above and to minimise the risk of misinterpretation of non-numeric data, this study has focused on the financial verifier determinants which were highlighted as the most important grouping in the study. The financial factors are largely quantifiable and the inputs for calculation of the financial metrics can be obtained from the company's annual financial statements.

The financial verifier determinants as identified through Holtzhauzen's (2011) research are listed in table 4.2 below. The constituent elements were developed through interviews with a specialist group and developed into a questionnaire, which was distributed to 200 bankers and responses obtained from 92 respondents. The study had a Cronbach's alpha of 0,744 which suggests high reliability (Holtzhauzen, 2011).

There were no interviews with management or company insiders performed to evaluate the performance of the companies or to confirm the existence of the verifier determinants. Similarly, to be consistent with the study by Pretorius and Holtzhauzen (2013) this study will evaluate the existence of the components of the verifier determinants based on publicly available company information such as Annual Financial Statements and SENS announcements using the evaluation criteria as outlined in Annexure D.

The constituent elements were further ranked in order of importance based on the responses received with 10 representing high importance and 1 representing low importance (Holtzhauzen, 2011).

Table 4.2 Financial verifier determinants weightings

	Financial Verifier Determinants	Ranking
1	Labour cost that is disproportionate for the type of business;	5
2	Absent or unrealistic cash-flow projections;	7
3	A high risk (or one big project) dependence;	9
4	Late submission of financial information;	10
5	Sensitivity on tax avoidance;	9
6	Not analysing internal financial information;	8
7	Underutilisation of assets	1
8	Creative accounting;	6
9	Pricing or discounts for cash generation;	2
10	Slowing down and stretching payments to suppliers;	4
11	High executive remuneration; and, finally,	3
12	Dividend payouts that are unstructured and considered too high.	7
		71
Ranking: 10 = High Importance; 1 = Low Importance		

Source: (Holtzhauzen, 2011)

In this study, we will calculate a financial ratio relating to each financial verifier determinants as listed in table 4.2 above to determine whether there is evidence that the verifier determinant is present in the company being evaluated. Holtzhauzen states that the performance cycle to test for verifier determinants incorporates four performance areas of importance including, underperformance, decline, distress and failure (Holtzhauzen, 2011). Therefore the financial ratios we calculate in this study seek to determine if there is a trend indication underperformance, decline, distress or failure.

4.7.3 Method of evaluation for each verifier determinant

4.7.3.1 Labour cost that is disproportionate for the type of business

i. Based on the AFS extracted from Bloomberg, calculate staff costs as a % of revenue over three years
ii. Calculate staff costs as a % of net income for a three year period: Calculated from AFS
iii. Compare the ratio above to comparable companies
iv. Review the revenue per employee ratio for the company: Ratio provided by Bloomberg.

v. Compare this measure to the industry average: Industry average provided by Bloomberg.

If the revenue and profit per employee are deteriorating or the revenue per employee lag the industry averages, we concluded that the verifier determinant was evident in the company. If there is evidence of the verifier determinant, the company scored 5 per the weighting allocated by Holtzhauzen (2011) and if there is no evidence of the verifier, the company scored 0.

4.7.3.2 Absent or Unrealistic cash flow projections

i. Based on the annual financial statements extracted from Bloomberg, review the balance sheet closing cash balance for the company over three years.
ii. Review the cash generated from operating activities over a three year period.
iii. Evaluate whether the cash balances of the company reflect an improving or deterioration trend.
iv. Review management forecasts which are in the public domain for cash flow projections.
v. Review cash flow projections formulated by investment analysts in relation to the company.

If the company has no cash flow projections in their budget and results presentations, this is seen as evidence of a verifier determinant. Alternatively, if management's projections are materially different from projections by analysts and a negative trend is evident in the company's cash flows, this is deemed to be evidence of a verifier determinant. If there is evidence of the verifier determinant, the company scores 7 per the weighting allocated by Holtzhauzen (2011) and if there is no evidence of the verifier, the company scored 0.

4.7.3.3 A High risk or one big project dependence

i. Review the sales or revenue note to determine the diversification of revenue sources
ii. Diversification is considered relative to the different products sold, geographies and markets.
iii. Review the revenue split analysis reported by Bloomberg and share data

Where a company demonstrates high dependence on a single products or market segment the verifier determinants is deemed to be evident. If there is evidence of the verifier determinant, the company scores 9 per the weighting allocated by Holtzhauzen (2011) and if there is no evidence of the verifier, the company scored 0.

4.7.3.4 Late Submission of Financial Information

i. Review the AFS release date as published on SENS relative to the statutory requirement to release results within 6 months of financial year end.
ii. Review SENS announcements for deferral of release date of financial information
iii. Determine if results were released after the statutory due date.

Conclude whether there is evidence of underperformance, decline, distress or failure and therefore whether the verifier is present or not. If there is evidence of the verifier determinant, the company scores 10 per the weighting allocated by Holtzhauzen (2011) and if there is no evidence of the verifier, the company scored 0.

4.7.3.5 Sensitivity on tax avoidance

iv. Based on the financial statements as extracted from Bloomberg, calculate the income statement tax expense as a % profit before tax for a three year period
v. Review the cash flow statement for tax paid in each year for three years
vi. Based on the consistency of the tax payment and tax expense trend evaluate if there is evidence of volatility in the tax charges.
vii. Compare the company specific effective tax rate to industry averages.

If the effective tax rate trend is volatile and an inconsistent with the industry trends, there is deemed to be evidence of a verifier determinant. If there is evidence of the verifier determinant, the company scores 9 per the weighting allocated by Holtzhauzen (2011) and if there is no evidence of the verifier, the company scored 0.

4.7.3.6 Not analysing internal financial information

i. Reviewed the market presentations conducted by the company for insights into expected performance and reasons for variances in data year on year.
ii. Reviewed SENS announcements for voluntary trading statements and other guidance to the market indicating insight into company financial information

Where the analysis provided is shallow or weak and instances where there's no guidance provided to the market regarding the company's expected performance, this was deemed to be evidence of the existence of a verifier determinant. If there is evidence of the verifier determinant, the company scores 8 per the weighting allocated by Holtzhauzen (2011) and if there is no evidence of the verifier, the company scored 0.

4.7.3.7 Underutilisation of assets, the following process will be followed

i. Calculate the return on assets over a three year period
ii. Evaluate if there if there is a trend of deterioration of efficiency
iii. Compare the company ratio to industry averages; The peer group analysis is obtained from Bloomberg)

Where there is a trend of significant deterioration in the return on assets or the company consistently lags its industry peers in terms of return on assets, this is deemed to be evidence of the existence of the verifier determinant. If there is evidence of the verifier determinant, the company scores 1 per the weighting allocated by Holtzhauzen (2011) and if there is no evidence of the verifier, the company scored 0.

4.7.3.8 Creative Accounting

i. The companies in the sample are all listed entities and are therefore required to be audited (JSE Limited, 2016)
ii. A review of the audit opinion of each company was performed to determine if the accounting policies, principles and standards had been consistently applied.
iii. A review of SENS announcements was also performed to determine if there is evidence of restatement of prior year reported numbers.

The verifier determinant is deemed to be evident where:

i. There was evidence of adjustments to reported prior year figures
ii. There is a change in accounting policy which was not substantiated or
iii. Where the auditors have issued a modified report on the basis of a lack of availability of accounting data

If there is evidence of the verifier determinant, the company scores 6 per the weighting allocated by Holtzhauzen (2011) and if there is no evidence of the verifier, the company scored 0.

The findings indicated structural breaks statistically significant in the temporal behaviour of the long-term Debt ratio (represented by the ratio between debt and net equity), with predominance in order to increase the leverage situation (Moura & Coelho, 2016), 4.7.3.9 Pricing and discounts for cash generation

i. Calculate the gross margins achieved by the company over a three year period
ii. Calculate the net margin over a three year period
iii. Compare the company gross margins, net margin and EBITDA margin to industry averages.
iv. Review the turnover or sales note for evidence of increasing customer discounts.

Verifier determinants are deemed to be present where there is a trend of deteriorating margins and increasing discounts to customers. Where margins are maintained or improving, this is deemed to be evidence that the verifier is not present. Where there is evidence of the verifier determinant, the company scores 2 per the weighting allocated by Holtzhauzen (2011) and if there is no evidence of the verifier, the company scored 0.

4.7.3.10 Slowing down and stretching payments to suppliers

i. Calculate the creditors turnover days over a three year period
ii. Calculate the current ratio over the three year period. The current ratio is calculated as current assets divided by current liabilities. Where creditors are being stretched, the current liabilities are likely to increase resulting in a decreasing current ratio.

The verifier determinant is deemed to be present where there is evidence of an increase in the creditors turnover days or there is a deterioration in the current ratio, which is driven by an increase in current liabilities. It was also essential to note that the deterioration in the current ratio was not driven by a decrease in assets.

Where there is evidence of the verifier determinant, the company scores 4 per the weighting allocated by Holtzhauzen (2011) and if there is no evidence of the verifier, the company scored 0.

4.7.3.11 High Executive Remuneration

i. Directors remuneration is disclosed in the company's annual report as recommended by the King report on corporate governance and required by the JSE listing requirements (JSE Limited, 2016)
ii. The total directors' remuneration was divided by the number of executive directors for each company to determine the amount paid per director. This amount is compared to the amount paid to directors of comparable companies.

iii. Director's remuneration as a percentage of net profit was also calculated and compared to the companies of similar size, same industry and revenue.

The verifier determinant is deemed to be present where the company directors are consistently paid a higher average salary than comparable companies. Where there is evidence of the verifier determinant, the company scores 3 per the weighting allocated by Holtzhauzen (2011) and if there is no evidence of the verifier, the company scored 0.

4.7.3.12 Dividend payouts that are unstructured and considered too high

i. Each company's dividend policy as disclosed in the annual financial statements was reviewed
ii. The three year history of the dividend per share ratio was reviewed and evaluated relative to the dividend policy. The trend in the pay-out was evaluated for consistency.

The verifier determinant is deemed to be present where:

i. the dividend payouts vary from the dividend policy or,
ii. Payouts are inconsistent.

Where there is evidence of the verifier determinant, the company scores 7 per the weighting allocated by Holtzhauzen (2011) and if there is no evidence of the verifier, the company scored 0.

4.7.4 Calculation of the aggregate score of default

The total scores for each company based on the verifier determinants which are evident in the companies were added together to determine the aggregate score of default for each company.

The weightings were allocated by Holtzhauzen based on the relative importance of each factor as identified by the respondents to the study (2011). An aggregate score of default will be calculated based on the frequency of observations of evidence of early warning signs.

Example of calculation of aggregate score of default

	Financial Verifier Determinants	Ranking
5	Sensitivity on tax avoidance;	9
8	Creative accounting;	6
9	Pricing or discounts for cash generation;	2
11	High executive remuneration; and, finally,	3
	Total	20
Ranking: 10 = High Importance; 1 = Low Importance		

For example; a company which displayed evidence of the existence of factor 5, 8, 9 and 11 as shown in table 4.2, would have an aggregate score of 20 out of 71 as demonstrated below. The aggregate score of default is therefore measurable as an ordinal value.

The total score of each company will therefore be expressed as an aggregate score of default as determined using verifier determinants, where the total possible score is 71. The aggregate default score will be used to classify the companies into three separate categories being high, moderate and low aggregate default scores. For example a company that displays all warning signs will score 71 of 71 and therefore be classified in the high aggregate score of default category.

4.7.4.1 Categorisation of companies using verifier determinants

An aggregate score of default will be calculated as outlined above. The maximum possible aggregate score of default that would be achieved if a company displayed signs of all the verifier determinants is 71 as illustrated in table 4.2. The following cut-off values were applied to classify the companies into three categories.

Table 4.3 Aggregate score of default cut off values

Company Classification	Aggregate score	Aggregate score as %
High aggregate score of default	If > 46.15	If > 65%
Moderate aggregate score of default	If > 25.85 but < 46.15	If > 35% but < 65%
Low aggregate score of default	If < 25.85	If < 35%

The consistency of classifications achieved through the application of the verifier determinants theory compared to the classifications achieved based on the application of the Altman Z-Score will be achieved via the use of a Confusion Matrix as illustrated in table 4.4.

4.8 Comparison of the Z-Score and Verifier Determinants Classifications

Two basic approaches can be used to assess consistency between derived and stated preferences (or to assess the outcome of the two models), correlational or the use of a confusion matrix.

4.8.1 Confusion Matrix (Cross Tabulations)

A simple method of evaluating the level of agreement between two models is to calculate the proportion (or percentage) of cases where both raters agree compared to all cases considered. The total number of agreements and disagreements can give a simple measure overall proportion of agreement.

A confusion matrix or cross tabulations provide an effective method of expressing this measure of agreement. the confusion matrix relies on the ordinal categorisation of the companies as by the Altman Z-Score as failing, grey area and non-failing compared to the classifications as high, moderate or low aggregate default score as achieved from the application of verifier determinants theory.

To create a confusion matrix, the results of the groupings of the companies as failing, grey area and non-failing as achieved by applying the two failure prediction or early warning methodologies will be plotted into the comparative matrix shown in table 4.3. The classifications by the two models relate to each other as follows:

Altman Z-Score results	Verifier Determinants Result
Failing	High aggregate default score
Grey Area	Moderate aggregate default score
Non- Failing	Low aggregate default score

A confusion matrix counts the (across subjects and stimulus objects) the number of correct (or consistent) predictions made by the model. The rows of the matrix represent ranks (or classifications) predicted by the model for an object; the columns represent the stated ranks (or alternative ranks achieved by the second model) for the same object (Wilcox & Austin, 1979).

Table 4.4 Classifications by Z-Score and Verifier Determinants

		Aggregate Default Scores			
		High	Moderate	Low	Total
Altman Z Score Results	Failing				
	Grey Area				
	Non Failing				
	Total				Total = 38

The confusion matrix allows for classification of every possible combination of classifications. For example, a company may be classified as failing by one model and grey are by another; a frequency matrix is developed counting the frequency of each combination of outcomes observed from the application of the models. The total observations as recorded on the frequency table must equal the total number of companies in the sample.

The frequency of the observations where classification by both models intersects can be observed as highlighted in the frequency model above. The total number of observations where the models classify the companies in the same categories can be expressed as a percentage of the total observations to determine the rate of consistency between the models.

The off-diagonal frequencies represent error or inconsistencies in the prediction and classifications whereas the diagonal frequencies signify consistent predictions or classifications (Wilcox & Austin, 1979). The percentage of frequencies appearing on the diagonal is the basis of the evaluation of the accuracy of the model (Wilcox & Austin, 1979).

The shortcoming of this method is that the overall proportion of agreement does not take account of instances where the models rate the companies the same purely by chance. The Cohen kappa is calculated to address this shortcoming.

4.8.2 Application of Cohen's kappa (k) Statistic

Cohen's kappa (κ) is a measure of inter-rater agreement for categorical scales when there are two raters (where κ is the lower-case Greek letter 'kappa') or where there are two rating scales (Laerd Statistics, 2016). This measure is appropriate for this study as we seek to evaluate the categorical ordinal classifications of companies as rated by the Altman Z-Score and the aggregate scores of default as determined through the application of verifier determinants theory.

The Cohen's kappa (κ) is a statistic that was designed to take into account chance agreement between two models or raters. Instead of measuring the overall proportion of agreement as done through the confusion matrix (cross tabulation) above, Cohen's kappa measures the proportion of agreement over and above the agreement expected by chance.

Cohen's kappa (κ) requires that the following assumptions are met for the model to be applicable:

i. The responses made by the two rates are measured on a categorical scale. This assumption holds in this study as the two models are used to categorise the companies on an ordinal scale and the categories are mutually exclusive.
ii. The responses are based on the observations of the same phenomenon or data by the two raters. In this study the two models were used to evaluate the same companies and assessed them for the same outcomes.
iii. The response variables are required to have the same categories and the cross tabulation must be symmetric. In this study both models are used to classify the models into three separate categories; failing, grey and non-failing.
iv. The two rating agents are required to be independent of each other and not dependent on one another. This assumption also holds as the two models were developed independently and are applied to the data independently.
v. The same two raters are used to judge all observations. In this study the same two models are used to evaluate all the companies in the sample.

The kappa coefficient is calculated by the following formula.

$$kappa\ (\kappa) = \frac{proportion\ of\ observed\ agreement - proportion\ of\ chance\ agreement}{1 - proportion\ of\ chance\ agreement}$$

(Laerd Statistics, 2016)

The Cohen's kappa (κ) coefficient is expressed as a value ranging -1 to +1, with -1 indicating that there was no observed agreement (i.e. the models do not agree on the classification of any of the elements) and 0 (zero) indicating that agreement was no better than chance (Laerd Statistics, 2016) . Kappa (κ) values increasingly greater that 0 (zero) represent increasing better-than-chance agreement for two raters, to a maximum value of +1, which indicates perfect agreement (i.e., the two raters agreed on everything).

The interpretation of the Cohen's kappa (κ) coefficient from the application of the calculation is interpreted based on the following table:

Value of Kappa (κ)	Strength of agreement
< 0.20	Poor
0.21-0.40	Fair
0.41-0.60	Moderate
0.61-0.80	Good
0.81-1.00	Very good

Source: (Laerd Statistics, 2016)

4.8.3 Spearman's Rank Correlation Coefficient

The Spearman's rank-order correlation (often abbreviated to Spearman's correlation) calculates a coefficient, *rs* or ρ (pronounced "rho"), which is a measure of the strength and direction of the association/relationship between two continuous or ordinal variables (Laerd Statistics, 2016).

The Spearman's correlation is most often used to analyse the results of two types of study design: (a) to determine if there is a relationship between two variables; and (b) to determine whether there is a relationship between one or more changes in variables. In this study design, we have taken paired observations of one group of companies based on the application of two models to determine if the there is a relationship between the two models.

The Spearman's rank correlation coefficient will be calculated to determine the consistency in rank order of the companies through the application of the two methods. The application of Spearman's rank correlation coefficient will however use the raw ratio data output obtained from the application of the two methods.

The correlation coefficient is used to identify and test the strength of a relationship between two sets of data. The correlation coefficient r, measures the correlation between two sets of data, even where data cannot be measured but can be ranked (Laerd Statistics, 2016).

Spearman's rank order coefficient is calculated by applying the formula as follows (Laerd Statistics, 2016):

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

(Laerd Statistics, 2016)

Where: di = difference in paired ranks;

:*n* = number of cases.

The formula is applied to calculate the

The Spearman's Rank Correlation Coefficient is a derivation of the correlation coefficient and therefore values must be between -1 and +1.

Where:

***r** = +1 means the rankings of data have a positive association and their ranking are exactly alike, or*

r = 0 where the rankings have no correlation or association and,

r = -1where the rankings have a perfect negative association.

The r value obtained from the computation is applied to the table of Critical Values of the Spearman's Ranked Correlation Coefficient for the given level of confidence and specific sample size.

Compare the obtained r and critical r values and determine whether to retain or reject the null hypothesis (that there is no rank order relationship between the variables in the population represented by the sample). The correlation values can be positive or negative, and therefore we will compare the absolute value of the obtained r to the critical r. (Laerd Statistics, 2016)

- If the absolute value of the obtained r is less than the critical r, then the null hypothesis is retained and we conclude that there is no rank order relationship between the two variables.
- If the absolute value of the obtained r is greater than the critical r, then reject the null hypothesis and conclude that there is a rank order relationship between the variables.

Based on the statistical test as detailed above we can conclude on whether to accept or reject the hypothesis.

4.8.3.1 Correlation between Altman Z-Scores and Aggregate Scores of Default

Spearman's rank correlation will establish if there is a statistically significant correlation in the ranking of the companies through the application of verifier determinants and the ranking that would be achieved using the Altman Z-Score.

In order to calculate the Spearman's rank correlation coefficient, we calculate the Z score of the companies in the sample and rank the companies from least likely to fail to the most likely to fail based on the Z-Scores; i.e. where a high Z score indicates less likelihood of failure. Note that the Z-Score is expresseddd as ratio data which can be ranked from the highest to lowest scores, where a high score indicates that a company is healthy and a low score indicates that the company has a higher likelihood of experiencing distress.

Similarly, the application verifier determinants theory will result in an aggregate score of default which can vary from zero to 71 as illustrated in table 4.2. The score can be expressed as a percentage of the maximum. The output from the application of verifier determinants is therefore also ratio data which will enable us to rank the companies based on their aggregate score of default. With this methodology however a low aggregate score represents a low likelihood of failure and a high aggregate score represents a higher likelihood of failure.

The correlation or consistency of the rankings of the companies as achieved via the application of the two methodologies is tested through the application of Spearman's rank correlation coefficient.

4.9 Limitations of the study

This study focused on one of the five categories of verifier determinants as introduced by Holtzhauzen (Holtzhauzen, 2011). Holtzhausen's study had concluded that financial verifier determinants were factors of high importance as early warning indicators of business decline or distress. The exclusion of the managerial, strategic, operational and banking verifier determinants could have added to the robustness of the conclusions on relating to the use of verifier determinants as early warning sign of business distress. The use of financial factors could have also contributed to the significance of the relationship between verifier determinants and the Altman Z-Score as the Altman model relies purely on financial data.

This study relied on publicly available financial information and used trends in accounting data to make evaluations on certain questions relating to management actions. This implies that the researcher's judgment was used to cake some conclusions regarding the existence of verifier determinants. It is possible that a different researcher presented with similar facts could come to different conclusions in relations to the evaluation certain company information.

This study relies on secondary data which was prepared for purposes other than the completion of this research. The researcher therefore had no control over the manner in which the data was collected and aggregated. Schuster Anderson & Brodowsky (2014) note the disadvantages of using secondary data including questioning the accuracy and relevance of the data for the particular study where the data was not principally compiled for the purposes of the study (Schuster, Anderson, & Brodowsky, 2014).

The evaluation of verifier determinants based on publicly available data limits the richness of the analysis as some of the verifier determinants are focused on internal company process which are not easily evaluated based on information in the public domain. i.e. financial verifier determinate 6, is concerned with the extent to which management analyses internal company data.

5 Results

The following chapter lays out the results generated from the statistical analysis of the data. The data is displayed and discussed in order of the research questions and hypotheses.

5.1 Descriptive Statistics

Descriptive statistics assist with the analysis of data to describe and summarise the data in a meaningful way such that a broad understanding and patterns may emerge from the data (Laerd Statistics, 2016). Descriptive statistics do not, however, allow us to make conclusions beyond the data we have analysed or reach conclusions regarding any hypotheses we might have made (Laerd Statistics, 2016). The detailed outcomes per company are reflected in Annexure B.

Table 5.1 Descriptive Statistics

Descriptive Statistics						
	N	Minimum	Maximum	Mean	Std. Deviation	Variance
Labour costs disproportionate to business type	38	0.00	5.00	2.3684	2.53005	6.401
Absent or unrealistic cash flow projections	38	0.00	7.00	2.0263	3.21724	10.351
High risk of product of single product dependence	38	0.00	9.00	1.6579	3.53574	12.501
Late submission of financial information	38	0.00	10.00	5.0000	5.06712	25.676
Tax sensitivity and avoidance	38	0.00	9.00	4.7368	4.55408	20.740
Lack of analysis of financial information	38	0.00	8.00	3.5789	4.03117	16.250
Underutilisation of assets	38	0.00	1.00	0.7105	0.45961	0.211
Creative accounting	38	0.00	6.00	3.0000	3.04027	9.243
Discounts for cash generation	38	0.00	2.00	0.6842	0.96157	0.925
Stretching supplier payments	38	0.00	4.00	1.3684	1.92313	3.698
High executive remuneration	38	0.00	3.00	1.1842	1.48607	2.208
Unstructured dividend pay-outs	38	0.00	7.00	5.3421	3.01596	9.096
Gross Aggregate Score: Verifier determinants	38	0.00	64.00	31.6579	20.18867	407.583
Altman Z Score	38	-17.33	23.72	1.5842	5.98909	35.869
Valid N (list wise)	38					

Table 5.1 above indicates that there were 38 observations for financial verifier determinant. This is consistent with expectations as there were 38 companies included in the sample. For each company evaluated, the company scored either 0 or a value equivalents to the rating attaching to the verifier determinant as assigned by Holtzhauzen (Holtzhauzen, 2011). The maximum value assigned to the most important verifiers was 10 (Holtzhauzen, 2011). The

minimum and maximum values for the individual verifier determinants as shown in table 5.1 are between 0 and 10 which is consistent with our expectations.

5.1.1 Gross Aggregate Score of default descriptors

The maximum gross aggregate score of default reported in table 5.1 is 64 relative to the maximum possible gross aggregate score of default of 71. There is therefore no company in the sample which showed evidence of all the verifier determinants. The minimum gross aggregate score of default is 0 which implies that there is at least 1 company which did not show evidence of any of the financial verifier determinants.

The mean value of the gross aggregate score of default is a measure of central tendency and reflects an average value of 31.65. The standard deviation is a measure of spread and it describes the dispersion from the mean. The standard deviation for the gross aggregate score of default is 20.18. A shift by one standard deviation would therefore change the classification of a company between failing and non-failing.

5.1.2 Altman Z-Score descriptive statistics

The Altman Z-Score model does no prescribe a possible minimum and maximum possible Z-Score. The minimum and maximum values of -17.33 and 23.72 are therefore acceptable. In his study Altman (1968) asserts that the best critical value for discrimination between failing and non-failing firms falls between 2.67-2.68 and therefore 2.675 is the midpoint chosen as the Z value that discriminates best between the bankrupt and non-bankrupt firms (Altman, 1968). The average Z-Score value per table 5.1 is 1.584 which falls below this cutoff point however the standard deviation of 5.98 is large enough to change the classification of a company from failing to non-failing.

5.2 Hypothesis 1

This study seeks to determine whether or not the aggregate default score as calculated through the application of verifier determinants theory can be used as a reliable method of predicting business failure and business distress. This was achieved by testing whether aggregate score of default ("ASD") as derived from the application of verifier determinants theory and the Z-Scores as derived from the application of the Altman Z-Score model to a sample of companies lead to any observed agreement in the classification of the companies by the two models as failing, grey area or non-failing.

The null hypothesis and alternate hypothesis were stated as:

$H1_0$: % of observed agreement between Z-Score and ASD = 0

$H1_1$: % of observed agreement between Z-Score and ASD > 0

The aggregate score of default as calculated for each company in the sample was used to classify each company as failing, grey or non-failing. Similarly, the Z-score for each company in the sample was calculated using the Z-score formula. The companies were categorised into three groups failing, grey and non-failing based on the results. The classification of the companies achieved are summarised in the cross tabulation as processed through SPSS.

The resultant preference ordering and classification from the application of each model was determined by the degree to which the vector of ranks derived by the primary model, the Altman Z-score model, are consistent with the vector of the second model being tested, Verifier determinants theory (Wilcox & Austin, 1979).

The frequency of the observations which were consistently classified by both models are represented in the diagonal blocks which are highlighted below (Wilcox & Austin, 1979). The off-diagonal frequencies represent error or inconsistencies in the prediction and classifications whereas the diagonal frequencies signify consistent predictions or classifications (Wilcox & Austin, 1979). The percentage of frequencies appearing on the diagonal forms the basis of the evaluation of the accuracy of the model (Wilcox & Austin, 1979)

Table 5.2 Cross tabulation: Aggregate score of default and Altman Z-Score classifications

		Aggregate Default Scores			
		High	Moderate	Low	Total
Altman Z Score Results	Failing	10	8	3	21
	Grey Area	0	3	3	6
	Non Failing	0	3	8	11
	Total	10	14	14	Total = 38

The frequency of observations as represented in the confusion matrix can be expressed as percentages as shown below.

Table 5.3 Cross tabulation: Percentage of agreement Aggregate Score of Default and Altman Z-Score classifications

		Aggregate Default Scores			
		Failing	Grey Area	Non-Failing	Total
Altman Z Score results	Failing	26.32%	21.05%	7.89%	55.26%
	Grey Area	0.00%	7.89%	7.89%	15.79%
	Non Failing	0.00%	7.89%	21.05%	28.95%
	Total	26.32%	36.84%	36.84%	100.00%

The models have consistently categorised the companies with 55,26%accuracy. Both models categorised: 26,32% of the companies as failing; 7.89% of the companies as being in the grey area and 21,05% of the companies as non-failing.

Failing Companies

The Altman Model however classifies 55.26% of the companies as failing compared to only 26.32% based on the calculated aggregate score of default. The aggregate default scores resulted in misclassification of the failing companies based on the Z-Score Model 54.5% of the time, that is 7.89% classified as grey are and 7.89% classified as failing relative to the total of 55,26% based on the Altman Z-Score.

Grey Area Companies

The Altman model however categorised 15.79% of the companies in the grey area compared to 36.87% based on the calculated aggregate score of default. The aggregate default scores resulted in misclassification of the grey are companies relative to the Z-Score Model 50,00% of the time that is: 0% classified as failing and 7.89% classified as non-failing relative to the total of 15.79% based on the Altman Z-Score.

Non-Failing Companies

The Altman Model classifies 28.95% of the companies as non-failing compared to 36.84% based on the calculated aggregate score of default. The aggregate default scores resulted in misclassification of the grey are companies relative to the Z-Score Model 27.25% of the time that is 0% classified as failing and 7.89% classified as grey relative to the total of 28.95% based on the Altman Z-Score.

The cross tabulations as represented in table 5.3 above enables us to determine the level of agreement between the two models. The simplest measure of agreement between two factors or models is a percentage of agreement or observed agreement, that is, “the percentage of observations on which the two models agree when the same data dataset is applied to them independently” (Artstein & Poesio, 2008).

The models reflect a 55.26% level of agreement and on the null hypothesis is rejected and accept the alternate hypothesis which states that the % of observed agreement between Z-Score and the Aggregate score of default is > 0

5.3 Hypothesis 2

The level of agreement between the models as reflected in 5.2 however does not take into account agreement by chance. In order to determine the level of agreement between the two models over and above chance agreement a Cohen kappa was calculated using SPSS.

The null hypothesis and alternate hypothesis were stated as:

$H2_0$: (κ) = 0, the kappa (κ) coefficient of agreement over chance agreement equals zero.

$H2_1$: (κ) > 0, the kappa (κ) coefficient of agreement over chance agreement is greater than zero.

Table 5.4 Cohen kappa statistic

Symmetric Measures		Value	Asymptotic Standard Error[a]	Approximate T[b]	Approximate Significance
Measure of Agreement	Kappa	0.351	0.102	3.454	0.001
N of Valid Cases		38			

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.

The Cohen's kappa (κ) achieved from the classifications achieved by the application of verifier determinants theory relative to the Altman Z-score is .351. This is the proportion of agreement by the two models over have over and above chance agreement. Cohen's kappa (κ) can range from -1 to +1. The Kappa coefficient is statistically significant as the reported *p*-value is < 0.05. The result is statistically significant result as a $p = 0.01$ has been reported.

The strength of agreement between the models can be interpreted relative to the evaluation table shown below.

Table 5.5 Cohen kappa statistic strength of agreement evaluation

Value of Kappa (κ)	Strength of agreement
< 0.20	Poor
0.21-0.40	Fair
0.41-0.60	Moderate
0.61-0.80	Good
0.81-1.00	Very good

Based on the results we therefore reject the null hypothesis and accept the alternate hypothesis. The alternate hypothesis says (k) > 0, the kappa (κ) coefficient, agreement over chance agreement is greater than zero.

Based on the table of evaluation as showed above, there is a fair agreement between the Altman Z-Score and the verifier determinants theory in the categorisation of companies between failing, grey area and non-failing companies as k =0.351, p =0.01 (p ,0.05)

5.4 Spearman correlation coefficient

The Spearman's rank-order correlation calculates a coefficient, *rs* or ρ which is a measure of the strength and direction of the association/relationship between two continuous or ordinal variables (Laerd Statistics, 2016). The spearman coefficient was applied in this study to evaluate if:

i. There is a statistically significant association in between the rank order (from most likely to experience failure or distress to the least likely to experience failure or distress) of the companies as achieved through the application of the Altman Z-Score compared to the rankings achieved from the aggregate scores of default as determined through the verifier determinants theory (Hypothesis 3).
ii. There is a statistically significant association between the twelve verifier determinants individually (Hypothesis 4).
iii. There is a statistically significant association between the individual financial verifier determinants and the calculated Z-Scores is zero (Hypothesis 5)

The results of the tests of associations are presented in table 5.6 and analysed further as part of the result of Hypothesis 3, Hypothesis 4 and Hypothesis 5.

The spearman correlation coefficient can vary in value from +1 to -1. This indicates a positive or negative association and a coefficient of zero (0) indicates no association. The association is considered to be stronger the closer the correlation coefficient is to +1 or -1, the stronger the association between the ranks (Laerd Statistics, 2016).

For each variable evaluated and presented in the table below, the first line indicated the correlation coefficient and the second line indicated the p-value. For the purposes of this study we will evaluate the results at the 0.01 level of significance. The significant relationships reported in table 5.6 have been highlighted in yellow for ease of reference.

Table 5.6 Spearman Coefficient SPSS Results output

Spearman's rho		Labour costs disproportionate to business type	Absent or unrealistic cash flow projections	High risk of product of single product dependence	Late submission of financial information	Tax sensitivity and avoidance	Lack of analysis of internal financial information	Underutilisation of assets
Labour costs disproportionate to business type	Corr. Coef	1.00	0.21	0.23	0.11	0.06	.524**	0.26
	Sig. (2-tailed)		0.21	0.17	0.53	0.74	0.00	0.12
Absent or unrealistic cash flow projections	Corr.Coef	0.21	1.00	0.15	.522**	0.26	0.24	.407*
	Sig. (2-tailed)	0.21		0.38	0.00	0.12	0.14	0.01
High risk of product of single product dependence	Corr. Coef	0.23	0.15	1.00	0.20	0.18	0.12	0.30
	Sig. (2-tailed)	0.17	0.38		0.22	0.28	0.48	0.06
Late submission of financial information	Corr.Coef	0.11	.522**	0.20	1.00	0.11	.370*	.522**
	Sig. (2-tailed)	0.53	0.00	0.22		0.53	0.02	0.00
Tax sensitivity and avoidance	Corr. Coef	0.06	0.26	0.18	0.11	1.00	0.11	.324*
	Sig. (2-tailed)	0.74	0.12	0.28	0.53		0.50	0.05
Lack of analysis of financial information	Corr.Coef	.524**	0.24	0.12	.370*	0.11	1.00	0.22
	Sig. (2-tailed)	0.00	0.14	0.48	0.02	0.50		0.18
Underutilisation of assets	Corr. Coef	0.26	.407*	0.30	.522**	.324*	0.22	1.00
	Sig. (2-tailed)	0.12	0.01	0.06	0.00	0.05	0.18	
Creative accounting	Corr.Coef	0.11	.406*	0.20	.789**	0.11	.370*	.406*
	Sig. (2-tailed)	0.53	0.01	0.22	0.00	0.53	0.02	0.01
Discounts for cash generation	Corr. Coef	0.32	.396*	.373*	.499**	0.13	.355*	.460**
	Sig. (2-tailed)	0.05	0.01	0.02	0.00	0.44	0.03	0.00
Stretching supplier payments	Corr.Coef	0.09	.396*	0.09	.499**	0.02	0.24	.338*
	Sig. (2-tailed)	0.58	0.01	0.61	0.00	0.92	0.14	0.04
High executive remuneration	Corr. Coef	0.10	.434**	0.17	.485**	0.23	0.03	.515**
	Sig. (2-tailed)	0.56	0.01	0.30	0.00	0.17	0.85	0.00
Unstructured dividend pay-outs	Corr.Coef	0.16	.356*	0.11	.557**	.339*	0.25	.463**
	Sig. (2-tailed)	0.35	0.03	0.53	0.00	0.04	0.13	0.00
Gross Aggregate Score: Verifier determinants	Corr. Coef	.416**	.686**	.421**	.807**	.428**	.572**	.638**
	Sig. (2-tailed)	0.01	0.00	0.01	0.00	0.01	0.00	0.00
Altman Z Score	Corr.Coef	-0.10	-.508**	-.362*	-.689**	-0.24	-0.22	-.701**
	Sig. (2-tailed)	0.57	0.00	0.03	0.00	0.15	0.18	0.00

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

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Table 5.6 Continued: Spearman Coefficient SPSS Results output

Spearman's rho		Creative accounting	Discounts for cash generation	Stretching supplier payments	High executive remuneration	Unstructured dividend payouts	Gross Aggregate Score: Verifier determinants	Altman Z-Score
Labour costs disproportionate to business type	Corr. Coef	0.11	0.32	0.09	0.10	0.16	.416**	-0.10
	Sig. (2-tailed)	0.53	0.05	0.58	0.56	0.35	0.01	0.57
Absent or unrealistic cash flow projections	Corr.Coef	.406*	.396*	.396*	.434**	.356*	.686**	-.508**
	Sig. (2-tailed)	0.01	0.01	0.01	0.01	0.03	0.00	0.00
High risk of product of single product dependence	Corr. Coef	0.20	.373*	0.09	0.17	0.11	.421**	-.362*
	Sig. (2-tailed)	0.22	0.02	0.61	0.30	0.53	0.01	0.03
Late submission of financial information	Corr.Coef	.789**	.499**	.499**	.485**	.557**	.807**	-.689**
	Sig. (2-tailed)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tax sensitivity and avoidance	Corr. Coef	0.11	0.13	0.02	0.23	.339*	.428**	-0.24
	Sig. (2-tailed)	0.53	0.44	0.92	0.17	0.04	0.01	0.15
Lack of analysis of financial information	Corr.Coef	.370*	.355*	0.24	0.03	0.25	.572**	-0.22
	Sig. (2-tailed)	0.02	0.03	0.14	0.85	0.13	0.00	0.18
Underutilisation of assets	Corr. Coef	.406*	.460**	.338*	.515**	.463**	.638**	-.701**
	Sig. (2-tailed)	0.01	0.00	0.04	0.00	0.00	0.00	0.00
Creative accounting	Corr.Coef	1.00	.610**	.388*	.377*	.557**	.747**	-.516**
	Sig. (2-tailed)		0.00	0.02	0.02	0.00	0.00	0.00
Discounts for cash generation	Corr. Coef	.610**	1.00	.415**	0.21	.402*	.668**	-.445**
	Sig. (2-tailed)	0.00		0.01	0.20	0.01	0.00	0.01
Stretching supplier payments	Corr.Coef	.388*	.415**	1.00	.326*	0.27	.537**	-.491**
	Sig. (2-tailed)	0.02	0.01		0.05	0.10	0.00	0.00
High executive remuneration	Corr. Coef	.377*	0.21	.326*	1.00	.323*	.518**	-.638**
	Sig. (2-tailed)	0.02	0.20	0.05		0.05	0.00	0.00
Unstructured dividend pay-outs	Corr.Coef	.557**	.402*	0.27	.323*	1.00	.664**	-.539**
	Sig. (2-tailed)	0.00	0.01	0.10	0.05		0.00	0.00
Gross Aggregate Score: Verifier determinants	Corr. Coef	.747**	.668**	.537**	.518**	.664**	1.00	-.727**
	Sig. (2-tailed)	0.00	0.00	0.00	0.00	0.00		0.00
Altman Z Score	Corr.Coef	-.516**	-.445**	-.491**	-.638**	-.539**	-.727**	1.00
	Sig. (2-tailed)	0.00	0.01	0.00	0.00	0.00	0.00	

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

5.5 Hypothesis 3

The outcomes of the application of the two models can be used to rank the companies in order of the most likely to fail or experience distress to the least likely to experience distress. The survival rank relationship achieved from the application of the models will be tested the following hypothesis:

$H3_0$: $\rho = 0$, the correlation coefficient between the ranking per the z-scores and aggregate scores of default is equal to zero in the population.

$H3_0$: $\rho \neq 0$, the correlation coefficient between the ranking per the z-scores and aggregate scores of default is not equal to zero in the population

The correlation or consistency of the rankings of the companies as achieved via the application of the two methodologies is tested through the application of Spearman's rank correlation coefficient. The table below is an extract from table 5.6 and only reflects the correlation between the aggregate score of default and the Z-Score.

Table 5.7 Aggregate score of default and Altman Z-Score correlation

Spearman's rho		Gross Aggregate Score: Verifier determinants	Altman Z-Score
Gross Aggregate Score: Verifier determinants	Corr. Coef	1.00	-.727**
	Sig. (2-tailed)		0.00
Altman Z Score	Corr.Coef	-.727**	1.00
	Sig. (2-tailed)	0.00	

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Table 5.7 above indicates that there a significant negative correlation between the result of the Altman Z-Score and the Aggregate score of default. The spearman rank correlation coefficient is -0.727 and it is statistically significant at the 0.01 level of significance.

The negative relationship between the variable is expected as a low aggregate score of default indicates good company health whereas a high Z-Score is indicative of good company health. There is therefore an inverse relationship between the two measures.

Due to the reported correlation between the variables and the significance of the correlation of association, we fail to reject the null hypothesis.

5.6 Hypothesis 4

The study seeks to determine if there is a statistically significant relationship between the twelve financial verifier determinants .i.e. do the individual financial verifier determinants show a statistically significant relationship between each other?

H_0 = the null hypothesis states that there is no statistically significant association between the individual financial verifier determinants.

H_1 = the null alternate hypothesis states that there is a statistically significant association between the individual financial verifier determinants

The study identified instances where one verifier has a statistically significant with other verifier determinants at the 0.01 level significance. The findings have been reported below per verifier determinant.

The following hypothesis was tested for each verifier determinant and the decision to accept or reject the null hypothesis will be made for each verifier.

$H3_0$: $\rho = 0$

$H3_1$: $\rho \neq 0$

All the tables in section 5.6 are extracts of table 5.6 focusing on the specific verifier under discussion.

5.6.1 Labour costs disproportionate to business type

Financial verifier determinant 1, labour costs disproportionate to business type only shows a statistically significant relationship with one other factor being "lack of analysis of internal financial information".

Table 5.8 Labour costs verifier and Altman Z-Score correlation

Spearman's rho		Lack of analysis of internal financial information	Gross Aggregate Score: Verifier determinants	Altman Z-Score
Labour costs disproportionate to business type	Corr. Coef	.524**	.416**	-0.10
	Sig. (2-tailed)	0.00	0.01	0.57

**. Correlation is significant at the 0.01 level (2-tailed) *. Correlation is significant at the 0.05 level (2-tailed).

This relationship is significant at the 0.01 level of confidence. The factor shows as statistically significant relationship with the overall gross aggregate score of default but not with the Altman

Z-Score. The strength of the association with the overall aggregate score of default is however moderate at 0.416.

Due to the reported statistically significant correlation between this verifier and other verifier determinants, we fail to reject the null hypothesis.

5.6.2 Absent or unrealistic cash flow projections

Financial verifier determinant 2, absent or unrealistic cash flow projections shows a statistically significant relationship with two other factors, late submission of financial information and high executive remuneration.

Table 5.9 Absent cash flow projections and Altman Z-Score correlation

Spearman's rho		Late submission of financial information	High executive remuneration	Gross Aggregate Score: Verifier determinants	Altman Z-Score
Absent or unrealistic cash flow projections	Corr.Coef	.522**	.434**	.686**	-.508**
	Sig. (2-tailed)	0.00	0.01	0.00	0.00

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

The association between the factors is moderate with the spearman coefficient reported as 0.522 and 0.434 respectively. Both associations are significant at the 0.01 level.

This verifier is also statistically significant with the overall aggregate score of default and the Altman Z-Score model. The spearman coefficient of association with the overall aggregate score of default is 0.686 which is moderate. The verifier also has a moderate association with the Altman Z-Score model reflected through a spearman correlation coefficient of -.508.

Due to the reported statistically significant correlation between the variables and the significance of the correlation of association, we fail to reject the null hypothesis.

5.6.3 High risk of product of single product dependence

Table 5.10 Risk of single product dependence and Altman Z-Score correlation

Spearman's rho		Discounts for cash generation	Gross Aggregate Score: Verifier determinants	Altman Z-Score
High risk of product of single product dependence	Corr. Coef	.373*	.421**	-.362*
	Sig. (2-tailed)	0.02	0.01	0.03

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Financial verifier determinant 3, High risk of product of single product dependence does not show a statistically significant relationship with any other financial verifier determinant at the 0.01 level of significance, however a statistically significant relationship is observed at with "discounts for cash generation" financial verifier at the 0.05 level of confidence. This verifier has also showed not significant association with the overall result achieved from the application of the Altman Z-Score at the 0.01 of significance but is statistically significant at 0.05 level of significance.

There is no statistically significant correlation between this verifier determinant and the other individual verifier determinants as reported above, we therefore reject the null hypothesis.

5.6.4 Late submission of financial information

Table 5.11 late submission of financial information and Altman Z-Score correlation

Spearman's rho		Absent or unrealistic cash flow projections	Underutilisation of assets	Creative accounting	Discounts for cash generation	Stretching supplier payments
Late submission of financial information	Corr.Coef	.522**	.522**	.789**	.499**	.499**
	Sig. (2-tailed)	0.00	0.00	0.00	0.00	0.00

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Spearman's rho		High executive remuneration	Unstructured dividend payouts	Gross Aggregate Score: Verifier determinants	Altman Z-Score
Late submission of financial information	Corr.Coef	.485**	.557**	.807**	-.689**
	Sig. (2-tailed)	0.00	0.00	0.00	0.00

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Financial verifier determinant 4, late submission of financial information shows a statistically significant relationship with seven other financial verifier determinants at the 0.01. The significant relationships noted are with the following factors:

> (i) Absent or unrealistic cash flow projections; (ii) Underutilisation of assets;(iii) Creative accounting; (iv) Discounts for cash generation;(v) Stretching supplier payments; (vi) High executive remuneration;(vii) Unstructured dividend pay-outs.

Late submission of financial information therefore appears to be a key indicator of underlying problems which could lead to distress or failure of a company.

Due to the reported statistically significant correlation between the variables and the significance of the correlation of association, we fail to reject the null hypothesis.

5.6.5 Tax sensitivity and avoidance

Table 5.12 Tax sensitivity and Altman Z-Score correlation

Spearman's rho		Underutilisation of assets	Unstructured dividend payouts	Gross Aggregate Score: Verifier determinants	Altman Z-Score
Tax sensitivity and avoidance	Corr. Coef	.324*	.339*	.428**	-0.24
	Sig. (2-tailed)	0.05	0.04	0.01	0.15

**.Correlation is significant at the 0.01 level (2-tailed) * Correlation is significant at the 0.05 level (2-tailed).

Financial verifier determinant 5, tax sensitivity and avoidance does not show a statistically significant relationship with any other financial verifier determinant at the 0.01 level significance.

There is no statistically significant correlation between this verifier determinant and the other individual verifier determinants as reported above, we therefore reject the null hypothesis.

5.6.6 Lack of analysis of financial information

Table 5.13 Lack of analysis of financial information and Altman Z-Score correlation

Spearman's rho		Labour costs disproportionate to business type	Gross Aggregate Score: Verifier determinants	Altman Z-Score
Lack of analysis of financial information	Corr.Coef	.524**	.572**	-0.22
	Sig. (2-tailed)	0.00	0.00	0.18

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Financial verifier determinant 6, lack of analysis of internal financial information only shows a statistically significant relationship with one other factor being “labour costs disproportionate to business type”. This relationship is significant at the 0.01 level of confidence.

Due to the reported statistically significant correlation between the variables and the significance of the correlation of association, we fail to reject the null hypothesis.

5.6.7 Underutilisation of assets

Table 5.14 Underutilisation of assets and Altman Z-Score correlation

Spearman's rho		Late submission of financial information	Discounts for cash generation	High executive remuneration	Unstructured dividend payouts	Gross Aggregate Score: Verifier determinants	Altman Z-Score
Underutilisation of assets	Corr. Coef	.522**	.460**	.515**	.463**	.638**	-.701**
	Sig. (2-tailed)	0.00	0.00	0.00	0.00	0.00	0.00

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Financial verifier determinant 7, Underutilisation of assets a statistically significant relationship with four other financial verifier determinants at the 0.01. The significant relationships noted are with the following factors:

(i) Late submission of financial information
(ii) Discounts for cash generation
(iii) High executive remuneration
(iv) Unstructured dividend payouts

Due to the reported statistically significant correlation between the variables and the significance of the correlation of association, we fail to reject the null hypothesis.

5.6.8 Creative accounting

Table 5.15 Creative accounting and Altman Z-Score correlation

Spearman's rho		Late submission of financial information	Discounts for cash generation	Gross Aggregate Score: Verifier determinants	Altman Z-Score
Creative accounting	Corr.Coef	.789**	.610**	.747**	-.516**
	Sig. (2-tailed)	0.00	0.00	0.00	0.00

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Financial verifier determinant 8, creative accounting has a statistically significant relationship with three other financial verifier determinants at the 0.01 level of significance. The significant relationships noted are with the following factors:

(i) Late submission of financial information
(ii) Discounts for cash generation
(iii) Unstructured dividend payouts

Due to the reported statistically significant correlation between the variables and the significance of the correlation of association, we fail to reject the null hypothesis.

5.6.9 Discounts for cash generation

Table 5.16 Discounts for cash generation and Altman Z-Score correlation

Spearman's rho		Late submission of financial information	Underutilisation of assets	Creative accounting	Stretching supplier payments	Gross Aggregate Score: Verifier determinants	Altman Z-Score
Discounts for cash generation	Corr. Coef	.499**	.460**	.610**	.415**	.668**	-.445**
	Sig. (2-tailed)	0.00	0.00	0.00	0.01	0.00	0.01

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Financial verifier determinant 9, creative accounting has a statistically significant relationship with four other financial verifier determinants at the 0.01 level of significance. The significant relationships noted are with the following factors:

(i) Late submission of financial information
(ii) Underutilisation of assets
(iii) Creative accounting
(iv) Stretching supplier payments

Due to the reported statistically significant correlation between the variables and the significance of the correlation of association, we fail to reject the null hypothesis.

5.6.10 Stretching supplier payments

Table 5.17 Stretching supplier payments and Altman Z-Score correlation

Spearman's rho		Late submission of financial information	Discounts for cash generation	Gross Aggregate Score: Verifier determinants	Altman Z-Score
Stretching supplier payments	Corr.Coef	.499**	.415**	.537**	-.491**
	Sig. (2-tailed)	0.00	0.01	0.00	0.00

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Financial verifier determinant 10, stretching supplier payments shows a statistically significant relationship with two other financial verifier determinants at the 0.01 level of significance. The significant relationships noted are with the following factors:

(i) Late submission of financial information
(ii) Discounts for cash generation

Due to the reported statistically significant correlation between the variables and the significance of the correlation of association, we fail to reject the null hypothesis.

5.6.11 High executive remuneration

Table 5.18 High executive remuneration and Altman Z-Score correlation

Spearman's rho		Absent or unrealistic cash flow projections	Late submission of financial information	Underutilisation of assets	Gross Aggregate Score: Verifier determinants	Altman Z-Score
High executive remuneration	Corr. Coef	.434**	.485**	.515**	.518**	-.638**
	Sig. (2-tailed)	0.01	0.00	0.00	0.00	0.00

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Financial verifier determinant 11, high executive remuneration shows a statistically significant relationship with three other financial verifier determinants at the 0.01 level of significance. The significant relationships noted are with the following factors:

(i) Absent or unrealistic cash flows
(ii) Late submission of financial information
(iii) Underutilisation of assets

Due to the reported statistically significant correlation between the variables and the significance of the correlation of association, we fail to reject the null hypothesis.

5.6.12 Unstructured dividend payouts

Table 5.19 Unstructured dividend pay-outs and Altman Z-Score correlation

Spearman's rho		Late submission of financial information	Underutilisation of assets	Creative accounting	Gross Aggregate Score: Verifier determinants	Altman Z-Score
Unstructured dividend pay-outs	Corr.Coef	.557**	.463**	.557**	.664**	-.539**
	Sig. (2-tailed)	0.00	0.00	0.00	0.00	0.00

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Financial verifier determinant 12, unstructured dividend payouts shows a statistically significant relationship with three other financial verifier determinants at the 0.01 level of significance. The significant relationships noted are with the following factors:

(i) Late submission of financial information
(ii) Underutilisation of assets
(iii) Creative accounting

Due to the reported statistically significant correlation between the variables and the significance of the correlation of association, we fail to reject the null hypothesis.

5.7 Hypothesis 5

The study further seeks to determine if there is a statistically significant relationship between the individual financial verifier determinants and the outcomes achieved through the application of the Altman Z-Score.

H_0 = the null hypothesis states that the correlation coefficient between the individual financial verifier determinants and the calculated Z-Scores is zero.

H_1 = the alternate hypothesis states that the correlation coefficient between the individual financial verifier determinants and the calculated Z-Scores is not zero.

For each of the twelve verifier determinants, the spearman correlation coefficient was run to determine if there is a statistically significant relationship between the individual verifier determinant and the Altman Z-Score model. For each of the twelve verifier determinants, this was tested via the following hypothesis test.

$H3_0$: $\rho = 0$

$H3_0$: $\rho \neq 0$

Table 5.20 Spearman Coefficient between Altman Z-Score and individual verifiers

Spearman's rho		Altman Z-Score
Labour costs disproportionate to business type	Corr. Coef	-0.10
	Sig. (2-tailed)	0.57
Absent or unrealistic cash flow projections	Corr.Coef	-.508**
	Sig. (2-tailed)	0.00
High risk of product of single product dependence	Corr. Coef	-.362*
	Sig. (2-tailed)	0.03
Late submission of financial information	Corr.Coef	-.689**
	Sig. (2-tailed)	0.00
Tax sensitivity and avoidance	Corr. Coef	-0.24
	Sig. (2-tailed)	0.15
Lack of analysis of financial information	Corr.Coef	-0.22
	Sig. (2-tailed)	0.18
Underutilisation of assets	Corr. Coef	-.701**
	Sig. (2-tailed)	0.00
Creative accounting	Corr.Coef	-.516**
	Sig. (2-tailed)	0.00
Discounts for cash generation	Corr. Coef	-.445**
	Sig. (2-tailed)	0.01
Stretching supplier payments	Corr.Coef	-.491**
	Sig. (2-tailed)	0.00
High executive remuneration	Corr. Coef	-.638**
	Sig. (2-tailed)	0.00
Unstructured dividend payouts	Corr.Coef	-.539**
	Sig. (2-tailed)	0.00
Gross Aggregate Score: Verifier determinants	Corr. Coef	-.727**
	Sig. (2-tailed)	0.00
Altman Z-Score	Corr.Coef	1.00
	Sig. (2-tailed)	

Table 5.20 shows the results of the spearman's correlation coefficient showing the relationship between the overall result achieved from the Altman model and the classifications achieved in rank order of classification of the sample companies if each individual financial verifier determinant was considered in isolation of the other verifiers.

For nine of the twelve financial verifier determinants, the spearman's factor indicates that the there is a statistically significant relationship between the verifier determinant and the Altman Z-Score model.

The relationships are negative as a high verifier determinants score indicates a higher risk of failure while a high Altman score reflects a low risk of failure. There is an inverse relationship in the manner in which the model outcomes are interpreted.

We would therefore reject the null hypothesis in relation to the following verifier determinants in relation to the Altman Z-Score.

(i) Absent or unrealistic cash flow projections
(ii) Late submission of financial information
(iii) Underutilisation of assets
(iv) Creative accounting
(v) Discounts for cash generation
(vi) Stretching supplier payments
(vii) High executive remuneration
(viii) Unstructured dividend payouts

The following verifier determinants do not show a statistically significant relationship with the coefficient of correlation with the outcomes of the Z-Score at the 0.01 of significance.

(i) Labour costs disproportionate to business type
(ii) High risk of product of single product dependence
(iii) Tax sensitivity and avoidance
(iv) Lack of analysis of financial information

We would therefore fail to reject the null hypothesis in relation to these verifier determinants in relation to the Altman Z-Score.

5.8 Summary of results of hypothesis testing

The overall level of agreement between verifier determinants and the Altman Z-Score was measured using three methodologies. A simple measure of agreement showed a 55.26% level of agreement and we therefore rejected Hypothesis 1.

A Cohen kappa coefficient was calculated to do determine the level of agreement between the models over and above chance agreement. A statistically significant kappa coefficient of 0.351 was reported at the 0.01 level of significance. We therefore rejected Hypothesis 2.

Spearman rank order correlation coefficient was calculated to determine correlation or consistency of the rankings of the companies as achieved via the application of the two methodologies is tested through the application of Spearman's rank correlation coefficient. A statistically significant result was achieved with a spearman coefficient of -0.727 at the 0.01 level of significance. We therefore rejected the null hypothesis.

The results of the hypothesis testing performed are summarised in the table as illustrated below.

Table 5.21 Summary of outcomes for Hypothesis1 to 3

Hypothesis	Null Hypothesis	Decision
Hypothesis 1	$H1_0$: % of observed agreement between Z-Score and ASD = 0	**Reject H_0**
Hypothesis 2	$H2_0$: (k) = 0, the kappa (k) coefficient of agreement over chance agreement equals zero.	**Reject H_0**
Hypothesis 3	$H3_0$: ρ = 0, the correlation coefficient between the ranking per the z-scores and aggregate scores of default is equal to zero in the population.	**Reject H_0**

Hypothesis 1, 2 and 3 were therefore focused on the performance of the model at the overall level. Hypothesis 4 and 5 focused on the performance on the individual verifier determinants.

The study further sought to determine if there is a significant association between the individual verifier determinants. The decision regarding the significance of the relationship that each verifier has with other verifier determinants was evaluated on an individual basis at a 0.01 level of significance.

The decision regarding the acceptance or rejection of the null hypothesis in relation to each verifier is summarised below.

Table 5.22 Summary of outcomes for Hypothesis 4

Hypothesis	Null Hypothesis	Decision
Hypothesis 4	H_0 = the null hypothesis states that there is no statistically significant association between the individual financial verifier determinants.	
	V_1: Labour cost disproportionate to business	**Reject H_0**
	V_2:Absent or unrealistic cash flow projections	**Reject H_0**
	V_3: High risk of single project dependence	**Do not reject H_0**
	V_4:Late submission of financial information	**Reject H_0**
	V_5:Tax sensitivity and avoidance	**Do not reject H_0**
	V_6: Lack of analysis of financial information	**Reject H_0**
	V_7: Underutilisation of assets	**Reject H_0**
	V_8: Creative accounting	**Reject H_0**
	V_9: Discounts for cash generation	**Reject H_0**
	V_{10}: Stretching of supplier payments	**Reject H_0**
	V_{11}: High executive remuneration	**Reject H_0**
	V_{12}: Unstructured dividend payments	**Reject H_0**

The study further sought to determine if there is a statistically significant relationship between the individual financial verifier determinants and the outcomes achieved through the application of the Altman Z-Score. The significance of the relationships was evaluated at the 0.01 level of significance.

The decision regarding the acceptance or rejection of the null hypothesis in relation to each verifier is summarised below

Table 5.23 Summary of outcomes for Hypothesis 5

Hypothesis	Null Hypothesis	Decision
Hypothesis 5	**H_0** = the null hypothesis states that the correlation coefficient between the individual financial verifier determinants and the calculated Z-Scores is zero.	
	V_1: Labour cost disproportionate to business	**Do not reject H_0**
	V_2:Absent or unrealistic cash flow projections	**Reject H_0**
	V_3: High risk of single project dependence	**Do not reject H_0**
	V_4:Late submission of financial information	**Reject H_0**
	V_5:Tax sensitivity and avoidance	**Do not reject H_0**
	V_6: Lack of analysis of financial information	**Do not reject H_0**
	V_7: Underutilisation of assets	**Reject H_0**
	V_8: Creative accounting	**Reject H_0**
	V_9: Discounts for cash generation	**Reject H_0**
	V_{10}: Stretching of supplier payments	**Reject H_0**
	V_{11}: High executive remuneration	**Reject H_0**
	V_{12}: Unstructured dividend payments	**Reject H_0**

As illustrated in table 5.23 above, four of the twelve verifier determinants did not show a statistically significant relationship with the Alman Z-Score result.

5.9 Conclusion

Based on the techniques applied to test the relationship between the aggregate score of default as determined through the application of verifier determinants theory and the Altman Z-Score, all the models applied to test the relationship between the overall models show that there is some relationship in the outcomes produced by the two models.

The tests performed in relation to the individual verifier determinants relative to the overall Z-score model and testing for the relationship between the verifier determinants themselves begins to highlight some variables, such as late submission of financial information and underutilisation of assets which have a strong association with the overall Z-Score model, the overall aggregate score of default and other individual verifier determinants. These relationships are explored further in chapter 6.

6 Interpretation of results

The findings from chapter five are discussed and analysed in in detail in this chapter. The analysis and discussion in this chapter will seek to interpret the results of the data analysis in the context of the literature and theory base as introduced in chapter two. In some instances the validation of findings may refer to other relevant literature which will be drawn into the study provided it is relevant and concluded in a context that validly substantiates the findings of this study. Literature that contradicts the findings of this study may also be drawn upon as this represents inconsistencies in the body knowledge and research performed in the area of business failure prediction.

The analysis is primarily conducted in an effort to meet the research objectives as expressed through the research hypothesis which were set out in chapter three and reported on in chapter five. The structure of the chapter and analysis herein will follow the same sequence and flow as the chapter three and chapter five, following the research hypothesis set out.

Hypothesis 1, 2 and 3 which deal with the relationship between the overall aggregate score of default compared to the Altman Z-Score will be addressed as separate headings. The results of Hypothesis 4 and 5 which explored the relationship of the individual verifier determinants will be addressed together using the headings of the individual verifier determinants. The analysis will demonstrate that the research objectives have been satisfied.

6.1 Hypothesis 1

The study sought to test if there is any agreement between the Altman Z-Score model and the verifier determinants theory in classifying companies as failing or non-failing. However to be consistent with the classifications used by the Altman model a grey category was also introduced. We therefore tested the classification of the sample of companies into three categories namely, failing non-failing and grey is based on the aggregate scores of default and the Altman Z-Score.

Based on the cross tabulation of classifications between the Altman Z-Score and the Aggregate score of default as shown in table 5. 3, the models classified 55, 26% of the companies consistently. This simple measure of agreement does not have a threshold to determine whether or not the level of agreement is significant. The fact that the level of agreement was greater than 50% is however a positive signal.

While the Altman Z-Score and the aggregate score of default were calculated using different methodologies, the calculation of both matrices relies on similar inputs. The Altman model focused on leverage, asset efficiency, liquidity and profitability of the business and the aggregate scores of default also considered the same elements. The aggregate score or default however takes into account other dimensions including qualitative information such as the late submission of financial information, lack of analysis of financial information by management and creative accounting.

The reliance on similar inputs by the two models as increases the likelihood of the models yielding the same or similar results. Table 6.1 summarises some of the similarities in inputs to the models.

Table 6.1 Summary of model inputs

Altman Z-Score	Aggregate Score of default
Liquidity inputs	
Total Current Assets Total Current Liabilities Working Capital Liquidity	Cash & Near Cash Items Cash From Operations Trade Payables Creditors Days Current Ratio
Leverage inputs	
Total Liabilities Retained Earnings & Other Equity Market Value of Equity	Total Liabilities
Asset Efficiency	
Total Assets Return on Assets	Total Assets Return on Assets
Profitability inputs	
Net profit (loss) Income Tax Expense Interest Expense Earnings Before interest and tax Turnover	Personnel Costs Turnover Net profit (loss) Personnel Costs Gross Margin Operating Margin
Other Factors	
	Change in accounting policy Dividend Payout Ratio Dividends Paid Timeous release of financial information Evidence of budgets, forecasts and planning

Despite the overall level of agreement, we observe differences or a degree of error within the subcategories of the cross tabulations. With reference to table 5.3, the Altman Model classifies 55.26% of the companies as failing compared to only 26.32% based on the calculated aggregate score of default. The aggregate default scores resulted in a 54.5% misclassification of the failing companies relative to the Z-Score model. This misclassification of failing companies as non-failing is a Type I as noted by (Gepp et al., 2010). Gepp et al (2010) state that in the case of business failure prediction it is a more critical error to classify a failing business as successful (Type I error) than to classify a successful business as failing (Type II error). The reason for this is that a Type II error only creates a lost opportunity cost from not dealing with a successful business (Gepp et al., 2010).

The results show us that the Altman Z-Score model was the more conservative model of prediction as it reflected a higher incidence of failing businesses at 55.26% compared to the 26.32% failure as determined through the application of the verifier determinants theory.

The verifier determinants theory classified 36.84% of companies in the sample as non-failing, this compared to 28.95% classified as non-failing through the application of the Altman Z-Score. The risk of misclassification which arises from the difference in the classifications by the two models is again a Type I error; i.e. a company may be classified as non-failing by the verifier determinants theory while it is in fact failing (Gepp et al., 2010). The Altman Z-Score is again the more conservative of the two models as it classifies a lower percentage of the companies in the sample as non-failing.

The cross tabulations as discussed above represent a simple measure of agreement between two the two models. That is, the percentage of observations on which the two models agree when the same data dataset is applied to them independently (Artstein & Poesio, 2008).

6.2 Hypothesis 2

The major problem with the use of simple cross tabulation is that the method does not take into account the agreement between the two models which may simply come about due to chance. This is particularly concerning as the agreement of classifications between the Altman Z-Score model and the verifier determinants theory is only 55.26% before any adjustment is made for agreement by chance.

The Cohen's kappa was calculated precisely to understand the level of agreement in the model which as attributable the performance of models over and above the agreement would come about purely due to chance. The model reflected a statistically significant result which reflected a fair level of agreement between the two models over and above the level of agreement that can be expected purely due to change. This is reflected by the Kappa coefficient of; k = 0.351, and p = 0.0001.

The kappa coefficient of .351 is lower than the simple overall proportion of agreement as determined by applying a simple confusion matrix or cross-tabulation table which reflected a 55,26% proportion of agreement. This is consistent with our expectations as the Kappa coefficient measure agreement over and above chance agreement.

The fact that the kappa coefficient shows a statistically significant level of agreement over and above chance agreement validates the use of verifier determinants as a method of business distress prediction.

6.3 Hypothesis 3

The outcomes of the application of the two models can be used to rank the companies in order of the most likely to fail or experience distress to the least likely to experience distress. The correlation or consistency of the rankings of the companies as achieved via the application of the two methodologies is tested through the application of Spearman's rank correlation coefficient.

A Spearman's rank-order correlation was run to assess the whether there was a statistically significant rank order relationship between the Altman Z-Score results and the Aggregate Scores of default derived from the application of verifier determinants theory. The spearman coefficient rho indicates the strength and the direction of the relationship between two models. With reference to table 5.7, a correlation coefficient of -0.727 indicates a strong negative relationship which is significant at the level of 0.01 significance.

Similar to the rationale as detailed in the discussion relating to the construction of the cross ablution and the calculation of the Cohen's Kappa above, the overall rank order was determined based on the computation of the two model outcomes. Both the Altman Z-Score and the verifier determinants theory take into account factors such as asset efficiency, liquidity and profitability of the business and the aggregate scores of default also considered the same elements. Table 6.1 lists some of the input factors for each model highlighting commonalities. This commonality of input variables therefore makes it more likely than not that the model would behave in a similar fashion as the underlying data relating to the companies changes.

6.4 Hypothesis 4 and 5

The study sought to determine if there is a statistically significant relationship between the twelve financial verifier determinants .i.e. do the individual financial verifier determinants show a statistically significant relationship between each other? It is valuable to understand the relationships between the individual verifier determinants as this could assist users with limited resources to focus on the few verifier determinants which show a significant association with other verifier determinants.

Similarly, this section also addresses the relationship of the individual verifier determinants with the overall Altman Z-Score model.

The individual financial verifiers which are found to have a statically significant with other verifier determinants and with Altman Z-score could be used as a proxy or a gauge of change in the businesses' risk of failure. It would be less onerous for business to monitor one or two factors than to monitor all twelve indicators at any given point in time.

6.4.1 Labour costs disproportionate to business type

Based on the findings reported in Table 5.8, excessive labour costs does not appear to be a significant indicator of the potential risk of business failure or distress. This verifier only showed a statistically significant relationship with one other factor being a lack of analysis of internal financial information.

While the cost of labour can cause pressure on margins and business profitability, Ton (Ton, 2009) makes an argument that higher skilled labour who offers superior quality service will demand higher wages. The findings of Ton's study on the relationship between labour and profitability confirm that while increasing labour is associated with an increase in service quality, no significant relationship between service quality and profitability.(Ton, 2009).

The lack of a causal relationship between labour and profitability partially explains why labour costs are a poor indicator of the like hood of business distress. While in some instances a higher cost base could result in improved service, this does not provide evidence of an impact on revenue and profitability. This finding indicates a lack of sensitivity of company profitability to labour costs. This is consistent with the results which indicate a moderate association between the labour cost verifier determinant and the overall aggregate score of default. The verifier also showed no significant relationship with the result derived from the Altman Score.

6.4.2 Absent or unrealistic cash flow projections

Cash flow management is essential to the survival of business and the lack of liquidity will result in an inability to pay debts and obligations as they fall due. The study by Crane and Bin (Crane & Bin, 2012) on the impact of cash flows on business failure finds that cash flow-based neural network model was a good predictor of business failure. In fact, the cash flow-based model outperformed the accrual-based model and classification results are comparable to previous neural network failure study results (Crane & Bin, 2012).

The definition of business failure as used by Beaver (1966) in literature review defined failure as the inability of a firm to pay its financial obligations.(Beaver, 1966). The ability to pay debts and obligation as they arise is a central part of cash flow planning which management undertakes for the business.

The findings of this study as reported in table 5.9 reflect a statistically significant association between the cash flow planning verifier and the overall aggregate score of default as well as the Altman Z-Score. The results also reflect an association between absent or unrealistic cash flow projections and late submission of financial statements. This association is not surprising as cash flow projections and financial reporting both form part of the financial planning and management activities of a business. A management team that is unable to plan their cash flows appropriately is could possibly also be negligent in the financial reporting to shareholders and other stakeholders.

6.4.3 High risk of product of single product dependence

Revenue diversification enables business to withstand fluctuations in the demand for one product or service. This in itself does not necessarily infer that a single product or service company is doomed to fail. In his research into the impact of revenue diversification on revenue stability, (Yan, 2012) concludes that the importance of revenue diversification reduces as in an economically stable environment. Revenue diversification is itself found to have a stabilising on the overall business. The revenue-stabilizing effect of diversification however diminishes as the economic instability of an enterprise increases and the business become of scale (Yan, 2012).

It therefore appears that the state of development of a company is important in the relative importance of revenue diversification. This study focused on listed South African corporate and a company generally needs to have some track record prior to initiating a listing. For this reason, the relative importance of revenue diversification as a factor influencing the survival of the companies in the study may be diminished.

This is supported by the results of the spearman rank order correlation as reported in table 5.10 which indicate that the high risk of single product dependence does not show a significant level of association with any of the other verifier determinants nor the Altman Z-Score model at the 0.01 level of significance.

If management of a company sought to create a short list of proxy measures to use in order to monitor the likelihood of failure or distress for a business, a focus on revenue diversification would not be one of the key measure to focus on. It is critical to note that this conclusion is based on the tests performed on a sample of large listed companies and the relative importance of this verifier may be different when dealing with smaller companies as suggested by Yan (2012).

6.4.4 Late submission of financial information

The findings of the study as reported in table 5.11 indicate that late submission of financial information is has a statistically significant relationship with seven other financial verifier determinants at the 0.01 and has a high coefficient of association of 0.87 in relation to the aggregate score of default. The sample in this study was drawn from JSE listed companies which have numerous public reporting responsibilities and in terms of the listing requirements are obliged to release financial information with six months of the company's financial year end (JSE Limited, 2016).

The financial statements of a listed companies are required to provide a comprehensive report relating to the financial performance of the company, compliance with rules and regulations relating to the company's operations, sustainability reporting, corporate governance and other stakeholder reports (JSE Limited, 2016). Financial reporting therefore offers the company an ability to communicate comprehensively with its shareholders and stakeholders at large.

Failure to release its financial information timeously could therefore be an indication of an underlying problem with numerous issues in the business. This verifier has a statistically significant and association of 0.789 with the creative accounting verifier determinant. This appears reasonable as pressure to release results could result in management adjustments to accounting figures which are not in keeping with accounting standard.

Late submission of financial statements also attracts fines (JSE Limited, 2016), which is not a prudent use of company resources and reflects a failure to by the directors to comply with their fiduciary duties to enhance shareholder value and act in the best interest of the company.

Underutilisation of assets, discounts for cash generation, stretching supplier payments, high executive remuneration, unstructured dividend pay-outs all reflect a moderate association with the late submission of financial information verifier with spearman's coefficient ranging from 0.485 to 0.557. Due to this relationship with numerous other verifier determinants, it is reasonable that the verifier has a strong association with the overall aggregate score of default. This verifier has a high association with the Altman Z-Score model reflected by the spearman coefficient of - 0.689 at a 0.01 level of significance.

While submission of financial information may appear to an accounting related issue at face value, given the wide scope issues which are required to be addressed in the financial report, the submission of results can be impacted by any of the issues that are addressed in the financial statements.

The significance of the relationship with other verifiers and the overall aggregate score of default and the Altman score indicate that late submission of financial information could be a key indicator of underlying problems within a company which could lead to distress or failure of a company.

Availability of financial information is a key factor for the utilisation of most failure prediction models as the models require financial information to predict failure. Ohlson (Ohlson, 1980) state that the predictive power of any model depends upon when the information (financial report) is assumed to be available.

6.4.5 Tax sensitivity and avoidance

Tax avoidance can be difficult for business outsiders to detect (Simone, Nickerson, & Seidman, 2016). A study into the reliability of financial statement proxies such as effective tax rates as proxies for determining tax evasion concluded that such proxies had limited ability to detect tax evasion depending on the nature of the evasion (Simone et al., 2016). Permanent tax avoidance was more easily detected than tax deferral (Simone et al., 2016).

In addition, financial reporting methodologies adopted by the company were found to have the potential of reducing the statistical power of tax evasion detection models (Simone et al., 2016). This finding could explain the poor statistical significance of association between tax sensitivity and avoidance with over verifier determinants and the overall Z-score model as this study relied on accounting information as a proxy for determining if there could instances of tax avoidance or tax evasion in the companies. The study is therefore subject to the accounting methodology related limitation as highlighted by Simone et al (2016).

As reported in table 5.12, this verifier was found to have no statistical significance to any of the other verifier determinants at the 0.01 level of significance. The verifier also did not have a statically significant association with the Altman Z-Score model.

6.4.6 Lack of analysis of financial information

The analysis of financial information by management is difficult for an outsider to measure effectively as it is an internal function which is not objectively reported on to external stakeholders. The communications by management with the investment community regarding development in the business are an indicator of the internal analysis done by the company.

The openness of a management team to new information is critical to their ability to perceive and receive early warning signs of failure. Literature notes that management has various filters surveillance, mentality and power filters (Ansoff, 1975) through which information needs to be processed before they are able to respond to early warning signs of failure (Ansoff, 1975). This in essence means that it is possible for management to see a weak signal however the mentality filter could hinder management's ability to recognise the new information if it does not fit with their existing frame of reference and therefore fail to act on it.

Based on the results reported in 5.13, this verifier determinant did not show a statistically significant relationship with the Altman Z-Score model and only shows a moderate association with the labour costs verifier determinant. The challenge in evaluating the existence of this verifier from an outsider's perspective could be a factor which influenced findings in relation to this verifier.

6.4.7 Underutilisation of assets

The utilisation of assets has been included in numerous failure prediction models including Altman (1968), Ohlson (1980) and Credit scoring models (Rankov & Kotlica, 2013). The return on assets is an asset efficiency ratio which measures the ability of the company to utilise the assets of the company to generate a return for the business.

A company may be profitable however if it has a large asset base that is used to generate the income, the amount of income generated must be sufficient to cover the cost of capital deployed in the within the company assets (1980). Underutilisation of assets therefore highlights deficiencies in the performance of companies. This factor was therefore expected to be a good indicator of performance.

The asset utilisation of a company is a good indicator overall performance and as confirmed by Abdel and Kabajeh (Abdel & Kabajeh, 2012) there is a positive relationship between Return on assets, Return on equity and return on investment(Abdel & Kabajeh, 2012).This is supported by the results as reported in 5.14 which indicate a moderate to high association between asset utilisation and Altman Z-score with spearman correlation coefficient of 0.701 at the 0.01 level of significance. This factor also shows a statistically significant association with four other verifier determinants being the late submission of financial information; discounts for cash generation; high executive remuneration and unstructured dividend pay-outs.

Company management therefore could use asset utilisation as a proxy for overall company performance in evaluating the risk of the company experiencing failure of distress.

6.4.8 Creative accounting

Creative accounting and misstatement of financial account may be motivated by a variety of factors but predominantly seeks to stress the positive attributes and downplay the negative concerns in a business or possibly conceal fraud (Zeff, 2012). Creative accounting is therefore typically undertaken in an attempt to mislead the users of financial information to avoid bad news coming to light.

The existence of bad news in a company which management seeks to conceal indicates that there is in fact a problem with the underlying business which management has become aware of but do not wish to bring the matter into the public domain. Creative accounting is in some sense, akin to manipulation of financial results. Evidence of creative accounting therefore provides a good indication of underlying problems within the business.

The results as reported in table 5.15 show that creative accounting verifier determinants has a moderate and statistically significant association with the Altman Z-Score reflected by a spearman correlation coefficient of -0.516. The verifier has a high association with late submission of financial statement and the overall aggregate score of default is reflected through the spearman coefficients of 0.789 and 0.747.

It is unsurprising that the verifier also has a significant association with the cash discounts verifier as a business in distress could offer discounts in an attempt to improve and accelerate sales and revenue.

6.4.9 Discounts for cash generation

The association between discounts for cash generation and stretching customer payments was expected to be significant as confirmed by this study and reported in table 5.16. Both techniques seek to improve liquidity in the business. Most failure prediction methods reviewed in the literature to this study reflected liquidity as one of the key attributes to consider when evaluating the likelihood of company distress. Beaver (Beaver, 1966) highlighted cash ratios as the major category of accounting ratios to be considered when evaluating the risk of failure.

Late submission of financial information, underutilisation of assets, stretching supplier payments and creative accounting have a moderate statistically significant association with this verifier reflected by the spearman correlation coefficients ranging between 0.415 and 0.610 at the 0.01 level of significance.

The verifier determinant of discounts for cash generation has a moderate association with the Altman Z-Score reflected by a spearman correlation coefficient of -0.445.

Aggressive cash discounts effectively erode margins which reduces profitability. Therefore while in the short term cash discount count increase sales and the cash generation ability of the business, the thin margins associated with the discounts will make it difficult for the business to yield appropriate returns on a sustainable basis.

6.4.10 Stretching supplier payments

The relationship between stretching supplier payments and discounts for cash generation is as discussed in 6.2.1.9 above. This verifier has a moderate statistically association with the Altman Z-Score model as reflected by the correlation coefficient of 0.491 at the 0.01 level of significance as reported in table 5.17.

6.4.11 High executive remuneration

Executive are remunerated based on many philosophies. While most companies and board like to claim that executive remuneration is performance related, the desire to maintain competitive executive pay in order to retain skills results in executives of underperforming companies receiving similar remuneration as executives of performing companies within the same sector (O'Byrne, 2013). This concept of market related pay makes it difficult to consider executive as an indicator of company performance.

The results of this study as reported in table 5.18 reflect a significant statistical association between the high executive remuneration verifier and the Altman Z-score as well as the overall aggregate score of default. This is reflected by the spearman correlation coefficients of - 0.638 and 0.518 respectively.

This factor also showed a statistically significant relationship with absent or unrealistic cash flows, late submission of financial statement and underutilisation of assets verifiers.

6.4.12 Unstructured dividend payouts

Shareholders are residual owners of a business and company law requires that dividends be paid only if the company is expected to be able to meet its future obligations to lenders, creditors and other stakeholders. While the literature on dividend theory has previously argued that a company's dividend policy is irrelevant, the ability of a company to pay a dividend is indicative of its expected future liquidity and solvency (Firth, 1996).

The study by Firth (1996) into the relationship between dividend changes, abnormal return and intra industry valuations finds that dividend changes are associated with significant abnormal returns and that dividends are a signal about the signal of future earnings of a company. Inconsistent or unstructured dividend payouts by a company would therefore signal inconsistent expectations with regards to the profitability of the company which in turn is underpinned by uncertainty relating to the performance of the company.

Inconsistency in dividend payment is therefore expected to be a good indicator of a company's like hood to succeed or fail. The result of this study as reported in table 5.18 supports this through the finding of a statistically significant spearman correlation coefficient of 0.539 between the unstructured dividend payment verifier and the Altman Z-Score at the 0.01 level of significance. The verifier also shows a significant association with late submission of financial information, underutilisations of assets and creative accounting verifiers which have all also prove to have a statistically significant relationship with the Altman Z-Score.

Dividend payout trends therefore appear to be a good indicator of company health.

6.5 Conclusion

This study has used three techniques to determine whether or not there is a relationship between the Altman Z-Score model and Verifier Determinants theory. A simple measure of agreement between the variables the models was calculated and reflected a 55.25% level of agreement between the models.

A Cohen kappa coefficient which takes into account the level agreement which occurs by chance was calculated to determine if there is a level agreement between the models over and above chance agreement. A Cohen kappa coefficient of 0.351 was calculated which is significant at the 0.01 level of significance.

A spearman rank order correlation was determined and a statistically significant relationship between the models established at the 0.01 level of significance and reflected by a spearman coefficient of association on -0.727. The negative relationship is expected as a high aggregate score of default indicates a high likelihood of failure while a high Z-Score indicates a low likelihood of failure.

In addition to the confirmation of the association which exists between the overall aggregate score of default and the Altman Z-score, this study also investigated the relationships amongst the individual verifier determinants. The existence of a relationship or association between the individual verifier determinants and Z-Score was confirmed.

The tests for associations using the individual verifier determinants revealed that the different verifier determinants had varying degrees of association with the Altman Z-Score. Table 6.2 highlights the individual verifier determinants which reflected a statistically significant relationship with both the Altman Z-Score, the overall aggregate score of default and a number of other verifier determinants.

Table 6.2 Summary of significant verifier determinants

Spearman's rho		Gross Aggregate Score: Verifier determinants	Altman Z-Score
Absent or unrealistic cash flow projections	Corr.Coef	.686**	-.508**
	Sig. (2-tailed)	0.00	0.00
Late submission of financial information	Corr.Coef	.807**	-.689**
	Sig. (2-tailed)	0.00	0.00
Underutilisation of assets	Corr. Coef	.638**	-.701**
	Sig. (2-tailed)	0.00	0.00

The absent and unrealistic cash flow projections verifier has a statistically significant relationship with the overall aggregate score of default and the overall Z score. The verifier also has a significant relationship with two other verifiers, late submission of financial information and high executive remuneration. The reliance on cash flows as an indicator of failure dates as far back as the original failure prediction model proposed by Beaver (Beaver, 1966). The cash flow verifier therefore is a robust factor to consider when evaluation the risk of failure.

Late submission of financial information also showed a statistically significant relationship with the overall aggregate score of default and the Z score. This verifier also has a statistically significant relationship with seven other verifier determinants, absent or unrealistic cash flow projections; underutilisation of assets; creative accounting; discounts for cash generation; high executive remuneration and unstructured dividend pay-outs. This study concludes that late submission of financial information is a key factor for consideration in business failure prediction.

Underutilisation of assets showed the highest level of association with the Altman Z-Score compared to any other individual verifier determinants. This could be attributable to the similarity of the measure with the inputs into the Z-Score model. Other failure prediction models including Ohlson (1980) also include asset efficiency ratios in their methodologies. A significant finding by Abdel and Kabajeh (2012) found that there is a positive relationship between return on assets, return on equity and return on investment validating the use of this measure as an indicator of business survival risk. This verifier has a statistically significant relationship with the overall aggregate score of default as well as the following individual verifier determinants, late submission of financial statement; discounts for cash generation; high executive remuneration and unstructured dividend pay-outs. This study concludes that this verifier is a significant factor to consider in business failure prediction.

These finding indicate not only that verifier determinants theory is a reliable tool in identifying early warning signs of business failure and distress but also that focusing on a number of select verifiers (i) Absent or unrealistic cash flow projections (ii) Late submission of financial information and (iii) Underutilisation of assets, management and other stakeholders are likely to be able to identify early warning signs of business distress.

7 Conclusion

Various business failure prediction methodologies have been developed beginning with Beaver's (1966) univariate model of analysis to sophisticated neural computing systems which use artificial intelligence and live market data in an attempt to predict the possibly of failure and distress in companies. These models, while found to yield superior predictive results, require a large input of data and resource in order to make assessments of the possibility of business distress Ko et al. (1992).

The multivariate, multiple discriminant analysis techniques as first introduced by Altman (1968) have remained popular and continue to produce a consistent and reliable prediction of failure. These models however do suffer numerous limitations which and are purely quantitative in nature and do not take into account the qualitative signals which may emerge indication the possibility of failure.

Altman recognised that failure did not occur as a sudden event, however it was Ansoff (Ansoff, 1975) who first recognised and articulated the concept of weak signals which consist of advanced and imprecise symptoms of impending future problems (Ansoff, 1975). In essence these are early warning signs of future problems that could lead to business failure or distress. These early warning signs could be financial or nonfinancial factors and they could manifest as quantitative or qualitative factors.

It is on the backdrop of the recognition of the importance of considering the different types of early warning signs, qualitative and quantitative that Holtzhauzen (2011) developed his research on modelling turn around strategies using verifier determinants. The verifier determinants which were key to the turnaround of business were found in essence to be the same factors that could be monitored to determine if a business is likely to experience distress in the future (Holtzhauzen & Pretorius, 2013).

The concept of verifier determinant is relatively new and had not been tested outside to the study performed by Holtzhauzen (2011) . This research sought to test the concept of verifier determinants as early warning signs which could be used to predict business decline and failure. This was achieved by applying two models, the Altman Z-Score Model and the verifier determinants theory to the same of companies. The verifier determinants were used to calculate an aggregate score of default based on the weighting of each verifier which was evident I a company and a Z score was calculated based on Altman's methodology. The companies were classified into three categories; failing, grey and non-failing companies based on the two models. The study compared the consistency of the classification of the companies into those three categories crossing simple cross-tabulations to determine the measure of agreement between the two models. The simplest measure of agreement between models is determined as percentage of agreement or observed agreement, that is, the percentage of observations on which the two models agree when the same data dataset is applied to them independently (Artstein & Poesio, 2008)

This simple measure of agreement does not take into account the possibility of agreement between the two models which is purely attributable to chance and to account for this a Cohen Kappa coefficient was calculated (Laerd Statistics, 2016). Cohen's kappa (κ) coefficient (Cohen, 1960) is one of a number of coefficients of agreement that have been developed that account for chance agreement (Artstein & Poesio, 2008).

The aggregate score of default calculated from the application of the verifier determinants theory is a numeric score varying between 0 and 71 where the higher the score the more likely it is that a company is expected to experience distress. The companies were therefore be ranked in order of their aggregate score of default from the least likely to fail to the most likely to fail. Similarly, the Altman Z-Score is a represented as a numeric value whereby the higher the Z-Score the higher the likelihood of survival. We therefore ranked the companies based on their calculated Z-Scores from least likely to fail to most likely to fail.

The ranking of the companies based on the two methodologies of failure prediction was compared for consistency using the spearman’s rank order correlation coefficient. This coefficient enabled us to conclude the degree of association and correlation between the rankings achieve through the application of the Z-Score compared to the rankings achieved from the application of the verifier determinants theory.

The study also sought to determine if there was an association between the individual verifier determinants and the Altman Z-Score but also whether there was an association amongst the individual verifier determinants themselves.

7.1 **Principal findings**

The verifier determinants theory as applied in this study produced a classification of companies between failed, grey and non-failed companies with moderate consistency to the application of the Altman Z-Score. The confusion matrix or cross tabulations showed 54.5% measure of agreement between the two models. When adjusted for agreement by chance the two models we still found to have a statistically significant degree of agreement as reflected by a reflected by the Kappa coefficient of; k = 0.351, and p = 0.001.

The spearman rank order correlation coefficient was found to be statistically significant at the 0.01 level of significance and with a high spearman coefficient of 0.727. This significance in the association between the outcomes of the two models is supported by the kappa coefficient which indicated that the agreement between the outcomes of the two models was not simply attributable to chance.

We can conclude therefore that the outcomes of the application of the Altman Z-Score and verifier determinants theory as performed in this study is expected to lead to the same classification of companies as failing, grey area and non-failing companies. We expect the ranking of companies based on the application of the two models to be largely the same.

The individual financial verifier determinants which appear to be most important for business distress prediction are late submission of financial results and underutilisation of assets. These verifiers were found to have a statistically significant association with both the overall aggregate score of default and the Altman Z-Score, the verifiers had spearman coefficient of association of 0.807 and 0.747 respectively in relation to the aggregate default score and 0.689 and 0.701 respectively in relation to the Altman Z-Score. These two factors also had the greatest number of statistically significant associations with the other verifier determinants with late submission of financial information showing significant associations with seven other financial verifiers and underutilisation of assets reflecting significant associations with four other financial verifier determinants. The findings of the study therefore suggest that if a company assessor was to use any single financial verifier determinant as a proxy for the overall model, late submission of financial information and underutilisation of assets would be the factors that are likely to give a result that could be a proxy for overall model.

The emergence of underutilisation of assets as a factor which has the highest level of significant association is understandable as this measure is determined using the same financial inputs that are applied in the calculation of the Altman Z- Score.

While the verifier determinants theory sought to introduce an alternative approach to early warning signs theory, we note that the similarity in the inputs to the models could be a key driver in the similarity of the results achieved by the models.

7.1.1 Impact of similarity of inputs between the Altman and Verifier determinants

The Altman Z-Score model uses accounting information relating to the liquidity, profitability and leverage ratios of the company, similarly the financial verifier determinants identified by Holtzhauzen (2011) include inputs relating to profitability, liquidity, leverage, asset efficiency and dividend policy. While the inputs for the calculation of the aggregate score of default are wider in scope and more than the inputs for the calculation of the Altman Z-Score, the commonality of variables in the models creates a degree of linearity between the models.

7.1.2 Verifier determinants as an internal vs external evaluation tool

Through the evaluation of the individual verifier determinants it emerged that some of the factors require the insight of insiders in order to appropriately evaluate whether or not the verifier was present in the company. Evaluation of verifiers such as absent or unrealistic cash flow projections, lack of analysis of data and creative accounting based on publicly available information is more difficult for an outsider to assess than if considered from an insiders perspective.

The model could therefore be a more valuable tool for management teams within a company to project for themselves where there may be areas of concern which could result in a decline. The model therefore appears to be better suited as an internal management tool managing company performance than as an external company evaluation and predictive tool.

7.2 Implications for Management

7.2.1 Management’s inability to recognise early warning signs

Where management does apply the tool, it is critical that the management team is open and responsive to the early warning sign as they emerge. Ansoff the filters of early warning sign a as surveillance, mentality and power filters (Ansoff, 1975). This in essence means that it is possible for management to see a weak signal however the mentality filter could hinder management’s ability to recognise the new information if it does not fit with their existing frame of reference (Kotsalo-Mustonen & Ilmola, 2004) . The power filter suggests that if the early warning sign is recognised by an expert with the business, management might reject and stop the interrogation of an idea if it is contradictory to their perceptions (Kotsalo-Mustonen &

Ilmola, 2004). This is a possible hindrance to the successful implementation of a model such as this which relies on weak signals to prompt action by the management team.

7.2.2 Aggregate Score of Default as a classification model (Not prediction tool)

The use of accounting proxies such as ratios and trends to identify whether or not a verifier is present makes the model subject to the same limitation as the classical statistical accounting models which rely on historical data in order to evaluate the risk of failure or decline. The trends which emerge from such analysis are based on historical data and therefore a trend of deterioration can only be identified once decline has already begun. There is no evidence to suggest the predictive power of the model however the model has proven to be reliable classification tool based on the result of this study.

The model would have to be applied intermitted to determine if the categorisation of a company changes over time and if there is a deterioration in the aggregate score of default of calculated for a company management can use this an indicator of the risk of decline. i.e. if in Quarter 1 the company scores aggregate score of 25 but then scores 31 quarter 3, this could serve as a useful indicator of deterioration. The fact that the aggregate score of default can be broken down into the individual components also provides management with an opportunity to pinpoint the specific verifiers which have deteriorated from one period to the next. Management should therefore act on such verifiers as such a trend emerges.

7.2.3 Cost-benefit analysis of failure prediction models

The cost of implementing a sophisticated failure prediction model may be large for business and distract management from their primary role of running the business. The verifier determinants theory requires a large number of inputs in order to be applied however there is no evidence to suggest that the outcome of the application of such a model would more beneficial than the use of a simpler model such as the Altman Z-Score. The additional effort and resources required to appropriately implement verifier determinants approach may not be justified if there is no clear additional benefit to doing so over and above the results that could be achieved from a simple multivariate model.

7.3 Limitations of the research

This study focused on one of the five categories of verifier determinants as introduced by Holtzhauzen (2011). Holtzhausen’s study had concluded that financial verifier determinants were factors of high importance as early warning indicators of business decline or distress.

The exclusion of the managerial, strategic, operational and banking verifier determinants could have added to the robustness of the conclusions on relating to the use of verifier determinants as an early warning sign of business distress. The use of financial factors could have also contributed to the significance of the relationship between verifier determinants and the Altman Z-Score as the Altman model relies purely on financial data.

This study relied on publicly available financial information and used trends in accounting data to make evaluations on certain questions relating to management actions. This implies that the researcher's judgment was used to cake some conclusions regarding the existence of verifier determinants. It is possible that a different researcher presented with similar facts could come to different conclusions in relations to the evaluation certain company information.

This study relies on secondary data which was prepared for purposes other than the completion of this research. The researcher therefore had no control over the manner in which the data was collected and aggregated. Schuster Anderson & Brodowsky (2014) note the disadvantages of using secondary data including questioning the accuracy and relevance of the data for the particular study where the data was not principally compiled for the purposes of the study (Schuster, Anderson, & Brodowsky, 2014).

The evaluation of verifier determinants based on publicly available data limits the richness of the analysis as some of the verifier determinants are focused on internal company process which are not easily evaluated based on information in the public domain. i.e financial verifier determinate 6, is concerned with the extent to which management analyses internal company data.

7.4 Suggestions for future research

Other researchers can expand the scope of this study by including the managerial, strategic, operational and banking verifier determinants in the analysis. This would help to evaluate whether the application of the other factors could result in a different result than was found in this study.

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9 Appendices

9.1 Appendix A: Component Elements of Verifier Determinants

	Component Elements of Verifier Determinants	Evident	Score
	Management Verifier Determinants		
1	No or limited management information system in operation;		
2	Managers education does not complement business type;		
3	Decision maker that is 'scapegoating' (blaming);		
4	Inflexibility when making decisions regarding change;		
5	Decision maker is absent from work and important meetings; impulsive decision making;		
6	Impulsive decision making;		
7	Decision maker not able to recall management information immediately (has to ask others);		
8	Absence of up-to-date management accounts;		
9	Important decisions are made on the golf course;		
10	Decision makers personal problems;		
11	Super cars and toys and finally		
12	A business that outgrew decision makers' skill set.		
	Financial Verifier Determinants		
1	labour cost that is disproportionate for the type of business;		
2	Absent or unrealistic cash-flow projections;		
3	A high risk (or one big project) dependence;		
4	Late submission of financial information in an attempt to postpone unfavourable news;		
5	Sensitivity on tax avoidance;		
6	Not analysing internal financial information;		
7	Underutilisation of assets		
8	Creative accounting;		
9	Pricing or discounts for cash generation;		
10	Slowing down and stretching payments to suppliers in an attempt to generate cash;		
11	High executive remuneration; and, finally,		
12	Dividend pay-outs that are unstructured and considered too high.		

	Strategic verifier determinants		
1	Forced growth attempts (through mergers and acquisitions);		
2	Overambitious growth strategy;		
3	Not willing to deviate from strategic plan;		
4	Non-responsive to small inefficiencies;		
5	Unclear strategy for product and market;		
6	Inability to adapt to business life cycles;		
7	Problematic fit between strategic posture, structure and industry life cycle;		
8	Overexpansion of capacity without considering market;		
9	Lack of strategy to combat decline;		
10	Lack of fusion between strategic issues and everyday operations.		
	Component Elements of Verifier Determinants		
	Operational and marketing verifier determinants		
1	inappropriate channels of distribution;		
2	Ageing production techniques;		
3	Decision maker not knowledgeable about new technology;		
4	Misinterpretation of competitive advantage;		
5	Declining emphasis on advertising;		
6	Poor service or products;		
7	Reliance on one customer;		
8	Failure to respond to high cost structure compared with competitors;		
9	Market forces ignored in planning;		
10	Core markets moving away from location.		
	Banking verifier determinants		
1	Regular stop payments on creditor obligations;		
2	Increase in short-term requests for cash flow purposes;		
3	Declining deposit balances and/or returned cheques;		
4	Rounded amounts paid to creditors;		
5	Overdraft advance funding other purposes such as asset acquisition;		
6	Funding structure does not complement business model.		
	Totals		

(Pretorius & Holtzhauzen, 2013)

9.2 Appendix B: Aggregate score of default and Z-Score per company

		Financial Verifier Determinants												Aggregate Score of Default	Altman Z-Score
Weights		5	7	9	10	9	8	1	6	2	4	3	7		
Number		V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12		
Company															
1	Company 1	5.0	7.0	-	10.0	9.0	8.0	1.0	6.0	2.0	4.0	-	7.0	59.0	0.9872
2	Company 2	5.0	7.0	-	10.0	-	-	1.0	6.0	2.0	4.0	3.0	7.0	45.0	1.1446
3	Company 3	-	-	-	-	-	-	-	-	-	-	-	-	-	6.2150
4	Company 4	5.0	-	9.0	10.0	-	8.0	1.0	6.0	2.0	4.0	-	7.0	52.0	-7.6980
5	Company 5	-	-	-	10.0	9.0	-	1.0	6.0	-	-	3.0	7.0	36.0	0.0909
6	Company 6	5.0	7.0	9.0	10.0	9.0	-	1.0	6.0	2.0	-	3.0	7.0	59.0	-1.2549
7	Company 7	5.0	-	9.0	-	9.0	8.0	1.0	-	-	-	-	-	32.0	2.9328
8	Company 8	-	-	-	10.0	9.0	8.0	-	6.0	-	-	-	7.0	40.0	5.4944
9	Company 9	5.0	7.0	9.0	10.0	9.0	8.0	1.0	6.0	2.0	-	-	7.0	64.0	1.0168
10	Company 10	-	-	-	-	-	-	1.0	-	-	-	-	-	1.0	1.5381
11	Company 11	-	-	-	-	-	-	-	-	-	4.0	-	-	4.0	6.7189
12	Company 12	5.0	7.0	-	10.0	-	8.0	1.0	6.0	-	4.0	3.0	7.0	51.0	0.6608
13	Company 13	5.0	-	-	-	-	8.0	-	-	-	-	-	-	13.0	12.8951
14	Company 14	-	-	-	-	9.0	-	1.0	-	-	-	3.0	-	13.0	2.9474
15	Company 15	-	7.0	-	10.0	9.0	8.0	1.0	6.0	2.0	4.0	-	7.0	54.0	1.7324
16	Company 16	5.0	-	9.0	-	9.0	-	1.0	-	-	-	3.0	7.0	34.0	2.0298
17	Company 17	5.0	-	-	10.0	9.0	8.0	1.0	6.0	2.0	4.0	3.0	7.0	55.0	0.4083
18	Company 18	5.0	-	-	-	-	-	-	-	-	-	-	-	5.0	3.6211
19	Company 19	-	-	-	-	-	-	-	-	-	-	-	-	-	23.7216

Appendix B: Aggregate score of default and Z-Score per company (Continued)

		Financial Verifier Determinants												Aggregate Score of Default	Altman Z-Score
Weights		5	7	9	10	9	8	1	6	2	4	3	7		
Number		V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12		
	Company														
20	Company 20	-	-	-	-	-	-	-	-	-	-	-	-	-	2.1175
21	Company 21	-	-	-	-	9.0	-	1.0	-	-	4.0	-	7.0	21.0	-0.1883
22	Company 22	-	-	-	10.0	-	-	1.0	-	-	-	-	7.0	18.0	1.7068
23	Company 23	5.0	7.0	-	10.0	9.0	8.0	1.0	6.0	-	4.0	3.0	7.0	60.0	-4.8592
24	Company 24	-	7.0	-	10.0	9.0	-	1.0	-	-	4.0	3.0	7.0	41.0	-2.2248
25	Company 25	5.0	-	-	-	9.0	8.0	-	-	-	-	-	7.0	29.0	4.0890
26	Company 26	5.0	7.0	-	-	9.0	8.0	1.0	-	2.0	-	3.0	7.0	42.0	0.0708
27	Company 27	-	-	-	-	9.0	-	-	-	-	-	-	7.0	16.0	2.0764
28	Company 28	5.0	-	-	10.0	-	8.0	1.0	6.0	2.0	4.0	3.0	7.0	46.0	0.8098
29	Company 29	-	7.0	-	10.0	-	8.0	1.0	6.0	-	-	3.0	7.0	42.0	-4.7143
30	Company 30	-	-	-	-	-	-	-	6.0	-	-	-	7.0	13.0	4.1594
31	Company 31	-	-	-	-	-	-	-	-	-	-	-	7.0	7.0	3.1463
32	Company 32	-	-	9.0	10.0	-	8.0	1.0	6.0	2.0	4.0	3.0	7.0	50.0	-4.9289
33	Company 33	-	-	-	-	9.0	-	1.0	6.0	2.0	-	-	7.0	25.0	3.7869
34	Company 34	-	7.0	9.0	10.0	9.0	-	1.0	6.0	2.0	4.0	3.0	7.0	58.0	-17.3324
35	Company 35	5.0	-	-	-	9.0	8.0	1.0	-	-	-	-	7.0	30.0	2.5754
36	Company 36	5.0	-	-	10.0	-	8.0	1.0	6.0	2.0	-	-	7.0	39.0	0.6624
37	Company 37	5.0	-	-	-	-	-	1.0	-	-	-	-	7.0	13.0	4.6080
38	Company 38	-	-	-	10.0	9.0	-	1.0	6.0	-	-	3.0	7.0	36.0	-0.5995
		90.0	77.0	63.0	190.0	180.0	136.0	27.0	114.0	26.0	52.0	45.0	203.0		

9.3 Appendix C: Ranking comparison of verifier determinants

Table 7.8 Ranking comparison of factors

		Specialist	Expert	Incumbent	Junior	Middle	Senior
f1	Managerial Verifier Determinants	High					
f2	Financial Verifier Determinants		High	High	High	High	
f3	Strategic Verifier Determinants			Low	Low	Low	High
f4	Operational/Market Determinants		Low				Low
f5	Banking Verifier Determinants	Low					

		Specialist	Expert	Incumbent	Banking 1-15	Banking 16-25	Banking26+
f1	Managerial Verifier Determinants	High					Low
f2	Financial Verifier Determinants		High	High	High		High
f3	Strategic Verifier Determinants			Low		Low	
f4	Operational/Market Determinants		Low		Low		
f5	Banking Verifier Determinants	Low				High	

		Specialist	Expert	Incumbent	Period < 5	Period > 5
f1	Managerial Verifier Determinants	High				
f2	Financial Verifier Determinants		High	High	High	High
f3	Strategic Verifier Determinants			Low	Low	Low
f4	Operational/Market Determinants		Low			
f5	Banking Verifier Determinants	Low				

Table Source: (Holtzhauzen, 2011)

9.4 Appendix D: Financial Verifier Determinants Evaluation

	Financial Verifier Determinants	Data Source	Evaluation	Verifier Present (Yes=Verifier Weight /No =0)
1	Labour cost that is disproportionate for the type of business;	Annual Financial Statements: Income statement	1. Determine staff costs as a % of revenue;	
			2. Calculate the five year trend in the changes in the cost	
			3. Calculate industry averages;	
			4. Determine whether the costs are reasonable relative to the industry.	
2	Absent or unrealistic cash-flow projections;	Annual Financial Statement: Cash Flow Statement	1. Determine the company's cash flows from operations.	
			2. Calculate the cash flows trend; is this positive or negative	
			3. Compare the cash generation with other companies in the industry.	
3	A high risk (or one big project) dependence;	Annual Financial Statements: Income Statement	1. Review the income statement and revenue note to determine if there is a concentration of revenue source in the business	
4	Late submission of financial information in an attempt to	JSE: Stock Exchange News Service	1. Review the AFS release date as published on SENS relative to the statutory requirement to release results within 6 months of Financial Year End. Determine if results were released after the statutory due date.	

	postpone unfavourable news;			
5	Sensitivity on tax avoidance;	Annual Financial Statements: Tax Note	1. Refer to the companies tax note to determine the tax rate over the past five years	
			2. Evaluate if there has been a significant change in the effective rate over the period	
			3. Compare the tax rate to the statutory rate and to the industry average to determine if there is significant variance	

	Financial Verifier Determinants	Data Source	Evaluation	Verifier Present (Yes=Verifier Weight /No =0)
6	Not analysing internal financial information;	Results presentations; Company's own estimates	1. Does the company have internal estimates (Balchaen & Ooghe, 2004) of future earnings? 2. Does the company provide an analysis of current performance relative historical estimates?	
7	Underutilisation of assets	Annual Financial Statements	1. Calculate the return on assets; determine the trend over five years; Establish the industry average	
8	Creative accounting;		1. Review the frequency of changes in accounting policies	

		Annual Financial Statements: Audit Opinion & Changes in accounting policy notes	2. Review the audit opinion for qualification or disclaimer opinions	
9	Pricing or discounts for cash generation;	Annual Financial Statements: Income Statement	1. Calculate gross margins over five years; determine if there is a trend of margin compression in the company	
			2. Evaluate if the gross margin is consistent with industry	
10	Slowing down and stretching payments to suppliers in an attempt to generate cash;	Annual Financial Statements: Balance Sheet	1. Calculate the average creditors (accounts payable days) over a five year period. Determine if there is a trend of an increase in the creditor's days over the period.	
11	High executive remuneration; and, finally,	Annual Financial Statements	1. Calculate the total executive team's remuneration as a % of net profits over a five year period; Evaluate if the % pay is in line with industry averages or not. And evaluate if there is an increasing or decreasing trend	
12	Dividend pay-outs that are unstructured and considered too high.	Annual Financial Statements	1. Review the dividend policy of the company; Review the trend of dividends paid over the past years; Evaluate whether the payments are in line with the policy or if adhoc payments are made.	

9.5 Appendix E: Extract of company SENS announcements

SENS | News

2016

Notice of annual general meeting and no change statement
Fri 30 Sep 2016 08:00 View

Dealing in securities by a director
Wed 7 Sep 2016 12:05 View

Dealing in securities by a director
Thu 1 Sep 2016 12:50 View

Group results for the year ended 30 June 2016
Tue 30 Aug 2016 08:00 View

Trading statement for the year ended 30 June 2016
Mon 22 Aug 2016 08:00 View

Exercise of options and sale of shares
Wed 15 Jun 2016 12:35 View

Dealing in securities by a director
Mon 13 Jun 2016 09:00 View

Exercise of options and sale of shares
Tue 24 May 2016 16:40 View

Dividend
Fri 29 Apr 2016 08:00 View

Production update Q3 FY2016
Mon 18 Apr 2016 08:00 View

Appointment of Company Secretary
Fri 11 Mar 2016 08:00 View

Report to Shareholders for the six months ended December 2015
Tue 16 Feb 2016 08:00 View

Trading statement for the 6 months ended 31 December 2015 & production update for the quarter ended 31 December 2015
Mon 8 Feb 2016 08:00 View

2015

Resignation of company secretary
Mon 30 Nov 2015 13:10 View

Results of annual general meeting
Thu 5 Nov 2015 13:30 View

Production update change to bi-annual reporting and request for shareholder details
Wed 28 Oct 2015 08:54 View

Notice of annual general meeting and no change statement
Wed 30 Sep 2015 08:00 View

Dealing in securities by a director
Mon 7 Sep 2015 10:26 View

Report to shareholders for the fourth quarter and year ended 30 June 2015
Tue 1 Sep 2015 08:00 View

Full capital redemption
Fri 26 Jun 2015 11:10 View

Notice of an acquisition of a beneficial interest in securities
Tue 5 May 2015 10:30 View

Report to shareholders for the third quarter and nine months ended 31 March 2015
Thu 23 Apr 2015 08:00 View

Partial capital withdrawal
Tue 7 Apr 2015 08:30 View

Acquisition of all the shares in Ergo Mining Operations (Proprietary) Limited not already owned