An Empirical Evaluation of the Altman (1968) Failure Prediction Model on South African JSE Listed Companies

A research report submitted by

Kavir D. Rama

Student number: 0700858N

Supervisor:

Gary Swartz

WITS: School of Accounting

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DECLARATION

I hereby declare that this thesis is my own original work and that all the sources have been accurately reported and acknowledged. It is submitted for the degree of Masters of Commerce to the University of the Witwatersrand, Johannesburg. This thesis has not been submitted for any degree or examination at this or any other university.

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Kavir Dhirajlal Rama

Johannesburg, South Africa

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ABSTRACT

Credit has become very important in the global economy (Cynamon and Fazzari, 2008). The Altman (1968) failure prediction model, or derivatives thereof, are often used in the identification and selection of financially distressed companies as it is recognized as one of the most reliable in predicting company failure (Eidleman, 1995). Failure of a firm can cause substantial losses to creditors and shareholders, therefore it is important, to detect company failure as early as possible. This research report empirically tests the Altman (1968) failure prediction model on 227 South African JSE listed companies using data from the 2008 financial year to calculate the Z-score within the model, and measuring success or failure of firms in the 2009 and 2010 years. The results indicate that the Altman (1968) model is a viable tool in predicting company failure for firms with positive Z-scores, and where Z-scores do not fall into the range of uncertainty as specified. The results also suggest that the model is not reliable when the Z–scores are negative or when they are in the range of uncertainty (between 2.99 and 1.81). If one is able to predict firm failure in advance, it should be possible for management to take steps to avert such an occurrence (Deakin, 1972; Keasey and Watson, 1991; Platt and Platt, 2002).

1 INTRODUCTION

1.1 Purpose of the study

The purpose of this research report is to establish whether the Altman (1968) failure prediction model is effective in predicting the failure of South African companies listed on the Johannesburg Stock Exchange (JSE).

The seminal paper by Altman (1968) introduced and empirically tested the model in the United States of America (USA) on manufacturing industries only. Reporting requirements have since changed materially (Grice and Ingram, 2001), and it is therefore necessary to test whether the Altman (1968) model is still applicable in the current context. In addition to this, the suitability of the models use within South Africa requires exploration. The Altman (1968) model exponents were derived for the USA market context, and specifically for the manufacturing industry, yet evidence indicates that the model is recognized as one of the most reliable in predicting company failure globally (Eidleman, 1995). The model is therefore mis-specified for both a South African context, and for industries outside of the manufacturing industry. This research report seeks to test the reliability of the Altman (1968) model in the South African context, to assess whether its use in that form is appropriate. It does not attempt to re-specify the model for the South African market.

1.2 Context of the study

The global economic recession was triggered in late 2007 by the liquidity crisis in the United States banking system, and was primarily a consequence caused by the overvaluation of assets (Demyank and Hasan, 2009). The cause of the overvaluation of assets was due to slack credit controls by financial institutions (Demyank and Hasan, 2009). Furthermore studies have indicated that credit has become one of the biggest and most important contributors to consumer spending (Cynamon and Fazzari, 2008). Therefore effective credit controls are important for all financial institutions.

Credit managers base their credit decisions primarily on the credit principles of ‘character’, ‘capacity’, ‘capital’, ‘collateral’ and ‘conditions’. These are referred to as the 5 C’s of credit granting (Firer, Ross, Westerfield and Jordan, 2004). Capacity, collateral and conditions to an extent are all assessed through review of the company’s financial statements.

Therefore financial statements play an important role in the decision to grant credit to firms or individuals, and in assessing the continued well being of an entity.

Over the years there have been many models developed to determine the probability of bankruptcy within a certain period. These models use the company’s financial statements to produce a score which then predicts the probability of insolvency within a certain period (Laitinen and Kankaanpaa, 1999). The evolution of company failure prediction models will be discussed under the history of failure prediction model developments.

1.3 Problem statement

1.3.1 *Main problem*

Is the Altman (1968) Z score failure prediction model able to predict financial distress in Johannesburg Stock Exchange (JSE) listed companies?

1.3.2 *Sub-problems*

The first sub-problem: Can the Altman (1968) failure prediction model be used to predict bankruptcies using recent financial statements?

The second sub-problem: Is the Altman (1968) failure prediction model adequately specified for use on South African JSE listed companies?

1.4 Delimitations of the study

The sample will include JSE listed companies that are listed on the main board. The following companies will be excluded from the sample:

- All companies in the financial industry,
- All companies in the mining industry
- All companies that make up the JSE Top 40 Index

The financial sector and the mining sector are both specialised industries with different asset and profitability structures, aggregation of the results from these companies with the remainder of the JSE is therefore not considered to be appropriate.

Altman's (1968) seminal paper indicates that the failure prediction model was created, therefore specified, using manufacturing companies.

The JSE Top 40 Index companies are by definition not likely to experience financial distress, and have therefore been excluded from the sample.

1.5 Definition of terms

Failure: Bankruptcy, or any condition whereby a company was forced to de-list due to liquidity and solvency problems (Bruwer and Hamman, 2006). Failure can also be defined as the state that the company is in, if it has negative profit after tax for a period of two years (Naidoo, 2006).

Healthy: Where a company has a positive profit after tax and a positive or zero real earnings growth (Naidoo, 2006).

Liquidity: The degree to which a company is able to meet its maturing financial obligations (Jacobs, 2007).

Debt Management Ratio's: The degree to which a company is able to meet its long term financial obligations (Correia, Flynn, Uliana and Wormald, 2007).

1.6 Assumptions

The following assumptions have been made regarding the study:

- The financial statements reflect the true performance and position of the company.
- The data period had no influences from different economic conditions as the period of the testing is conducted from 2008 to 2010 and therefore in a recessionary environment.
- Multicollinearity is not present in this study.

1.7 Organisation of the research report

This research report has been organised as follows: Section 2 comprises of a literature review, which will provide an overview of why companies fail, the reasons why the market needs failure prediction models, and a summary of previous studies in failure prediction models. Section 3 details the methodology and sample data used in this study, while section 4 discusses and interprets the results. Section 5 revisits the research problems to ensure that this study answers the posed questions. Section 6 provides a conclusion and suggests future avenues for research. Section 7 lists all the references used in this study.

2 LITERATURE REVIEW

There has been large amount of research conducted in the field of company failure prediction models throughout the world (Ooghe and Spaenjers, 2010). Many of these studies are focused on the development of new company failure prediction models based on different statistical techniques. The driving factor for research in this field is that firm bankruptcy could cause substantial losses to creditors and stockholders. Therefore it is important to create a model that predicts potential business failures as early as possible (Deakin, 1972).

Studies have indicated that discrimant analysis and logit analysis were the two most used statistical techniques for company failure prediction models; however the use of discriminant analysis is ever increasing (Wilson and Sharda, 1994; Altman, Haldeman and Narayanan, 1977). The Altman Z Score model is predominately used in dicriminant analysis (Jo, Han and Lee, 1997).

The literature review has been organised as follows. A summary of the causes of corporate failure is visited. Once causes of corporate failure are identified, a history of failure prediction models will be discussed. We then look at the Altman (1968) failure prediction model and discuss its composition as well as how to interpret the Z scores. Alternative statistical methods used to develop company failure models are then visited together with shortcomings in failure prediction studies and disadvantages with statistical techniques used to develop failure prediction studies. The report, thereafter, addresses some developed international and local failure prediction studies.

2.1 Causes of Corporate Failure

Causes of corporate failure can be classified under two factors; internal factors and external factors. Internal factors consist of employee cynicism to change in technology;

break down in communications between senior staff and lower management; and fraud and misfeasance (Dambolena and Khoury, 1980).

According to Margolis (2008), the impact of management style on a business is important for its survival. This paper indicates that leaders do no fail because investor's expectations for the company are different from the leader. Leaders do not fail as a result of what they doing; they fail as a result of how something is done. Thus company failure is caused by leaders making mistakes in judgement between their business and their people.

Dambolena and Khoury's (1980) study aimed to investigate the stability of financial ratios, over time, for healthy and bankrupt firms. The investigation consisted of analysis of 19 financial ratios that could be broken into three categories, profitability measures; activity and turnover measures; liquidity measures; and indebtedness measures. The results of the study indicated that the bankrupt firms' ratios three years prior to failure were unstable. Whereas healthy firms' financial ratios were fairly stable. Therefore financial ratio analysis plays an important role in determining company failure (Dambolena and Khoury, 1980).

2.2 Review of the Development of Failure Prediction Models

The first company failure prediction model was first developed around the 1960's using linear discriminant analysis (Laitinen and Kankaanpaa, 1999). Since then, there has been new statistical methods developed to generate a failure prediction model in efforts to increase its predictive accuracy (Laitinen and Kankaanpaa, 1999). During the 1970's and 1980's discriminant analysis was replaced with logit analysis. Recursive partitioning and survival analysis was used during the late 1980's; however, these techniques never became as popular as discriminant analysis and logit (Laitinen and Kankaanpaa, 1999). Subsequently, artificial neural networks have been introduced to as a possibly more effective approach to predict financial failure (Laitinen and Kankaanpaa, 1999).

There have been many studies (Yoon, Swales and Margavio (1993); Jo, Han and Lee (1997); Wilson and Sharda (1994); Laitinen and Kankaanpaa (1999)) comparing the predictive powers of artificial neural networks and discriminant analysis. Although the researchers such as Leshno and Spector (1996); Zhang, Hu, Patuwo and Indro (1999) believe that artificial neural networks has better accuracy rate than discriminant analysis, discriminant analysis is still the most used technique in failure prediction as this is the easiest to use (Deakin, 1972; Altman, Haldeman and Narayanan, 1977; Edmister, 1972; Laitinen and Kankaanpaa, 1999; Yoon, Swales and Margavio, 1993; Ooghe and Spaenjers, 2010).

2.3 Altman Failure Prediction Model

In a seminal paper, Altman (1968) introduced the Z-score failure prediction model. The aim of this model was to bridge the gap between traditional ratio analysis and more rigorous statistical techniques. The statistical technique used to develop this model was multivariate discriminant analysis.

The Altman (1968) model was developed using a sample of 33 bankrupt and 33 non-bankrupt manufacturing firms from 1946-1965. Although the models received high accuracy rates, it had not been tested for companies outside its original sample industry. Nevertheless, this model has been used in a variety of business situations involving prediction of failure and other financial stress conditions. This model is used by commercial banks as part of periodic loan review process and by investment bankers for security and portfolio analysis (Grice and Ingram, 2001).

Altman's model is as follows (Altman, 1968):

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

Where: X_1 = net working capital/total assets
X_2 = retained earnings/total assets
X_3 = EBIT/total assets
X_4 = Market value of common and preferred stock/ book value of debt
X_5 = sales/total assets

Z = Overall index

X_1 - Net working capital/total assets: This ratio measures the net liquid assets of the firm relative to the total capitalisation. Working capital is defined as the difference between the current assets and current liabilities. A firm experiencing consistent operating losses will have shrinking current assets in relation to total assets.

X_2 - Retained earnings/total assets: The age of the firm is implicitly considered in this ratio. This ratio measures the cumulative profitability over time. For example: a relatively young company will have a low retained earnings/total assets ratio as it did not have time to build up its cumulative profits.

X_3 - Earnings before interest and taxes/ total assets: This measures the true productivity of the firm's assets as it excludes effects of interest and taxes.

X_4 - Market value of equity/ book value of debt: This ratio indicates the extent to which a firm's assets can decrease before its liabilities exceed its assets.

X_5 - Sales/total assets: This is a standard ratio that illustrates the firm's sales generating ability of the firm's assets.

The result of the above equation is a Z-score which can be interpreted as follows: The mid-point of this distribution is 2.675 and between 1.81 and 2.99, there is a zone of uncertainty. This means that if a company's Z-score fell between 1.81 and 2.99, a classification cannot be made with certainty. A score lower than 1.81 indicates that the company was almost certain to fail while a score higher that 2.99 indicates that the company was almost certain to succeed (Correia et al., 2007).

From around 1985 onwards, Altman's (1968) failure prediction model has been used by auditors, management accountants, courts, and credit granters across the world (Eidleman, 1995). Although it has been designed for publicly held manufacturing firms, Altman's (1968) model has been used in a variety of contexts and countries (Eidleman, 1995).

2.4 Alternative Failure Prediction Statistical Techniques

Due to a need to develop techniques with increased predictive accuracy (Laitinen and Kankaanpaa, 1999), a number of statistical techniques were used to develop prediction models. These techniques include: (1) Multivariate Discriminant Analysis; (2) Logit Analysis; (3) Recursive Partitioning; (4) Artificial Neural Networks; (5) Univariate Analysis; (6) Risk Index Models; (7) Case-based Forecasting; (8) Human Information Processing Systems; and (9) Rough Sets.

The next section illustrates the different types of statistical methods used to create company failure prediction models. The evolution of failure prediction models could be attributed to the different statistical methods developed (Laitinen and Kankaanpaa, 1999) and therefore it is important to understand these techniques.

2.4.1 *Multivariate discriminant analysis*

The Altman (1968) failure prediction model is based on multivariate discriminant analysis (MDA). This technique is used if dichotomous classification (fail or healthy) is required (Zavgren and Friedman, 1988). The analysis consists of a linear combination of variables, which provides the best distinction between failing and non failing firms. MDA attempts to derive a linear equation that best fits the variables. Thus the discriminant function is derived in such a way so that it minimizes the possibility of misclassification (Leshno and Spector, 1996). The MDA technique has the advantage of considering the entire profile of characteristics common to the relevant firms, as well of the interactions of these properties (Altman, 1968).

MDA consists of three steps. The first step is to estimate coefficients of the variables. The next step is to calculate the discriminant score of each individual observation/case. The third step is to classify these cases based on a cut off score (Jo and Han, 1996; Laitinen and Kankaanpaa, 1999).

This is the most popular method used in failure prediction (Eidleman, 1995). In most MDA techniques, a low discriminant score indicates that the chances of the firm failing are higher than with a high discriminant score. The analysis ranks firms using an ordinal scale (Balcaen and Ooghe, 2006). The advantage of using MDA as oppose to univariates analysis is that variables that may seem insignificant on the univariate actually provide significant information in the MDA technique (Altman, 1968).

Deakin's (1972) study concluded that statistical models such as discriminant analysis can be used to predict business failure from accounting data. Company failure can be predicted from as far as three years in advance with a fairly high accuracy rate.

2.4.2 *Logit Analysis*

This technique is one of the latest and most advanced techniques used in many fields of the social sciences to model discrete outcomes. It was developed through discrete choice theory (Jones and Henser, 2004). Discrete choice theory is concerned with the understanding of discrete behavioural responses of individuals to the actions of business markets and governments when faced with two or more possible incomes (Jones and Henser, 2004). Therefore the theoretical underpinnings of this model are derived from microeconomic theory of consumer behaviour (Jones and Henser, 2004). Lo (1986) indicated in his study, which aimed to identify the superior technique between logit and discriminant analysis in predicting corporate failure, that logit and discriminant analysis are closely related.

The logit model assumes that actual responses are drawings from multinomial distributions with selection probabilities based on the observed values of individual characteristics and their alternatives. These are often viewed as causal type models. In causal models, we find that:

1. It is natural to specify problems in terms of selection probabilities,
2. Forecasting leads to problems within this model based on the selection probabilities,
3. The model makes it meaningful to analyze the effects of policy affecting the explanatory variables (McFadden, 1976).

The logit analysis classifies failing firms and non failing firms based on their logit score and a certain cut off score for the model (Balcaen and Ooghe, 2006). This logit score is then compared to its cut off point and the interpretation is that if the logit score is higher than the cut off point, it is more likely that the firm will fail and vice versa if the score is lower than the cut off point. The logit analysis assumes that the dependent variable is dichotomous and that the cost of defining *type I* and *type II* error rates should be considered when defining the optimal cut off score (Balcaen and Ooghe, 2006). An advantage of logit analysis is that they do not require their variables to be normally distributed; there is evidence that they do remain sensitive to extreme non-normality (Balcaen and Ooghe, 2006). These types of techniques are also extremely sensitive to multicollinearity (Balcaen and Ooghe, 2006). Logit analysis is also said to be robust, therefore it is applicable for a wider class of distributions than MDA (Lo, 1986; Collins and Green, 1982). Lau's (1987) study revealed that logit analysis was a superior statistical method to discriminant analysis. The logit analysis provided a measure of a firms financial position on a continuous scale.

2.4.3 *Recursive Partitioning*

Recursive partitioning is a nonparametric and nonlinear technique that is graphically explainable to users. In this method, a classification tree is hierarchical and consists of a series of logical conditions (tree nodes) (Bruwer and Hamman, 2006; Laitinen and Kankaanpaa, 1999). The original sample is located on the top of the tree. The sample is thereafter divided into two subsamples according to the 'best splitting' rule. There are two steps for each split; the first is to determine the independent variable for which it will be the best discriminator for the observations; and the second step is finding the variable that will best classify the classes of the node. Splitting of tree branches may continue until each observation cannot be further split, resulting in extremely high classification accuracy (Bruwer and Hamman, 2006; Laitinen and Kankaanpaa, 1999)

2.4.4 *Artificial Neural Networks*

Artificial neural networks are based on the present understanding of the human neurophysiology (Yoon, Swales and Margavio, 1993). Information processing in humans takes place through the interaction of many billions of neurons. Each neuron sends excitatory or inhibitory signals to other neurons. Artificial neural networks try to emulate what human neurons do (Yoon, Swales and Margavio, 1993).

This technique is useful for solving many tasks, and is most practically used in modelling and forecasting, signal processing, and expert systems (Odom and Sharda, 1990). The method used by neural networks for predicting is referred to as generalisation. The neural network is trained and a predicted output is given for every new data input (Odom and Sharda, 1990).

Artificial neural networks have been applied to many different fields and have demonstrated its capabilities in solving complex problems (Yoon, Swales and Margavio, 1993; Yoa and Lui, 1997; Dutta, Shekhar and Wong, 1994). In the business environment, artificial neural networks analysis techniques have proven to outperform MDA analysis in cases such as bond prices and stock price performance (Yoon, Swales and Margavio, 1993; Yoa and Lui, 1997; Dutta, Shekhar and Wong, 1994).

Hawley, Johnson and Raina's (1990) study on artificial neural networks found that unlike an expert system, artificial neural network systems do not rely on a pre-programmed knowledge base. It learns through experience and is able to continue learning as the problem environment changes. The system is well suited to deal with unstructured problems, inconsistent information and real time input (Hawley et al. 1990). Some of the disadvantages of this technique are that the internal structure of the network makes it difficult to trace the steps from which the output is reached (Hawley et al. 1990). There is no accountability and that means if the systems malfunctions, the decision maker will not be aware. The second disadvantage is that these networks need to be trained with large training samples (Laitinen and Kankaanpaa, 1999).

Altman, Marco and Varetto (1994) demonstrated that the following conclusions can be drawn from artificial neural networks. Firstly they are able to approximate the numeric values of the scores generated through discriminant analysis; results come close to MDA. Secondly they are able to accurately classify firms into healthy or non-healthy groups (Altman, Marco and Varetto, 1994). Thirdly the memory that artificial neural networks contain has shown to have considerable power and flexibility. However, their paper also indicates that artificial neural networks are sensitive to structural changes and that they may provide decisions that are illogical. This is regarded as the major problem with artificial neural networks. Another important issue raised by Altman, Marco and Varetto (1994) is that artificial neural networks are not transparent, in that one does not know how the decision is arrived at. In taking all the above into account, Altman, Marco and Varetto (1994) conclude that artificial neural network systems are not a superior failure prediction method to the traditional statistical techniques such as MDA.

2.4.5 *Univariate Analysis*

In this failure prediction technique, each measure or ratio is compared to an optimal cut off point. This classification procedure is based on, comparing the optimal points for each measure to the firm's value (Balcaen and Ooghe, 2006). One of the greatest advantages of this is that the technique is simple and does not require any statistical knowledge (Balcaen and Ooghe, 2006). On the other hand, one of its disadvantages is that this analysis is based on the stringent assumption of a linear relationship between all measures and the failure status (Balcaen and Ooghe, 2006).

2.4.6 *Risk Index Models*

Tamari (1966) created a simple risk index model. This model is based on a point system. His argument stems from the point of view that all those responsible for granting credit to institutions should have a way of determining the degree of risk arising from the client's financial position. Many banks often use ratio analysis to indentify future client risks. This is done so that they able to hedge themselves appropriately (Tamari, 1966). The study was conducted on sixteen industrial firms which had been given consolidated loans or granted a moratorium on their debts for a considerable period and were virtually bankrupt. The study revealed that:

- Five years prior to bankruptcy, the financial ratios of these companies were lower than those for the industry as a whole (Tamari, 1966).
- And in most cases, the financial ratios had fallen during the period investigated (Tamari, 1966).

His research had also found that the following ratios helped to identify bankruptcy:

- Ability to Pay: It was noted that 70% of the companies in the sample had a current ratio of less than 1:1 in the year before bankruptcy (Tamari, 1966).
- Long Term Financing: An indicator of a firm's liquidity position is the ratio of long term liabilities to long term investments. The norm should be long term liabilities should finance long term assets, however from the analysis, it showed that long term financing was insufficient to cover long term

investments. Consequently many firms had a low current ratio as short term financing was used to finance long term investments (Tamari, 1966).

- Profitability: Generally a high profit level may hide a shaky financial structure; however, this was not the case. It was found that companies which went bankrupt, the weak financial position was connected with low profits (Tamari, 1966).

Based on the above findings, a risk index model was created (Tamari, 1966). The index included ratios such as profit trends, current ratio, sales divided by receivable and value of production over inventory. Based on these ratios, an index points are awarded. The best index points a firm could obtain was 100 (Tamari, 1966). The point system can be interpreted as firms with less than 30 points are more likely to go bankrupt than firms with above 60 points (Tamari, 1966). The only disadvantage indentified by Balcaen and Ooghe (2006) was that the allocations of points to the ratios or weights are subjective. Although Tamari's (1966) aim of the study was not to create a failure prediction, it was to identify whether financial ratios could be used as an indicator for company failure. The study found that company failure and there preceding financial ratios were correlated.

2.4.7 *Case-based Forecasting*

Managers generally extrapolate what has happened in the past to predict the future (Jo, Han and Lee, 1997; Jo and Han, 1996). Case based forecasting systems work in a similar manner. There are three steps in case-based forecasting (Jo, Han and Lee, 1997; Jo and Han, 1996). The steps are as follows:

Step 1: Identifying key attributes from past cases involves investigating the important attributes of factors which are critical to identifying analogous cases.

Step 2: Judgement and retrieval is the step in which the similarities of the cases from the past are correlated to the investigated case.

Step 3: Generating a forecasted outcome is the final process. Dependent on the retrieved cases, a forecast is generated by consolidating all their prior outcomes.

This technique has a significant amount of estimation and case adjustment (Jo, Han and Lee, 1997; Jo and Han, 1996). This is done as it is impossible to have an exact historical case. This type of forecasting technique has been used in practice; however, it has not been recognized as primary a forecasting tool (Jo, Han and Lee, 1997).

Case based reasoning was used to solve the learning problem and is used fairly frequent in practice however, it has not been recognized a primary forecasting tool nor has it been applied on a regular basis (Jo and Han, 1996).

2.4.8 *Human Information Processing Systems (HIPS)*

Human Information Processing Systems (HIPS) is a research trend that studies the behaviour of decision makers (Laitinen and Kankaanpaa, 1999). The objective of HIPS in accounting is to understand, describe, evaluate and improve decisions made, and the decision process used, on the basis of accounting information (Laitinen and Kankaanpaa, 1999). This represents the relationship between judgment and cues rather than the explanation of the actual information processing used to form judgements (Laitinen and Kankaanpaa, 1999).

2.4.9 *Rough Sets*

Rough set approach discovers relevant subsets of financial characteristics and represents them in terms of all important relationships between the image of a firm and its risk of failure (Dimitras, Slowinski, Susmaga and Zopounidis, 1999). This method analyses the facts hidden in the input data and communicates an output in the manner in which is relevant to the decision maker. Rough sets offer the following advantages (Dimitras' et al. (1999)):

- Discovers hidden facts in data and expresses it in a way that a decision can be made;
- Accepts both qualitative and quantitative methods;
- Can contribute to lower time and cost for decision makers;
- Offers transparency of classifying decisions and therefore allows for argumentation;

- Takes into account the background knowledge of the decision maker

Dimitras' et al. (1999) concluded that failure prediction using rough sets proved to be better than traditional discriminant analysis techniques.

2.5 Shortcomings in Failure Prediction Studies

There have been many failure prediction studies throughout the last 50 years. All studies document their disadvantages and shortcomings. The following lists the most important disadvantages and shortcomings identified in such studies (Bruwer and Hamman, 2006):

- The samples for most of the studies were either companies that have failed or are healthy, thereby ignoring the 'grey area' between these extremities (Bruwer and Hamman, 2006).
- There is a lack of testing the prediction accuracy of models developed on an independent test sample (Bruwer and Hamman, 2006). The problem lies with the amount of bankruptcies; as the number of bankruptcies is limited, the population of bankrupt firms are used together with a sample of successful companies (Bruwer and Hamman, 2006).
- The population proportions are ignored in samples (Bruwer and Hamman, 2006). Many off the studies conducted on failure prediction, even number sample sizes of failed and non- failed firms were selected. This leads to the issue of the proportion of the sample to the population being ignored (Bruwer and Hamman, 2006).
- The data used for the testing covered different economic conditions and no consideration was given to economic influences (Bruwer and Hamman, 2006). Bruwer and Hamman (2006) refer to Mensah's (1984) study where he investigates the occurrence that researchers pool data from companies over various years, without considering the different economic environments during those years.

All of the above shortcomings have been taken into account in making the decision on which prediction technique to use.

2.6 Disadvantages with Classical Statistical Techniques

The following have been identified as the shortcomings across the various statistical techniques used for company failure prediction models (Balcaen and Ooghe, 2006):

2.6.1 *Issues relating to the classical paradigm*

Classical paradigm relates to the firms set of descriptor variables and known outcomes, which allow companies to be assigned to an outcome class on the basis of the descriptor variables (Balcaen and Ooghe, 2006):

a. ***Arbitrary Definition of Failure***

Techniques are based on an arbitrary separation of firms into failing and non failing firms. In most cases, the definition of failure is bankruptcy or financial distress or cash insolvency (Balcaen and Ooghe, 2006). The criterion on which failure is chosen is therefore based on an arbitrary basis. In reality, failure is not well defined dichotomy. Thus deciding to base failure on dichotomy is inappropriate (Balcaen and Ooghe, 2006).

b. ***Data instability and non stationary relationship***

Failure prediction techniques are based on the paradigm that the distributions of the variables do not change over time (Balcaen and Ooghe, 2006). This means that the relationship between the independent and dependent variables are stable. In reality, data variables change as a result of inflation, interest rates, phases of the business cycle, changes in the competitive nature of the market, corporate strategy and technology (Balcaen and Ooghe, 2006). It is popular practice that when data for failure prediction techniques is gathered across different years, the prediction model requires that the relationships among the variables are stable across time. If data across different periods are not stable, they may have severe consequences for the prediction model (Balcaen and Ooghe, 2006). The consequence of data instability is models having poor predictive capabilities; models becoming unstable over time (variable weightings are incorrect); and the need to constantly change the variable weighting (Balcaen and Ooghe, 2006).

c. ***Sampling Selectivity***

Failure predictive studies should be based on the assumption that random sampling design is used (Balcaen and Ooghe, 2006). The reason for this is we are then able to infer the result of the sample to the population. Many studies used non random samples of firms (Balcaen and Ooghe, 2006). There are two main reasons for this. Firstly, firms are chosen if researchers have the availability of annual financial statements (Balcaen and Ooghe, 2006). Secondly, as there is a low frequency rate of failing firms in the economy, researchers draw a state based sample, thereby over sampling the failing firms (Balcaen and Ooghe, 2006). This may lead to a choice based sample bias. Many techniques are created based from using matching pairs of failing and non failing firms (paired sample technique). Paired sampling techniques are incorrect because of low frequency rate of failing firms in the economy (Balcaen and Ooghe, 2006).

d. ***Choice of optimisation criteria***

When models are used to classify firms into failing and non failing, the cut off point is based on the measure of goodness of fit (Balcaen and Ooghe, 2006). This indicates that these models depend on the choice of optimisation measure (generally ratios). If marginal improvements of these ratios exist, the cut off point will change. Therefore, these models fail to take into account the real nature of corporate failure prediction (Balcaen and Ooghe, 2006).

2.6.2 *Issues relating to the time dimension of failure*

Many models ignore the fact that companies change over time, and this causes various problems and limitations (Balcaen and Ooghe, 2006). Firstly, it is assumed that these companies don't change their nature of business (Balcaen and Ooghe, 2006). Secondly, these models fail to account for time series behaviour (Balcaen and Ooghe, 2006). Many authors believe that failure is dependent on more than one annual account or a change in financial health, however, past information regarding corporate performance has been ignored. Thirdly, the repeated application of a failure prediction model to consecutive annual accounts of one particular firm may result in a whole list of potentially conflicting predictions (Balcaen and Ooghe, 2006). This problem is referred to the signal inconsistency problem. Lastly, these models do not consider possible differences in failure paths (Balcaen and Ooghe, 2006). All the models assume that all companies follow a uniform failure process. This is contradictory to practice, where there are a wide variety of failure paths.

2.6.3 *Linearity Assumption*

The univariate and MDA models are based on the assumption of linearity (Balcaen and Ooghe, 2006). This is a very important and strong assumption as these models assume that if a firm's value for a certain predictor is higher (or lower) than a certain cut off point, this signals strong (poor) financial health (Balcaen and Ooghe, 2006). In practice, this assumption does not hold as some variables indicate financial problems when they have a very low or very high value (Balcaen and Ooghe, 2006). For this reason, the classifications of failing and non failing firms are questionable.

2.6.4 *Use of annual account information*

Many classic cross sectional techniques use financial ratios from the accounting information obtained (Balcaen and Ooghe, 2006). These ratios are seen to be very hard as they are objective measures and they are based on publicly available information. On the other hand, financial ratios have come under much criticism and accounting information has proven to suffer from some serious drawbacks (Balcaen and Ooghe, 2006). Many failure prediction models have been restricted to large businesses as information available to the public are generally large firms who are obliged to publish their financial statements (Balcaen and Ooghe, 2006). The first criticism with financial ratios are that their inputs may have errors or are missing values (Balcaen and Ooghe, 2006). The second criticism is that the annual accounts do not reflect all relevant failure indicators (Balcaen and Ooghe, 2006). The third criticism is that there is no consensus on type of financial ratio (Balcaen and Ooghe, 2006). The fourth criticism is that there is an assumption that the annual financial statements are fair, complete and reliable (Balcaen and Ooghe, 2006). The fifth criticism includes the manipulation of earnings and the use of inconsistent accounting methods across various firms within the same industry (Balcaen and Ooghe, 2006).

2.7 Shortcomings of Multivariate Discriminant Analysis

The previous section listed the shortcomings of statistical techniques in general. The Altman (1968) failure prediction model uses multivariate discriminant analysis to predict firm failure. Listed below are the shortcomings of multivariate discriminant analysis as these should be noted by firms when relying on this model:

- There are certain statistical requirements compulsory on the distributional properties of the predictors (Ohlson, 1980). For example the variance-covariance matrix has to be the same for both failed and non failed groups.
- The output Z-score has little intuitive interpretation, since it follows an ordinal ranking (Ohlson, 1980).
- The financial variables chosen on this model were based on an arbitrary basis with no theoretical or empirical evidence to support it (Zavgren and Friedman, 1988)
- This type of analysis does not permit assessment of the significance of any variable as this cannot be determined independently of other variables in the model (Zavgren and Friedman, 1988).
- The prediction of most of the earlier models were dichotomous classifications, either failure or healthy (Zavgren and Friedman, 1988).
- Multicollinearity is not absent in the model. Although some believe that multicollinearity is needed in this analysis, most authors agree that severe correlation among independent variables may cause instability and difficult to explain parameter estimates and misleading model accuracy (Balcaen and Ooghe, 2006).

Before one makes a decision on the outcome of the Altman (1968) failure prediction model, one should understand and take these limitations into account. Therefore firms should not only rely on failure prediction models but also take into account the surrounding circumstances (Altman, Marco and Varetto, 1994).

2.8 International Survey of Business Failure Prediction Models

Altman (1984) surveys and discusses numerous studies, including published and unpublished, that attempted to develop and test failure prediction models outside of the United States of America. Financial ratios as well as failure indicators (specifically Z scores) are examined. The following data was extracted from Altman (1984) and Altman and Narayanan (1997) surveys:

2.8.1 *Japan (Altman, 1984)*

Prior to 1982, the number of business failures in Japan are relatively the same as in the United States of America. Ko (1982) had developed a model similar to Altman Z Score. The study sample included 41 paired bankrupt and healthy firms between the period 1960- 1980. This study modified and analysed the data by making several accounting corrections, adjustments, and transformations. Then a variable trend analysis was done on the data set to reduce the biases held to be inherent in conventional Japanese reporting practises. The accuracy rate on the model was 90.8% for the original sample. The model used 3 out of the 5 coefficients as Altman's Z score and a cut off point of 0. Any firm that had a Z score above 0 indicated a healthy situation where the probability of classification of bankruptcy was less than 50%.

2.8.2 *Federal Republic of Germany and Switzerland (Altman, 1984)*

In Switzerland, Weibel (Altman and Narayanan, 1997) constructed a failure prediction model. The sample included 36 paired bankrupt and non bankrupt companies during 1960 – 1971. Forty one ratios were indentified from the sample firms of which twenty were selected for dichotomous testing. Cluster analysis was used to reduce collinearity, and the paper concluded that six ratios were especially effective in discriminating between the paired groups. This model's results during the classification stage were relatively accurate; however no further studies have been performed on this model (Altman and Narayanan, 1997).

There were a number of studies conducted in Germany to investigate the causes and problems of insolvencies. One of the first models developed was by Beerman (Altman and Narayanan, 1997). The sample included 21 paired bankrupt and non bankrupt firms during the period 1966 – 1971. The model used dichotomous and linear discriminant testing. The main ratios that were analysed were profitability, cash flow, fixed asset growth, leverage, and turnover. The model yielded classification errors of 9.5%, 19%, 28.6% and 38.1% for the four years prior to failure (Altman and Narayanan, 1997).

2.8.3 *Brazil (Altman, 1984)*

In 1979, Altman, Baidya and Riberio-Dias (1979) modified the Altman Z score model to suit the Brazilian Economy. The only variable that changed was the second coefficient. The second coefficient was changed to total equity less capital contributed by shareholders divided by total assets. The empirical results revealed from the 58 company sample that there was 88% accuracy, with the Type 1 error being 13% and the Type 11 error being 11.4%.

2.8.4 *Australia (Altman, 1984)*

Castagna and Matolcsy (Altman and Narayanan, 1997) developed a failure prediction for Australian firms. One of the most difficult requirements for company failure prediction analysis outside of United States of America was that to create a data base of failed companies large enough to perform a reliable discriminant analysis (Altman, 1984). Castagna and Matolcsy (Altman and Narayanan, 1997) assembled a sample of only 21 industrial firms during the period 1963- 1977. Unfortunately the results of the model were not definitive as the firms used in the study were not subsequently followed up to verify whether the model was accurate or not.

2.8.5 *Ireland (Altman, 1984)*

In 1981 Cahill (Altman, 1984) did some exploratory work on a small sample of 11 bankrupt listed companies during the period 1970 – 1980. The work involved identifying financial ratios that showed a significant deterioration as failure approaches and whether the auditor’s report expressed any reservations or uncertainty about the continuance of the firms as a going concern. The analysis revealed a number of ratios indicating clear distress signals one year prior to failure and the signals were less clear two years prior to failure. Only one of the auditor’s report indicated a going concern issue existed.

2.8.6 *Canada (Altman, 1984)*

Knight's (Altman, 1984) research analysed the records of a large number of small firms as well as conducting interviews with key personnel involved. The findings were that a firm usually fails early in its life and that some type of managerial incompetence accounts for almost all failures. He also attempted to classify failure using a discriminant analysis model. The accuracy rate of the sample was only 64%.

2.8.7 *Netherlands (Altman, 1984)*

There were many studies conducted in the Netherlands on company bankruptcies. One of the models developed was by Bilderbeek (Altman, 1984) in 1977. The original sample size was 38 bankrupt firms and 59 healthy firms during the period 1950 -1974. Bilderbeek (Altman, 1984) analysed 20 ratios using discriminant analysis and developed a five variable Z score model. The model's accuracy ranged between 70%-80% and further testing revealed an accuracy of around 80%.

2.8.8 *France (Altman, 1984)*

A study by Bontemps (Altman and Narayanan, 1997) in 1981, achieved high accuracy rates for his developed model. He had a large sample size which consisted of 34 paired bankrupt and non bankrupt industrial companies. His analysis indicated that three variables were found to be useful indicator of bankruptcies. The accuracy rate achieved on the model was 87%.

2.8.9 *Overall Review*

As stated above, there have been vast studies in firm failure prediction models throughout the world (Laitinen and Kankaanpaa, 1999). International failure prediction studies are integral as many countries outside of United States of America will face large firm bankruptcy and knowing international knowledge may help obviate the consequences or reduce the number of these failures (Altman and Narayanan, 1997).

2.9 Prior Applications of Dichotomous Models in South Africa

Research and development of failure prediction models globally are ever increasing, however research in South Africa is minimal. There have been a few studies on company failure prediction using dichotomous analysis. A brief summary of some of these studies are described below (Naidoo, 2006):

- Strebel & Andrews (Naidoo, 2006) - This study used a sample of sixteen failed and thirteen non-failed companies from the period 1971 to 1976. Their research indicated that cash flow to total debt ratio was a powerful predictor of corporate failure.
- Daya (Naidoo, 2006) – This study analyses thirty one pairs of failed and non-failed companies in South Africa in the period 1966 to 1976. His research also indicated that the cash flow to average total current liabilities ratio to be the best predictor of corporate failure for a one year period.
- De La Rey (Naidoo, 2006) – A model was developed using financial information of twenty-six pairs of failed and non-failed listed companies from the period 1972 to1979. This model was similar to the Altman Failure Prediction Model except that listed companies as well as non-listed companies could apply this model. This model had a 96% overall accuracy over one year prior to failure.
- Clarke, Hamman and Van der Smit (Naidoo, 2006) – This model was developed for privately owned companies. Their sample consisted of twenty-nine companies that failed or experienced financial distress between the period 1985 to 1990 and forty- three healthy companies. The predictive accuracy for year 1 to 4 was in the range of 74% and 78%.
- Court, Radloff, and Van der Walt (Naidoo, 2006) – The sample consisted of nineteen non-failed companies and twenty-one failed companies from the period 1974 to 1985. This model was used to detect failure of a company over one year as well as over two year.

2.10 Prior Application of the Altman (1968) Failure Prediction Model in South Africa

In an MBA dissertation by Jacobs (2007), the Altman (1968) model was applied to non listed companies in South Africa. The study included a sample of 40 companies between 2003 and 2006, 20 of which were liquidated and 20 that were still trading.

The Jacobs (2007) study concluded that the Altman (1968) model was 75% accurate on these companies, which was considered to be extremely high. In addition to this, the study indicated that the companies that were in the 25%-inaccurate range had unusually high Z-scores or that their Z-scores fluctuated greatly from one year to the next. It was therefore suggested that unusually high Z-scores or fluctuating Z-scores may invalidate the use of the Altman (1968) model (Jacobs, 2007). This research report will provide a comparison to Jacob's (2007) results.

2.11 Post Literature Comment

The bulk of the literature review pertained to studies outside of South Africa. The thought process began with looking at the causes of corporate failures. It is important to note the reasons for company failure as once company failure is detected, management can take step to prevent this occurrence (Deakin, 1972).

The history of failure prediction models was then discussed. This was done to illustrate the type of developments in failure prediction models in order to evaluate the work performed thus far. In the next section, the Altman (1968) model was described. The determinants and the explanation of each variable was discussed in accordance to Altman's (1968) seminal paper.

Thereafter, a brief summary was provided on alternative failure prediction models developed thus far. Shortcomings and disadvantages of failure prediction studies and statistical models were discussed.

One of the conclusions reached was that decision makers should not only use these failure prediction models to make a decision, but they should also assess surrounding circumstances to help with their decision (Altman, Marco and Varetto, 1994).

The next section provided a brief description of various international studies on failure prediction models. Most of these models showed accurate results.

The scope of failure prediction studies was then narrowed to South Africa. A discussion of dichotomous failure prediction models and the use of Altman (1968) failure prediction models in South Africa were explored.

In summary, there are many studies on failure prediction models, however none of which related to South African JSE Listed companies. A study conducted found that there were no significant differences between the different statistical methods used for firm bankruptcy prediction (Bruwer and Hamman, 2006). This could possibly be the reason that many firms still use the Altman (1964) failure prediction model.

3 RESEARCH METHODOLOGY

The methodology used in this research report is purely quantitative. The Altman (1968) failure prediction model is empirically tested in a South African context. This section includes the detailed specification of the various variables included in the model.

The exponents of the Altman (1968) model were derived for the USA market context, and specifically for the manufacturing industry, yet evidence indicates that the model is recognized as one of the most reliable in predicting company failure globally (Eidleman, 1995). The model is therefore mis-specified for both a South African context, and for industries outside of the manufacturing industry. As this model is used throughout the world, the aim of this study is to assess its viability in the South African context

The initial sample size is composed of 227 companies, which has been divided into 2 groups. The sample has been limited by excluding firms in specialised industries, with peculiarities specific to their nature, as this would distort the results of the study due to homogeneity issues which would manifest in the specifications within the model variables. It is however recognised that the sample is still not completely homogenous due to remaining industry, and size differences, these differences are however not considered to be significant enough to distort the results. The period selected for the study is the 2008 year for the accumulation of data.

This year has added interest as the economic situation was that of a recessionary environment caused by the global credit crisis. The period was selected due to the Altman (1968) failure prediction model predicting company failure over a two year horizon, and data being available for the 2008, 2009 and 2010 years. Data for the variables was sourced from McGregor BFA. Microsoft Excel was used to compute the statistics needed for this study.

The Altman (1968) failure prediction model was applied to the sample in order to form two groups of companies, those that are predicted to fail, and those that are predicted to succeed. Thereafter the performance of the two samples was investigated over a 2 year period (2009 and 2010) to determine whether the model successfully predicted failure or success. In addition, an investigation was performed where companies have failed, but were not identified by the model as failing companies.

The Altman (1968) failure prediction model is represented as follows:

$$Z = 0.012X1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5$$

Where: X_1 = net working capital/total assets

X_2 = retained earnings/total assets

X_3 = EBIT/total assets

X_4 = Market value of common and preferred stock/ book value of debt

X_5 = sales/total assets

Z = Overall index

The variables in the Altman (1968) model have been specified as follows:

Working Capital	Current assets less current liabilities
Total Assets	Comprises of all tangible and intangible assets. As BFA McGregor splits tangible and intangible assets, the data will comprise of both types of assets. It would be preferable to include the market value of assets in this line item; the information available however limits the

	study to the use of book values only. This will be considered when interpreting the results.
Retained Earnings	Distributable reserves will be used, any non distributable reserves will not be included as these are typically not cash returns, and therefore may not be realisable.
Sales	Turnover per the statement of comprehensive income will be used.
Market value of common and preferred stock	The market capitalisation will take into account the value of both common and preferred shares. Both will be obtained as current market values.
Book value of Debt	As the model tests the going concern of the company, the total long term liabilities will be used to represent the book value of debt. In some companies extended use is made of current debt, in such cases finance is used to fund long term assets. No adjustment has been made for such cases as presumably this increased risk would manifest in the working capital variable already.

In order to test the robustness of the model, the companies were divided into ten deciles, ranked by Z-score, in order to measure the level of predictive ability of the model in various ranges of the score guidelines. The accuracy of the predictive power of each decile was measured as to either a correct prediction, or a missed prediction.

Due to the low accuracy rate of the 10^{th} decile, the companies within this decile were split further into three categories. The companies were split based on their Z-score. A further investigation was performed to investigate the accuracy of the Altman (1968) failure prediction model when the Z-score was positive and negative.

4 RESULTS AND DISCUSSION

4.1 Introduction

The Altman (1968) failure prediction model was conducted on a non paired sample in order to identify whether the model can accurately predict company failure over a two year recessionary horizon.

The decision criterion used to evaluate the accuracy of the model, was how well the model classified a company as being either healthy or failing. Altman (1968) provides the following classification criterion for the model, based on an ordinal scale:

- Z –Score > 2.675 : Financially Healthy
- Z –Score < 2.675 : Company is likely to fail within the next two years
- 2.99 > Z –Score > 1.81 : Grey Area

4.2 Overall Accuracy

Using the entire sample of 227 companies, the Altman (1968) failure prediction model provided a high overall accuracy rate of 91.63% on South African JSE Listed companies in the 2008 to 2010 period. Therefore, the Altman (1968) model predicted either healthy, or likely to fail within 2 years correctly for 91.63% of the sample. This is in line with the results of Jacobs (2007), who found a 75% accuracy rate for the model using unlisted South African companies. This average is explained by:

Table 1: Overall Accuracy.

Accuracy	
Healthy	93.47%
Fail	78.57%
Average	***91.63%***

The ability to predict a firm to be healthy over the two year horizon is 93.47%. Out of the sample of 227, 206 of the firms have succeeded or remained healthy over the two year horizon.

The ability to predict whether a firm will fail over a two year horizon was 78.57%. There were 26 firms, in total, that failed over this period. This accuracy rate is relatively high, however due to the small amount of firms in this category, further analysis was performed below.

4.3 Decile Analysis

The analysis of success versus failure was further investigated by splitting the companies into ten deciles based on the number of firms in the sample. The details of the ten deciles are reflected in the table below:

Table 2: Accuracy rate per Decile

Decile	Range		Accuracy
	Start	End	
1	42378.34	764.562	95.65%
2	674.295	212.723	100.00%
3	175.878	102.058	100.00%
4	97.878	49.812	100.00%
5	49.009	26.483	95.65%
6	17.177	17.329	100.00%
7	17.177	8.918	95.65%
8	8.828	4.933	100.00%
9	4.640	2.683	95.45%
10	2.641	-8.649	28.57%
		Average	***91.63%***

The analysis by decile indicated that the first nine deciles yielded an accuracy rate of 95.45% or higher. Therefore when the Z-score is between the range 42378.34 and 2.683, the predictive accuracy of this model is extremely high.

The 10th decile however yielded a poor accuracy rate of 28.57%. Therefore when the Z – score is between the range of 2.641 and -8.649, it would appear that a reliable decision cannot be made in this range. This result was further investigated by splitting the 10th decile into different Z-score ranges.

4.4 10th Decile Split Test

Further analysis needed to identify reason for the low accuracy for the 10th decile. The intention was to clarify whether the low accuracy rate was as a result of the Z–scores overlapping the 'grey area' or 'zone of uncertainty' (Correia et al., 2007), and whether the negative Z–scores tainted the Z –score accuracy.

The 10th decile was therefore split further into three equal groups, with groupings determined by Z-score range. The following results were obtained:

Table 3: Accuracy rate- 10th decile split

10th Decile Split	Range		Accuracy
	Start	End	
First	2.641	1.355	0.00%
Second	1.185	0.051	57.14%
Third	-0.003	-8.649	28.57%

The results indicated that the first third of the split yielded 0% accuracy. The range for the Z–scores was 2.641 and 1.355. The 'zone of uncertainty' lies within this third and therefore suggests that if the Z–score falls in the 'zone of uncertainty', an accurate prediction cannot be made.

The second third was in the Z–score range of 1.185 and 0.051. The accuracy in this third was fairly good (above 50%), yielding 57.14%. It is important to note that this range was not in the 'zone of uncertainty' nor did it include any negative Z- scores.

The final third was in the Z–score range of -0.003 and -8.649. The accuracy in this third yielded a poor 28.57%. This suggested that when there is a negative Z –score, a reliable decision cannot be made.

4.5 Positive and Negative Test

The results from the 10th decile split were insightful. This lead to a final test of positive versus negative Z-scores. This was performed to determine whether the Altman (1968) failure prediction model can be used for all Z-scores (positive and negative).

The following results are reputed:

Table 4: Accuracy rate- Positive and Negative

Test	Range		Accuracy
	Start	End	
Positive	42378.34	0.051	93.64%
Negative	-0.003	-8.649	28.57%
		Average	***91.63%***

The results for the positive Z–scores were therefore high, whereas the results for negative Z–scores were poor as the accuracy rate is less than 29%.

It is therefore concluded that the Altman (1968) failure prediction model cannot accurately predict failure for companies with negative Z–scores.

4.6 Overall Discussion

The results obtained from this study indicate that the Altman (1968) failure prediction model can be used on South African JSE Listed companies to predict corporate failure. These results are consistent with Altman's (1968) original work and with Jacobs' (2007) dissertation. This is irrespective of the fact that the model exponents are specified using the USA market, using only the manufacturing sector. Therefore the use of the Altman (1968) model in its original form remains relevant in the current recessionary economic climate. The purpose of this research was not to re-specify the original model. However, results may further be improved should such be done, which would represent a valuable area of investigation for later studies.

Altman's (1968) seminal study/paper reflected a 95% accuracy rate in predicting future firm bankruptcies (Altman, 1968; Deakin, 1972). Although the results of this study are slightly lower, it is considered that an overall accuracy rate of 91.63% (refer to 4.2) is close enough to conclude that this model remains effective on JSE listed firms.

Jacobs (2007) indicated that unusually high Z -scores may invalidate the Altman Failure Prediction model. This is inconsistent with the results obtained by this study. This study yielded that the Altman (1968) model was not reliable when the Z -score is between the zone of uncertainty and, when the Z -score is negative.

5 REVISITING THE RESEARCH PROBLEM

It is imperative that the research problems are revisited so that the questions this study seeks to address are answered.

5.1 Main problem

Can the Altman (1968) failure prediction model be used to predict bankruptcies using recent financial statements?

The Altman (1968) failure prediction model can be used to predict bankruptcies. This study yielded an overall accuracy rate of 91.63%: however, it should be noted that negative Z scores and Z score falling within the zone of uncertainty may invalidate the model.

5.1.1 *First sub problem*

Is it practical to use the Altman Failure Prediction Model on South African JSE listed companies?

The use of the Altman (1968) Failure Prediction Model is practical for the following reasons:

- The calculation of Z scores can be easily performed systematically once the data is gathered.
- The accuracy rates for the model on JSE listed companies were shown to be high.

5.1.2 *The second sub-problem*

Is the Altman (1968) failure prediction model adequately specified for use on South African JSE listed companies?

As stated in Altman's (1968) seminal paper, this model was developed by using companies within the manufacturing industry. Yet today, many credit granters still use the Altman (1968) failure prediction model to predict firm failure for all types of customers (Jacobs, 2007).

It is clear from the results of this study that the Altman (1968) failure prediction model can be effectively applied to companies listed on the JSE.

6 CONCLUSION

This report established whether the Altman (1968) failure prediction model was effective in predicting the failure of South African companies listed on the JSE.

Credit managers use the Altman Failure Prediction model when assessing whether to grant firms credit (Eidleman, 1995).

This study empirically tested the Altman (1968) Failure Prediction Model on JSE listed firms. These were the following outcomes from this study:

- The Altman (1968) failure prediction model can be used by credit managers as a tool to predict company failure. However the model has certain limitations:
    - The model is not accurate work when Z –scores are negative
    - The model is not accurate when Z –score are in the range of the 'grey area', or area of uncertainty.

It can be concluded that the Altman (1968) failure prediction model should be used by credit managers as a tool when assessing credit worthiness as it is accurate and practically viable to predict company failure for JSE listed companies.

6.1 Further Avenues for Research

Given the following inherent limitations of this study, the following avenues of research are suggested:

1. The Altman (1968) Failure Prediction model could be evaluated by further increasing the number of years that the model is tested. This would enhance the creditability and robustness of the model accuracy.
2. Even though there is no impact of survivorship bias on this study, a sample free of survivorship bias could be examined on companies that are not listed.
3. The weighting of each of the variables could be recalculated to accommodate current accounting practice, country specific specifications, and sector specific specifications.
4. Correlations of the financial ratios could be examined in more detail. It may be possible that some ratios are repeated and may taint the model.
5. A similar model could be generated for companies in the financial and mining sector as those firms as highly specialised fields.

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