PREDICTING THE BUSINESS FAILURE OF JSE LISTED COMPANIES USING THE ALTMAN Z AND DE LA REY FAILURE PREDICTION MODELS

By

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DECLARATION OF WORK AUTHENTICITY

I, Mphongo Chikondi Kayesa declare that this dissertation is the work done by me and is submitted in partial fulfilment of the requirements of the Master of Business Administration degree, in accordance with rules of Regenesys Business School, Sandton, South Africa. It has not been used, presented or submitted in the past for any degree or examination at any other university or educational institution.

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ABSTRACT

The results of business failure have been seen worldwide, this suggest the need to predict it, since failure results in heavy losses for companies, both financially and non-financially. Hence, there is a need for a model that could precisely predict business failure earlier for relevant stakeholders, such as organisational management, shareholders, government, suppliers, customers, employees, amongst others. The prediction of business failure is a significant and challenging issue that has served as a drive for various academic and organisational research.

The main objective of the research was to determine the applicability of Altman's Z-score and De La Rey's K-score failure prediction models on companies listed on the Johannesburg Stock Exchange (JSE). The research target sample was 25 companies listed on the JSE that failed between 2014 and 2017. All 25 failed companies, from different sectors, who were insolvent during the period, were chosen for the study. The data used was secondary from financial reports of these failed companies on the JSE.

The outcome of the study discovered that Edward Altman's Z-score failure prediction model was applicable in 20 out of the 25 failed companies that were analysed, which shows an 80% successful prediction of the model. De La Rey's K-score failure prediction model was applicable in 23 of the 25 delisted companies that were analysed, which depicts a 92% successful prediction of the model. The study concludes that De la Rey K-score prediction model is effective and beneficial in respect to predicting the company failure of JSE listed companies while Altman Z-score model is relatively not effective or beneficial due to it's relatively lower success in predicting the failure of JSE listed companies.

Key words: Failure; Healthy; Liquidity and Debt Management Ratio's

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LIST OF ACRONYMS

AN - Artificial Neurons

CUSUM – Cumulative Sum Control Chart

EBIT/TA - Earnings before Interest and Taxes/Total Assets

EBITDA – Earnings before Internet Taxes, Depreciation and Amortisation

GA – Genetic Algorithms

LPM – Linear Probability Model

MDA – Multi Disbarment Analysis

MVE/TL – Market Value of Equity/Total Liabilities

NN – Neural Networks

RE/TA - Retained Earning/Total Assets

UDA – Univariate Discriminant Analysis

WC/TA – Working Capital /Total Assets

CHAPTER 1: ORIENTATION AND BACKGROUND OF THE STUDY

1.1. INTRODUCTION AND BACKGROUND

Insolvency is one of the most important threats for numerous businesses today, in spite of the “nature of their operations and size; corporate liabilities have default risk and there is always a chance that a corporate borrower will not meet its contractual obligations and may renege from paying the principal and interest due” (Kirui, 2012: 1). Even for the typical high-grade borrower, there is default risk regardless of being small and knowing this risk is extremely important to a company, since it can escalate quickly and with little warning. Moreover, the margins in corporate lending are very tight, and even small miscalculations of default risks can undermine the profitability of lending. However, most importantly, “many lenders are themselves borrowers, with high levels of leverage and unexpected realisations of default risk have destabilised, decapitalised, and destroyed many internationally active lending institutions” (Charitou et al., 2002:3).

According to Gerald (2002), there have been widespread debates among numerous stakeholders in trying to identify firms likely to go bankrupt and/or become financially distressed. This is due to the high economic cost of business failure and the evidence indicates that the market value of the distressed company declines substantively as well, disturbing “suppliers of capital, creditor, management and employees”. Furthermore, Boritz (1991:133) argues that the “auditors will face the threat of potential law suits if they fail to provide early warning signals about failing firms through the issuance of qualified audit opinion”.

There are different factors that cause the failure of business; various economists point to the phenomenon of high interest rates, recession-squeezed profits and heavy debt burdens (Gerald, 2002). In addition, specific industrial characteristics, such as the following: government regulation and the nature of operations, can contribute to a firm’s failure (Wang & Deng, 2006).

The business failure patterns of developed countries, such as the United Kingdom (UK), the United States of America (US), Canada and Australia, establish that small, private and newly started companies with ineffective control procedures and poor cashflow planning are more prone and vulnerable to financial distress than large well-established companies. Eventually, this calls for the development of a model that will predict signs of corporate failure, promptly and accurately.

Numerous statistical methods have been established to predict corporate failures. The statistical methods such as those adopted by Beaver (1966), as cited Appiah and Abor (2010:435), begs the “question of dependence on a single ratio rather than taking a holistic view of possible complex factors that may indicate future bankruptcy”. Zavgren (1993) argues that Univariate Discriminant Analysis (UDA) creates inconsistent signals since different variables could give conflicting forecasts. Consequently, alternatives that guarantee consistency are imperative. Altman (1968) and Da Le Rey have been considered by numerous researchers and have proven to offer better predictions of corporate failure.

In Altman's models, the highest contributor of business failure was the profitability ratio, earnings before interest and taxes/total assets, whilst the least was working capital/total assets. Altman (1968) claims that the profitability ratios’ contribution is not astounding, considering that the incidence of profitable firms' failure is almost nothing.

1.1.1. Business failure

Financial failure may take the form of insolvency or bankruptcy. Insolvency refers to a “situation where a firm is unable to meet its current obligations as and when they fall due; this happens when the current liabilities exceed the current assets” (Kirui, 2012: 2), while bankruptcy is defined as a “situation where the totals liabilities exceed the fair value of assets” (Kirui, 2012: 2). Financial statements are normally utilised to measure the organisational performance and its management.

The financial statements commonly used are profit and loss statement, balance sheet and cash flow statements. From the financial statements, various ratios can be calculated to assess the current performance and future prospects of the concerned firm. Some of the ratios used are the “current ratio, quick ratio, and working capital to total debt ratio, total debt to total assets ratio, profit margin to sales and return on total assets ratio” (Ahn, 2000:66).

A possible way to prevent business failure is to investigate the various elucidations for corporate failure. Previous studies have concentrated on detecting reasons for failure as a remedy for prevention. Research conducted by Altman (2003) used financial ratios to predict the occurrence of bankruptcy and he was able to predict 94% occurrence correctly, one year before bankruptcy occurred and 72% two years before its actual occurrence. The significant ratios identified by Altman with respect to bankruptcy prediction were “working capital over total assets, retained earnings over total assets, earnings before interest and taxes over total assets, market value of equity over book value of total liabilities and sales over total assets” (Altman, 2003:590).

1.1.2. Business failure prediction models

The use of cash flow analysis towards the bankruptcy prediction of a firm has been augmented by Ward and Foster (1997). The authors compared the trends in the various components of a cash flow statement - operating cash flow, investing cash flow and financing cash flow. They discovered that healthy companies have a tendency towards comparatively stable relationships amongst the three components of a cash flow: operating, investing and financing activities. Altman (1981:12) states that multivariate discriminant analysis (MDA) is a “statistical technique used to classify an observation into one of several *a priori* groupings dependent upon the observation’s individual characteristics”. It is used mainly to categorise and/or make predictions in problems where the dependent variable appears in qualitative form, for instance, male or female, bankrupt or non-bankrupt, failed and non-failed. Consequently, the first step is to establish explicit group classifications. Some analysts refer to discriminant analysis as “multiple” only when the number of groups exceeds two. After the groups are established, data is collected for the objects in the groups; MDA in its most simple form attempts to derive a linear combination of these characteristics which “best” discriminates between the groups.

Neural computing is yet another model that has generated considerable research interest and has been applied in various areas, including the prediction of corporate bankruptcy or financial distress. Neural computing is a computer system that consists of a network of interconnected units called artificial neurons (AN). Artificial neurons are organised in layers inside the network. The first layer is the input layer, and the last is the output layer. Hidden layers exist between the input and output layers, and there can be several hidden layers for complex applications.

Prior to the development of quantitative measures of firm performance, agencies were established to supply a qualitative type of information, assessing the creditworthiness of particular merchants. One of the classic works in the area of ratio analysis and bankruptcy classification was performed by Beaver (1967). Beaver (1967:77) posits that a “number of indicators could discriminate between matched samples of failed and non-failed firms for as long as five years prior to failure. The study implies a definite potential of ratios as predictors of bankruptcy”.

Overal, ratios measuring profitability, liquidity, and solvency prevailed as the most important indicators. Nevertheless, the order of their importance is not clear since almost every study cited a different ratio as being the most effective indication of impending problems.

1.2. THE RESEARCH CONTEXT

The liquidity crunch or crisis in late 2007 due to the global recession had triggered the USA banking crisis, and was chiefly a resultant initiated by over-valuation of assets (Demyank & Hasan, 2009). The reason for over-valuation of assets was a result of relaxed credit controls by the banking sector (Demyank & Hasan, 2009). Moreover, previous research has shown that credit has become one of the major and most significant contributors to spending by consumers (Cynamon & Fazzari, 2008). Consequently, effective credit controls are imperative for all financial institutions.

Firer, Ross, Westerfield and Jordan (2004) argue that access to credit decisions are based predominantly on the credit principles' 'character', 'capacity', 'capital', 'collateral' and 'conditions'. These are commonly known as the 5 C's of credit granting. Capacity, collateral and conditions, to an extent, are all considered and evaluated through reviewing the company's financial statements. It is against this background that financial statements play an essential role in decision making to offer a credit facility to corporates or individual households for evaluating their financial position. A number of models have been promulgated to determine the likelihood of bankruptcy within a certain period of time. These models utilise the financial statements of the company to yield a score which will predict the probability of insolvency within a certain period of time (Laitinen & Kankaanpaa, 1999). The development of company failure prediction models is presented and discussed in detail under the history of failure prediction model developments.

1.3. THE STATEMENT PROBLEM

The prediction of a corporate's chance of failing is an important exercise for most organisational stakeholders. As a result, the need for reliable empirical models that predict business failure on time and precisely, is imperative to permit the stakeholders concerned to take either corrective or preventive action (Fauzias & Chin, 2002). The economic cost of business failures is significant; evidence indicates that the market value of the distressed companies decline substantially prior to their ultimate collapse and therefore, if an organisational failure could be detected early, it would be possible to minimise failure associated cost by undertaking such actions as shareholders withdrawing their investment, consumers looking for alternative markets, the managers making turn-around strategies before it is too late.

The listed JSE companies play an important role in the growth and economic development of the country through generating foreign currency, creating employment and beneficiation of products, including many more. Despite what can be dubbed as a good industry performance over the period, the stock exchange has experienced the collapse of some of the companies. With their collapse, billions of Rands in investments have been lost. This therefore calls for the companies to disclose adequate information to allow investors to make informed decisions.

A number of studies have been conducted on predicting business failure. Keige (1991) conducted research on business failure prediction, utilising a discriminant analysis model. He found that the discriminant model adopted is not free from defects because it largely depends on some restrictive assumptions, such as linearity, normality and independence, amongst input variables (Keige, 1991). In addition, Kiragu (1993) researched on the prediction of business failure, using price adjusted accounting data, whereas Kogi (2003) conducted research on the analysis of the discriminant corporate failure prediction model, based on the stability of financial ratios. Odipo and Sitati (2000) carried out research on the evaluation of the applicability of Altman's revised model in prediction of financial distress. In conclusion, corporate failure models derived in one country, cannot be generalised to another country for various reasons.

Grice and Dugan (2001:155) carried out research to evaluate the Zmijewski (1984) models and discovered that the "models are sensitive to time periods; whereby, accuracy of the models decreased when applied to different periods of the original models". The above discussed researchers have attempted to test the validity of already existing models in different set-ups without necessarily attempting to localise the model to a particular setting. It is on the basis of this gap that the current study compares the results of failure prediction by using two models: the Altman Z-score model and the De Le Rey K-score model.

1.4. PURPOSE OF THE STUDY

The main aim or purpose of this study is to establish whether the Altman Z-score and De La Rey K-score failure prediction models are effective in forecasting the failure of companies listed on the Johannesburg Stock Exchange (JSE).

1.4.1. Objective of the study

The objective of the research is as follow:

i. To examine whether the Altman Z and De La Rey models are beneficial in predicting corporate failure in the JSE listed companies.

1.4.2. Research questions

i. Are the Altman Z-score and De La Rey K-score failure prediction models able to predict financial distress of companies listed on Johannesburg Stock Exchange (JSE)?
ii. Can the Altman Z-score and De La Rey K-score failure prediction models be applied to predict bankruptcies, using current financial statements?
iii. Are the Altman Z-score and De La Rey K-score failure prediction models sufficiently specified for application on companies listed on the JSE?

1.5. SIGNIFICANCE OF THE STUDY

The comprehension of models in predicting company failure will assist government, policy makers and other relevant stakeholders to plan targeted policies and programmes that will actively stimulate the growth and sustainability of the firms in the country, as well as helping policy makers to support, encourage, and promote the establishment of companies. Regulatory bodies such as Capital Markets and the South African Revenue Authority will also be able to use the results of the study to improve the regulation framework.

The study findings will benefit all stakeholders, including management and staff, of companies who will gain insight into how their institutions can effectively predict the risk of default and bankruptcy and as a result of the same, put in place effective policies to lessen the risk.

This study also creates a monograph which could be replicated in other parts on the of the South African economy such as private companies not listed on the JSE and State owned Enterprises (SOE's). Most importantly, this research contributes to the literature on the prediction of corporate failure and the findings will be valuable to academics, who may find useful research gaps that may stimulate interest in further research in future and recommendations made on possible areas for future direction of the study.

1.6. DELIMITATIONS OF THE STUDY

The study is limited to suspended and delisted JSE companies. The corporates sample is drawn from different sectors 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.

1.7. ASSUMPTIONS

The following assumptions have been made regarding the study:

- The financial statements reflect the true performance and position of the company.
- The information period had no influence from different economic conditions as the period of the testing is conducted from 2014 to 2017.

1.8. KEY WORDS DEFINITIONS

- **Debt Management Ratio's**: "The degree to which a company is able to meet its long term financial obligations" (Correia, Flynn, Uliana & Wormald, 2007).
- **Failure**: "Bankruptcy, or any condition whereby a company was forced to be suspended or delisted due to liquidity and solvency problems (Bruwer &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).

1.9. THE STRUCTURE AND OUTLINE OF THE STUDY

This study is divided into six (6) chapters which are as follow:

- Chapter 1: This chapter presents the orientation and background of the study.
- Chapter 2: This offers the review of the literature of the study answering the problems mentioned and the purpose of the study.
- Chapter 3: This offers a detailed discussion of the research design and the methodology process followed to accomplish the study.
- Chapter 4: The presentation and interpretation of the results are offered in this chapter.
- Chapter 5: Discussion of the results is presented in this chapter through revisiting the research problems to ensure that this study answers the posed objectives.
- Chapter 6: This chapter provides a summary of the dissertation, conclusion, recommendations and suggestions for future research.

1.10. CHAPTER SUMMARY

This chapter provided an overview of the study. A comprehensive introduction was provided and thereafter, a broad reflection on the background of the study was provided. Thereafter, a discussion on business failure in the South African context was highlighted. The unit clearly stated the problem that necessitated the pursuit of this study, after identifying a gap in literature. The purpose of this study primarily hinged on the problem and the identified gap, while the research objectives and questions stemmed from the aim of the study. The research gap and research questions are formulated. They were answered using a quantitative research methodology. The significance and delimitation of the study were discussed. The next chapter presents the literature review of the study.

CHAPTER 2: LITERATURE REVIEW

2.1. INTRODUCTION

This chapter presents the literature review of both theoretical and empirical studies on the research subject matter. The extant literature on empirical studies on the influence of predicting company failure and the theory thereon is discussed in detail in order to answer the objectives of the study. The chapter is divided into theoretical frameworks of corporate failure followed by bankruptcy prediction variables, corporate failure and evidence in the empirical literature.

2.2. THEORETICAL FRAMEWORK

Business failure comprises business rescue or liquidation (Bankruptcy Yearbook & Almanac, 2001:123). In theory, corporate insolvency is shown either by a fall in the asset value or due to a liquidity shortage and thus the organisation fails in the ability to raise capital to finance projects. There are many ways in which the likelihood of business failure may be reviewed. Whilst normative theories try to elucidate by deductive reasoning why a certain proportion of businesses might be expected to fail, positive theories try to explain by inductive reasoning why in practice, they do fail.

These theories are generally supported by empirical outcomes. While most bankruptcy research was carried out using the positivistic paradigm, a few scholars succinctly acknowledged a core theory. Alternatively, they selected the potential predictor variables based on their perception, reputation and predictive success in earlier related research. Nevertheless, the weakness that relates to the lack of theoretical analysis is lessened through the validation of the model against a sample from a specified time period.

2.2.1. Theories of Credit Risk

Credit risk theories, meticulously associated to Basel I and Basel II accords, typically refer to the financial health of the firm. The “Basel II framework involves three standpoints: minimum capital requirements, presently set equal to 8%, according to a purposely-defined capital ratio, supervisory review of an institution's internal assessment process and capital adequacy, effective use of public disclosure to strengthen market discipline as a complement to supervisory efforts" (Westgaard & Wijst, 2000:13).

Credit risk is defined as the "risk that a borrower/counterparty will default" (Westgaard & Wijst, 2000:13). Credit risk consists of all of the counterparties and reasons for which they may default on their obligations to repay. Following Basel II guidelines, in previous years, efforts have been made to develop internal assessment models to assess credit risk. A few of them have gained more respect than others, including JP Morgan's Credit Metrics, Moody's KMV model, CSFP's Credit Risk+ and McKinsey's Credit Portfolio View. More importantly, with one or two exceptions, these models and risk predictions thereof have been based on either micro or macroeconomic corporate finance theories. Therefore, collectively, these models are called credit risk theories.

The most famous microeconomic theory is related to the theory of option pricing as proposed by Black and Scholes (1973) and later advanced by Merton (1974). An option is a "security that gives the holder a right to execute a transaction (to buy or sell an asset) in future at a price determined today" (Merton, 1974:143). Options are divided into two categories: a call option gives the right to buy, while the put option means the right to sell. Options are used in many instances, including speculation, hedging and borrowing, capital preservation, covered call, etc. A simple example is a call option on a common stock, in which the pay-out on the call is determined solely by the value of the stock. Excess of stock price over the strike price determines the pay-out to the holder who will exercise the call. In the opposite case, pay-out will be zero and the holder will not exercise his right. Right pricing or valuation of options is important.

Black and Scholes (1973) presented a complete general equilibrium theory of option pricing that constructed a valuation formula, which is based on observable variables. Both Black and Scholes (1973) and Merton (1974) recognised that their approach could be used in developing a pricing theory for corporate liabilities in general. They determined the option value as the solution of a partial differential equation to which the price of any option must conform, subject to boundary conditions given by the form of the pay-out. Under this asset value option pricing approach, firms' default process is endogenously related to its capital structure. As a result, companies would default on their obligations to the bank if the value of their assets fell below certain critical levels determined by the respective credit risk model.

2.2.2. Cash Flow Theory

Cash flow theory proposes that cash flow from operating activities is the most significant predictor of financial distress; other net cash flows should also have incremental predictive usefulness (Ward, 1992). Cash flows that are essential in predicting financial distress in one industry may not be important in predicting financial distress in another industry (Gilbert et al, 1990). Since earlier scholars usually match healthy and distress companies by industry and pool data across various industries, outcomes may mislead because strong results in one industry could be offset by weak results of the industry therefore, presenting weak statistical interference when pooled across industries (Ward, 1992).

The cash flow theory can be traced back to the notion of financial flexibility supported by Heath (197:26) who claims that "financial flexibility is the capacity of the firm to control cash receipt and payment to survive a period of financial adversity". The final purpose of financial flexibility is to attain a state of equilibrium in total cash flow so that available purchasing power will be equal to the needs set by established limits and management decisions. This concept of financial flexibility shows that the occurrence of certain events activates an unanticipated drop in total cash flow, hence forcing a firm to take corrective action to regain cash flow equilibrium.

2.2.3. Gambler's Ruin Theory

The theory is connected to the game of a gambler, who plays with an arbitrary sum of money. The gambler plays with some likelihood of gain and loss. The game would carry on until the gambler loses all his money (Morris, 1998). With reference to a company's financial distress, the company would be like a gambler. A company would continue to operate until its net worth goes to zero point where it would go bankrupt. The theory assumes that the enterprise has some given amount of capital in cash, which would keep entering or exiting the firm on a random basis, depending on the firm's operations. In any given period, the firm would experience either positive or negative cash flow. Over a run of periods, there is one possible composite probability that cash flow will be always negative. Such a situation would lead the firm to fail and declare bankruptcy, as it has run out of cash. Therefore, under this method, the company remains solvent as long as its net worth is greater than zero. This net worth is "calculated from the liquidation value of stockholders' equity" (Morris, 1998:12).

2.2.4. Balance Sheet Decomposition Measure Entropy theory

Another option to identify companies' financial distress is to look at the changes taking place in the balance sheets. Dimitras et al. (1999:53) argue that "like any enterprise, firms would tend to maintain a state of equilibrium that ensures sustaining the firms existing structure". If a company's financial statements reflect significant changes in their balance sheet composition of assets and liabilities over a reasonable period of time, it is more likely that the firms are unable to maintain the equilibrium state. Since these changes are probable to become uncontrollable in future, one can foresee financial distress in these firms. This economic rationale of these companies' likely failure is the argument entropy theory (Dimitras et al. 1999).

One of the most important threats for many companies nowadays, despite their size and the nature of their operations, is insolvency. Corporate liabilities have default risk and there is always a chance that a corporate borrower will not meet its contractual obligations and may renege from paying the principal and interest due. Even for the typical high-grade borrower, these default risks are there and even though it may be small, they are highly significant to an organisation since they can increase quickly and with little warning. Further, the margins in corporate lending are very tight, and even small miscalculations of default risks can undermine the profitability of lending. But most importantly, many lenders are themselves borrowers, with high levels of leverage and unexpected realisations of default risk have destabilised, decapitalised, and destroyed many internationally active lending institutions (Charitou et al., 2002).

In the post Enron-Andersen debacle era, there has been widespread debate among various stakeholders in the quest to identify firms likely to go bankrupt and/or become financially distressed (Gerald, 2002). This is because the economic cost of business failure is large and evidence shows that the market value of the distressed firms decline substantially, as well as affecting suppliers of capital, creditors, management and employees. Further, the auditors will face the threat of a potential law suit if they fail to provide early warning signals about failing firms through the issuance of qualified audit opinion (Boritz, 1991). The factors that lead businesses to failure vary. Many economists attribute the phenomenon to high interest rates, recession-squeezed profits and heavy debt burdens.

Furthermore, industry-specific characteristics, such as government regulation and the nature of operations, can contribute to a firm’s financial distress (Wang & Deng, 2006). Studies of patterns of business failure in the UK, US, Canada and Australia found that small, private and newly founded companies with ineffective control procedures and poor cash flow planning are more vulnerable to financial distress than large well-established public firms. As a result, there is a need for the development of a model that will predict signs of corporate failure, promptly and accurately. Several statistical methods have been developed to predict corporate failures.

The statistical techniques, such as those adopted by Beaver (1966), as noted by Appiah and Abor (2010), beg the question of dependence on a single ratio rather than taking an holistic view of possible complex factors that may indicate future bankruptcy. Zavgren (1993) argues that UDA creates inconsistent signals since different variables could give conflicting forecasts. Therefore, alternatives that guarantee consistency are imperative. Altman (1968) has been reviewed by many scholars and has proven to provide a better predictor of corporate failure. In this model, the top contributor of business failure was the profitability ratio, earnings before interest and taxes/total assets, whilst the least was working capital/total assets. Altman (1968) contends that the profitability ratios' contribution is not surprising, considering that the incidence of profitable firms' failure is almost nothing.

2.3. REASONS CAUSING BUSINESS FAILURE

A number of variables have been identified that affect the failure rate of an organisation. The following are some of the factors that influence the failure of the firms:

2.3.1. Liquidity

Hoshi et al. (1991:123) discovered that "liquidity constraints of group member firms are weaker than those of stand-alone companies". If access to cash is less restricted within an organisation, this could lead to a situation where companies belonging to a business group pay less attention to liquidity as compared to stand-alone companies, as the latter have no choice but to resort to expensive short-term financing in case of liquidity shortages. In support of Hoshi et al. (1991), Deloof (2008:132) shared the same sentiment that "firms belonging to a business group, with liquidity needs therefore, may not necessarily reflect a higher probability of failure". For many small and newly formed businesses, liquidity is often the single most important reason for business failure. The problem arises when the money coming into the company from sales is not enough to cover the costs of production. It is important to remember that it is a case of having the money to be able to pay debts when the debts are due, not simply generating enough revenue during a year to cover costs (Patrick, 2004).

2.3.2. Performance

A business group may decide to keep a subsidiary afloat, even if it incurs severe losses and has been doing so for several years. This may be an economically sound decision, based on strategic, taxation, control or other group-specific reasons. Alternatively, internal capital markets may cause "socialism" within a group or conglomerate; a situation where stronger divisions subsidise weaker ones (Scharfstein & Stein, 2000). Empirical evidence of this phenomenon is reported in Claessens, Fan and Lang (2002).

To reinforce this point, Lamont (1997) shows that US oil companies subsidised under-performing non-oil activities during the early 1980s when profits from oil operations were extremely high. He points out that after the oil shock of 1986, subsidised non-oil investments were significantly reduced or stopped altogether. The preceding findings and arguments imply that adding information on group level performance could be useful for bankruptcy prediction purposes. Specifically, strong group performance should positively affect the survival chances of subsidiaries.

Falling sales might be a sign that there might be something wrong with the product or the price or some other aspect of the marketing mix. Sometimes, the fall in sales might be as a result of the competition providing a better product or service - in part the business can do something about this, but they have to recognise it in the first place (Moyer, 2006).

Changing tastes, technology and fashion can cause demand for products to fall – the business needs to be aware of these trends. Demand might fall for other reasons not in the firm's control. It might be due to a change in the economic climate of the country. If the economy is experiencing a downturn, then maybe people may not have as much money to spend on the businesses products or services. The central bank of the country may have increased interest rates and this may have led to people cutting back their spending (Sipika & Smith, 2002).

2.3.3. Leverage

High firm leverage may be less important for the survival chances of group member companies as compared to those of stand-alone firms. Hoshi et al. (1990) argue that the costs arising from information asymmetries at debt renegotiations are smaller within business groups. These decreased potential costs of financial distress allow group members to *ex ante* take on more debt, thus realising more tax gains and avoiding relatively expensive equity issues (Myers & Majluf, 1984). A coinsurance effect across activities in diversified groups could further decrease costs of debt, but according to Berger and Ofek (1995), this should be of rather limited importance.

Moreover, an intra-group optimisation process may take place via the internal capital market to reduce costs at all levels (Faccio et al., 2001; Bianco & Nicodano, 2002), again increasing *ex ante* optimal leverage. Finally, the subsidiary may also receive intragroup debt guarantees which could increase debt bearing capacity even more. Many new businesses will have to put together a business plan to present to the bank before it receives loans or financial help. The time and effort put into these plans is crucial for success. Bad planning or poor information on which the plan is based is likely to lead to difficulties for the firm. For example, if the firm plans to sell 2,000 units per month in the first year, because it used only limited market research and ends up only selling 500 per month, it will soon be in serious danger of failling (Chiritou, 2002).

2.3.4. Size

Ceteris paribus, larger companies have a higher capacity to bear debt throughout difficult business periods and should have a lower risk of failure (Rajan & Zingales, 1995). Because of the close ties between the different group members, group size may better measure the size effect than the size of the subsidiary proper. This is empirically confirmed by, for instance, Manos and Green (2001). These authors find that the size of Indian group affiliates has no impact on their capital structure, but that group size does. Belonging to a – preferably large - business group may also have other non-quantifiable beneficial effects: the group's reputation may change perception and the behaviour of banks and other creditors, thus increasing access to external finance in times of need (Schiantarelli & Sembenelli, 2000).

2.3.5. Efficiency

Following Altman (1968), managerial efficiency in the bankruptcy prediction literature is often defined as sales-generating ability (proxied by a capital turnover ratio). *Ceteris paribus*, the more efficient a business group, the better its performance. As argued above, this may have positive effects on the survival chances of the subsidiary. Costs of production can rise for a number of reasons. There may have been wage rises, raw material prices might have increased (for example, the price of oil or gas), the business might have had to spend money on meeting some new legislation or standard, and so on. In many cases, a firm can plan for such changes and is able take them into account, but if the costs rise unexpectedly, this can catch a firm off guard and tip them into insolvency (Kip, 2002).

2.4. INDIGENISATION THEORIES OF CULTURE TRANSPLANTATION

Management has a vital role in the success or failure of a business given there day to involvement in the management of an organisation (Fuller and Shikaloff, 2016). With the JSE being in South Africa management in Africa plays an important role in this study. Scholarly conceptualisation from Europe and the United States of America concerning management in Africa have tended to disparage its development, creating some binary management systems of “developed” western management theories and concepts and “underdeveloped” African management thoughts. Gbadamosi (2003: 274) aptly notes that: “Western management concepts and writings have dominated the thinking of academics and managers in Africa for a long time. Such writings have not shown how culture might be taken into account in managerial practice”.

Any management education programme that facilitates the entrenchment of western management theories and practices in Africa is not desirable. According to Fashoyin (2005: 45), the desire for training “must enable the African manager to transform imported theories and concepts into acceptable cultural norms which can then be applied to management practices in Africa”. This can further create the opportunity for the development of indigenous African management principles and practices, which will recognise and accommodate our cultural social, political and environmental factors.

2.4.1. Extant knowledge of management in Africa

Management as a human responsibility and a process that drives economic development and activities is as old as human civilisation or history. Africa, as part of the global community, has existed in her own unique ways and unique cultures and managed the environment consistently throughout history. The quiet of this environment was extensively disrupted in the 19th century when the Europeans scrambled for and partitioned Africa. This marked the beginning of colonialism in Africa where the people's thought processes and cultures were altered through western "civilization" influences. African management thought was a major victim of these western influences. Unfortunately, despite the acknowledgement of the existence of such high-level management skills in Africa, management, as practiced in Egypt, was tagged "prescientific", a connotation of uncivilised management practice. Even though the Egyptian management accomplishments were significant and remembered today, "they provided limited information about how to actually manage" according to Bartol and Martin (1991: 41). The authors went further to distinguish between management practice and management knowledge by stating: "Thus there is a major difference between practicing management well and adding to knowledge about the field of management so that others also can learn to manage" (Bartol & Martin, 1991:41).

Formal treatment of the history of management theories and practices among western scholars are wont to trace their provenance to classical theories and scientific management theory or Taylorism (Youngcourt & Watrous, 2006; Yoo, Lemak & Choi, 2006). These textbooks and publications make no reference to other great ancient civilisations in Africa like Timbuktu, Songhai, Empire of Mali, and Mapungubwe (Diop,1987). The composite effect of colonialism and the disparagement of scholarship in management is the denial of the African management system, and the continuing subjugation of African management to western management theories and practices.

2.4.2. Management Principles

Building a case for African management theories and practices, As to be applied to JSE listed companies requires one to understand the principles. The principles of management enhance the individual's understanding of what management entails, and also prepares him for the task of analysing management issues and appreciating their values in society. Principles in management are considered as fundamental truths existing at a given time, and which explain the relationships that exist between two or more sets of variables. Principles are intended to guide thoughts and actions. They are developed from experience acquired through our interaction with the environment in the normal course of working, and carrying out responsibilities in an organisational setting.

There are several of these principles of management in western management literature, for example, Fayol’s (1949) fourteen principles of management. The African situation is rather unfortunate since colonialism did not permit the nurturing of indigenous management principles. If these principles had been developed, they would have furnished the framework for theorising in management, within the African context. The benefits of developing African management principles would be the promotion of research in management. The principles would also help in the attainment of social objectives (Jaja & Zep-Obipi, 1992). Through the application of principles, the manager co-ordinates the efforts of individuals, thereby reaching the social attainment by summation of the various individual objectives. Principles facilitate management analysis and set the benchmark for the training of managers. Osuala (2000) notes the value of management principles in helping managers make more accurate decisions, since principles are developed from experience and can be applied. Principles enable people to pass information from one generation to the next and thus avoid re-inventing the wheel.

2.4.3. Management Theories

Management theory increases managerial efficiency by providing the guidelines to help the managers solve problems in the organisation. The theory also helps in crystallising the nature of management – in terms of analysing management jobs and the training of managers. Management theory formulation brings about improvements in research and management practice, leading logically to the attainment of social goals and human development. Porth and Mccall (2001) note that management theories emphasise the importance of an organisation’s ability to acquire and leverage knowledge that produces meaningful change and innovation.

A related concept to management theory that needs clarification for our purpose is organisation theory. Organisation theory, as a discipline, studies the structure and design of the organisation. It explains, “how organizations are actually designed and suggests the appropriate structural design to improve organizational effectiveness” (Robbins, 1983:7). Organisation theory is therefore the study of the structure and functioning of organisations and the behaviour of social groups and individuals within them (Pugh, 1966). The central concern here is with people who are aggregated into departments and organisations - both recognising differences in structure and behavioural differences.

Organisation theory as a way thinking about the organisation is different from management theory. Organisation theory is considered as a set of variables describing the parameters of organisation. It attempts to predict the effect of certain structural arrangements on performance and behaviour (Rao & Narayana, 1998). On the other hand, management theory is interested in facts and sound principles, which prescribe what to do to achieve the desired outcome in the organisation (Daft,1986). Management theory is therefore related to management practice.

2.5. METHODS OF APPLIED THEORY TO PREDICTING BUSINESS FAILURE

2.5.1. De La Rey (1981)

De La Rey developed a model using financial information on twenty-six pairs of failed and non-failed South African listed companies, with the failed companies taken from the 1972 to 1979 period. Unlike Altman’s Z-score model which used “Market value of Equity / Book value of Total Debt” as a variable, implying its use only on listed companies, the De La Rey model could be used for both listed and unlisted companies. By using Multiple Discriminant Analysis (MDA) and twenty-five variables, the following model was developed (Naidoo, 2006: 32):

$$k = -0.01662a + 0.0111b + 0.0529c + 0.076d + 0.0174e + 0.01071f - 0.068811$$

Where,

a = Total Outside Funding / Total Assets x 100

b = EBIT / Average Total Assets x 100

c = (Total Current Assets+Listed Investments) /Total Current Liabilities

d = PAT / Average Total Assets x 100

e = Cash flow Profit after Tax / Inflation adjusted Total Assets x 100

f = Inventory / Inflation adjusted Total Real Assets x 100

A K-score < -0.19 implies potential failure, with a K-score > 0.20 implying a "Healthy" company and a zone of ignorance exists between a score of -0.19 and +0.20 implying that a company cannot be classified as either "Healthy" or "a candidate for potential failure". The model was found to classify companies as either "Healthy" or "Likely to Fail" with a 96% overall accuracy one year prior to failure. This model forms part of the INET BFA financial analysis service.

2.5.2. Traditional Ratio Analysis

The detection of company operating and financial difficulties is a subject which has been particularly amenable to analysis with financial ratios. Prior to the development of quantitative measures of company performance, agencies were established to supply a qualitative type of information, assessing the credit-worthiness of particular merchants. One of the classic works in the area of ratio analysis and bankruptcy classification was performed by Beaver (1967). According to Beaver (1967), a number of indicators could discriminate between matched samples of failed and non-failed firms as early as five years prior to failure. The study implies a definite potential of ratios as predictors of bankruptcy. In general, ratios measuring profitability, liquidity, and solvency prevailed as the most significant indicators. However, the order of their importance is not clear since almost every study cited a different ratio as being the most effective indication of impending problems.

Grunert et al. (1997) pointed out that although these works established certain important generalisations regarding the performance and trends of particular measurements, the adaptation of the results for assessing bankruptcy potential of firms, both theoretically and practically, is questionable. In almost every case, the methodology was essentially univariate in nature and emphasis was placed on individual signals of impending problems. According to Altman (1981), ratio analysis presented in this fashion is susceptible to faulty interpretation and is potentially confusing. For instance, a firm with a poor profitability or solvency record may be regarded as a potential bankruptcy. However, because of its above average liquidity, he points out that the situation may not be considered serious. The potential ambiguity as to the relative performance of several firms is clearly evident. Altman further argues that the question that will eventually have to be asked on the use of ratios in predicting corporate failure is on which ratios are most important in detecting bankruptcy potential as well as determining what weights should be attached to those selected ratios.

2.5.3. Discriminant Analysis

Although not as popular as regression analysis, multiple discriminant analysis (MDA) has been utilised in a variety of disciplines since its first application in the 1930's. During those earlier years, MDA was used mainly in the biological and behavioural sciences. Altman et al. (1981) discuss discriminant analysis in-depth and review several financial application areas. According to Altman (1981), MDA is a statistical technique used to classify an observation into one of several *a priori* groupings, dependent upon the observation's individual characteristics. It is used primarily to classify and/or make predictions in problems where the dependent variable appears in a qualitative form, for example, male or female, bankrupt or non-bankrupt. Therefore, the first step is to establish explicit group classifications.

Some analysts refer to discriminant analysis as "multiple" only when the number of groups exceeds two. After the groups are established, data are collected for the objects in the groups; MDA, in its simplest form, attempts to derive a linear combination of these characteristics which "best" discriminate between the groups. If a particular object, for instance, a corporation, has characteristics (financial ratios) which can be quantified for all of the companies in the analysis, the MDA determines a set of discriminant coefficients. When these coefficients are applied to the actual ratios, a basis for classification into one of the mutually exclusive groupings exists. The MDA technique has the advantage of considering an entire profile of characteristics common to the relevant firms, as well as the interaction of these properties. A univariate study, on the other hand, can only consider the measurements used for group assignments one at a time.

2.5.4. Logistic Regression Analysis

There are five financial ratios that can give an indication on the likelihood of a company failing or facing financial distress. These ratios include current asset turnover; asset turnover; day's sales in receivables; cash flow to total debt from cash flow ratio group; and total liabilities to total assets from debt ratio. The asset turnover ratio measures the firm's efficiency at using its assets to generate sales or revenue and it has a negative correlation with the dependent variable in this study. This means that the higher the asset turnover ratio, the lower the probability of a firm going into financial distress. This is because when a company is productive in generating sales or revenue; there will be a higher level of cash inflows into the particular company, reducing the risk of falling into financial distress. The asset turnover variable is found to be a significant ratio in Altman (1968) and Lavallee's (1981) failure prediction research. Days sales in receivables is another significant variable, as it is reflected through the average number of days that a firm takes to collect revenue after a sale has been made. The faster revenue is collected, the faster it can be used to settle debts. As such, liquidity of the firm is higher lowering the probability of a firm to fall into financial distress. This demonstrates a positive relationship with the dependent variable; the lower the day's sales in receivables ratio, the lower the chances of corporate failure.

Cash flow to total debt ratio is negatively correlated to the probability of a firm going into financial distress. Cash flow to total debt ratio is found to be significant in Westgaard and Van der Wijst (2001). This means that the higher the ratio, the lower the probability of a firm to fall into financial distress. If a firm has more earnings than its liabilities, it will be less likely to face bankruptcy. The total liabilities to total assets ratio is another significant financial ratio and it has a positive relationship with the probability of a firm going into financially distress. The higher the ratio, the higher the probability of a firm falling into financial distress as a company with more debt than assets is more likely to fail. This is consistent with the results reported by Nur Adiana et al. (2008).

Altman set out to combine a number of ratios and developed an insolvency prediction model - the Z–Score model. This formula was developed for public manufacturing firms and eliminated all firms with assets less than $1 million. This original model was not intended for small, non-manufacturing, or non-public companies, yet many credit granters today still use the original Z-score for all types of customers as we do this study. Two further prediction models were formulated by Altman (sometimes referred to as model 'A' and model 'B') to the original Z score (Altman, 1968).

Altman's 1968 model took the following form:

$Z = 1.2A + 1.4B + 3.3C + 0.6D + 0.999E$……………………………..Eq (1)

When, $Z < 2.675$; then the firm is classified as "failed"

Where:

A = Working Capital/Total Assets

B = Retained Earnings/Total Assets

C = Earnings before Interest and Taxes/Total Assets

D = Market Value of Equity/Book Value of Total Debt

E = Sales/Total Assets

Rather than simply inserting a proxy variable into an existing model to calculate the Z scores, Altman advocated for a complete re-estimation of the model, substituting the book values of equity for the Market value in D. This resulted in a change in the coefficients and in the classification criterion and related cut-off scores. The revised Z score model took the following form:

$$Z' = 0.717T1 + 0.847T2 + 3.107T3 + 0.420T4 + 0.998T5 \ldots\ldots\ldots\ldots\ldots\ldots Eq\ (2)$$

Where:

T1 = (Current Assets-Current Liabilities) / Total Assets

T2 = Retained Earnings / Total Assets

T3 = Earnings before Interest and Taxes / Total Assets

T4 = Book Value of Equity / Total Liabilities

T5 = Sales/ Total Assets

Zones of Discrimination:

$Z' > 2.9$ - "Safe" Zone

$1.23 < Z' < 2.9$ - "Grey" Zone

$Z' < 1.23$ - "Distress" Zone

T1: Working Capital/Total Assets (WC/TA).

The working capital/total assets ratio, frequently found in studies of corporate problems, is a measure of the net liquid assets of the firm relative to the total capitalisation. Working capital is defined as the difference between current assets and current liabilities. Liquidity and size characteristics are explicitly considered. Ordinarily, a firm experiencing consistent operating losses will have shrinking current assets in relation to total assets and therefore the working capital ratio is valuable in predicting a firm's propensity to go under. Two other liquidity ratios tested were the current ratio and the quick ratio. These were found to be less helpful and subject to perverse trends for some failing firms.

T2: Retained Earnings/Total Assets (RE/TA).

Retained earnings is the account which reports the total amount of reinvested earnings and/or losses of a firm over its entire life. The account is also referred to as earned surplus. It should be noted that the retained earnings account is subject to "manipulation" via corporate quasi-reorganisations and stock dividend declarations.

While these occurrences are not evident in this study, it is conceivable that a bias would be created by a substantial reorganisation or stock dividend and appropriate readjustments should be made to the accounts. The age of a firm is implicitly considered in this ratio. For example, a relatively young firm will probably show a low RE/TA ratio because it has not had time to build up its cumulative profits. Therefore, it may be argued that the young firm is somewhat discriminated against in this analysis, and its chance of being classified as bankrupt is relatively higher than that of another older firm, *ceteris paribus*.

T3: Earnings Before Interest and Taxes/Total Assets (EBIT/TA).

This ratio is a measure of the true productivity of the firm’s assets, independent of any tax or leverage factors. Since a firm’s ultimate existence is based on the earning power of its assets, this ratio appears to be particularly appropriate for studies dealing with corporate failure. Furthermore, insolvency in a bankrupt sense occurs when the total liabilities exceed a fair valuation of the firm’s assets with value determined by the earning power of the assets. This ratio continually outperforms other profitability measures, including cash flow.

T4: Market Value of Equity/Book Value of Total Liabilities (MVE/TL)

Equity is measured by the combined market value of all shares of stock, preferred and common, while liabilities include both current and long term. The measure shows how much the firm’s assets can decline in value (measured by market value of equity plus debt) before the liabilities exceed the assets and the firm becomes insolvent. It also appears to be a more effective predictor of bankruptcy than a similar, more commonly used ratio; net worth/total debt (book values). At a later point, we will substitute the book value of net worth for the market value in order to derive a discriminant function for privately held firms (Z’) and for non-manufacturers (Z”). More recent models, such as the KMV approach, are essentially based on the market value of equity and its volatility. The equity market value serves as a proxy for the firm's asset values.

T5: Sales/Total Assets (S/TA).

The capital-turnover ratio is a standard financial ratio illustrating the sales generating ability of the firm’s assets. It is one measure of management’s capacity in dealing with competitive conditions. This final ratio is quite important because it is the least significant ratio on an individual basis. In fact, based on the univariate statistical significance test, it would not have appeared at all. However, because of its unique relationship to other variables in the model, the sales/total assets ratio ranks second in its contribution to the overall discriminating ability of the model. Still, there is a wide variation among industries in asset turnover, and we will specify an alternative model (Z”), without X5 at a later point.

2.6. MODERN RESEARCH IN PREDICTING BUSINESS FAILURE

Litschutz and Jacobi (2010) conducted a study to investigate whether it is possible to rely on two versions of the Altman Model (1968) to predict financial failure of publicly traded companies in Israel between 2000 and 2007. The findings of the study indicated that, given the sample and the study term, the preferable model for predicting financial failure of Israeli companies is the Ingbar version of the Altman Model with a critical value of 1 and with the addition of the grey area. In particular, a survival index above 1 predicts a high likelihood of survival, while a lower index predicts low likelihood of survival. According to the study, the model was able to predict bankruptcy of companies with a 95% accuracy rate, one year prior to bankruptcy and with an 85% accuracy rate two years prior to bankruptcy. The study noted that the Altman Model is only a single tool in evaluating the risk of bankruptcy for companies and therefore other information, both qualitative and quantitative, must be used to evaluate the solvency of companies. This is done in the banking industry as part of managing and controlling credit risks. They concluded that the most important advantage of the model compared to more advanced ones, is its simplicity and the low cost of its application.

Using an objective, quantitative indicator represented by a single number, the credit risk can be estimated. They believed the issue to be of great importance now, in light of the significant growth in recent years in the amount of information companies include in financial statements. The model allows users to focus attention on a single number in an era when we are "flooded" with financial information, when we “cannot see the forest for the trees". Gerantonus, et al. (2008) carried out a study of all firms listed on the Athens exchange using Altman’s (1993) Z-score model and evidence from findings indicated that the model was useful in identifying financially troubled companies that may fail up to two years before bankruptcy, the model is useful, probably because it matches both accounting data and market value. The model predicted 54% of failure of companies one year before failure.

The results were interesting for both portfolio managers and company management. If companies have the abilities to improve their financial position during good years in capital markets, while being unable to improve them in the long run, then Altman Z scores are useful indications to the company management to proceed to a merger with other companies or be acquired, in order to preserve the company’s value. Ghodrati, et al. (20012) carried out research on the efficiency of the Altman, Shirata, Ohlson, Zmijewsky, CA Score, Fulmer and Farajzadeh Gentitie and McGkee Genetic models, in terms of providing accurate prediction results, and compared the efficiency and predictive results of these models with each other and determined the power of these models, in predicting the bankruptcy of these companies admitted to the stock exchange of Tehran. The results of tests of the first hypothesis showed that the Zmijewsky, Springate, CA. Score, Farajzadh Genetic and McGkee Genetic models used to predict financial distress are sufficiently able to predict continuation of activities of those companies admitted to the stock exchange of Tehran. The second hypothesis was also confirmed and it was proven that those models developed by artificial intelligence techniques were more capable than those developed by statistical techniques (Classical models) in terms of bankruptcy prediction.

2.7. CURRENT PREDICTION MODELS

Generally, the bankruptcy prediction models can be categorised into three categories namely; statistical models, artificial intelligent expert system models (AIES) and theoretical models. Statistical models focus on symptoms of failure that are drawn mainly from the company financial statements and could be univariate or multivariate in nature. Thus, they follow the classical standard modelling. The artificial intelligent expert system model is as a result of technological advances and international advances and depends heavily on computer technology. A recent trend in the bankruptcy prediction models is the theoretical based model which focuses mostly on the qualitative causes of failure. It is drawn mainly from information that could satisfy the theoretical argument of firm failure. The method usually adopts a statistical technique to provide a quantitative support to theoretical arguments.

Under the statistical models of corporate failure, the probit model advanced by Morris (2008) is considered a recent model in which the dichotomous dependent of logit model is the logarithm of odds (probability) that an event of (fail/not fail) will occur. Such transformation of the linear probability model (LPM) is accomplished by replacing the LPM distribution, with a logistic distribution cumulative function of a vector of explanatory variables. In application to bankruptcy, a probability of 0.5 implies an equal chance of company failure or non-failure. Therefore, where 0 indicates bankruptcy, the closer the estimate is to 1 the less the chance of the firm becoming bankrupt. Cumulative Sum Control Chart (CUSUM) procedures are among the most powerful tools for detecting a shift in a distribution from one state to another. In the case of bankruptcy prediction, the time series behaviour of the attribute variables for each of the failed and non-failed firms is estimated by a finite order VAR model (Kahya & Theodossiou, 2009).

The overall performance of the firm at any given point in time is assessed by a cumulative (dynamic) time-series performance score (a CUSUM score). As long as a firm’s time-series performance scores are positive and greater than a specific sensitivity parameter, the CUSUM score is set to zero, indicating no change in the firm’s financial condition. A negative score signals a change in the firm’s condition. Neural networks (NN) (Yang et al., 1999) perform classification tasks in a way intended to emulate brain processes. The ‘‘neurons’’ are nodes with weighted interconnections that are organised in layers. Each node in the input layer is a processing element that receives a variety of input signals from source objects (information about firms, in the case of bankruptcy prediction) and converts them into a single output signal. The latter is either accepted as a classifying decision, or re-transmitted as an input signal to other nodes (possibly including itself). Signal processing continues until a classifying decision is reached (with some probability, the firm will fail) that satisfies pre-specified criteria.

Genetic algorithms (GA) (Shin & Lee, 2002) are based on the idea of genetic inheritance and the Darwinian theory of natural evolution (survival of the fittest). The genetic algorithms work as a stochastic search technique to find an optimal solution to a given problem from a large number of solutions. It executes this search process in three phases: genetic representation and initialisation, selection, and genetic operation (crossover and mutation). The process continues until the actual population converges towards increasingly homogeneous strings. In order to solve a classification problem like bankruptcy, researchers extract a set of rules or conditions using GAs. These conditions are associated with certain cut-off points. Based on these conditions, the model would predict whether or not a firm is likely to go bankrupt.

However, studies show that the statistical techniques (MDA and Logit models in particular) have been most frequently used, while the AIES approach is relatively new, and that theoretical models are relatively uncommon. While predictive accuracy is observed to be generally good across all models, it also suggests that AIES and theoretical models have slightly better average predictive accuracy than statistical models, although this measured superior performance is based on a smaller number of studies. On the other hand, the consistently high predictive accuracy of MDA and Logit models and their low Type I and II error rates has been achieved in a relatively large number of studies (with smaller adjusted standard deviations), suggesting that these models may provide overall, the most reliable methods of bankruptcy prediction.

2.8. SUMMARY OF THE CHAPTER

The concept of business/corporate failure has been explained and its causes and effect on businesses' operations in both existing literature and empirical research conducted on the subject matter. To zero in, a number of models have discussed each model used to predict the company failure for various enterprises. The significance of selecting a useful model to precisely predict the failure of business was emphasised in the discussion due to the severe costs that a failed business will confront. As an alternative, the literature suggests a number of corporate failure models without necessarily suggesting an appropriate model for a given circumstance.

CHAPTER 3: RESEARCH DESIGN AND METHODOLOGY

3.1. INTRODUCTION

The previous chapter entailed detailed insight of the extant literature. This chapter explains the research design and methodology on how the data was gathered and analysed from the target population. In order to explain the research design, the target population, the selection of the sample, the secondary data used, the sources of data, the methods of analysis employed on data analysis are discussed in detail in this unit.

3.2. RESEARCH STRATEGY

3.2.1. Research philosophy – positivism

This study uses a positivism research philosophy through application of a deductive reasoning approach. The positivist research philosophy implies that there is ultimately a single objective reality to any research situation, regardless of the view of the researcher and that the universe follows laws of causation that are typically permanent and rigid (Aliyu, Bello, Kasim & Martin, 2014). Essentially, the goal of the positivist researcher is to make generalisations that are time and context free, using rational and logical approaches to research, otherwise known as a scientific method (Aliyu, et al., 2014). A potential problem resulting from deductive reasoning is that the certainty of the conclusions formed, is based ultimately on the overall certainty of the principle around which the study revolves (Walliman, 2011).

3.2.2. Research design

A research design basically shapes how a study will be undertaken and this involves how the information shall be gathered, by which tools, and how they will be used to collect the information that will be analysed (Creswell & Poth, 2017). Furthermore, the research design provides a framework for the gathering and analysis of information and as a result, implies which research methods are the most suitable (Walliman, 2011). There are three chief research designs: causal research, descriptive research and exploratory research, where causal and exploratory research more commonly involves quantitative data and exploratory research primarily involves the use of qualitative data (Creswell & Poth, 2017).

The research used a cross-sectional study in which data was gathered between the years 2014 to 2017. As such, the study was undertaken in a non-contrived setting with no researcher interference. The unit of analysis was the individual JSE suspended and delisted firms. This study used the secondary data of the published financial statements of JSE listed companies.

3.3. SAMPLING DESIGN PROCEDURE

According to Lohr (2009:32), the sampling process is defined as “the procedure required to determine which part of the population will be used in the study ranging from defining the target population to the physical selection of the appropriate sample elements”. In addition, Creswell and Poth (2017) note that the sampling process is comprised of four interrelated steps: defining the target population; identifying the sampling frame; determining the sampling method and determining the sampling size.

3.3.1. Target population

Greenland (2005:276) refers to the target population as “the population about which information is wanted”. In addition, Banerjee and Chaudhury (2010) defined target population as that from which the sample is selected suitably. For this study, the target population was restricted to all suspended and delisted companies between the period of 1 January 2014 and 31 December 2017. It was then determined as to whether or not these companies were suspended or delisted because they failed and were either placed under business recuse or liquidation. This was determined by reviewing each individual company’s published news on the Stock Exchange News Service (SENS) of the JSE which will state why the company has been suspended or delisted and whether it has been placed under business rescue or liquidation. These companies were then grouped by sector, as classified by the JSE, and one corresponding control company within the same sector with similar operations, or the closest such comparable company, with such control companies being fully functional and in operation.

3.3.2. Sample frame and sampling method

The sampling frame is said to warrant that there is some probability of selection for each element in the target population and is hereby defined as “the portion of the population from which the sample was selected” (Warnecke, 2005). The sampling frame for this study was JSE listed companies. In order to obtain a representative sample from the population, a number of filters were applied. Observations of firms with anomalies such as negative values in their total assets, current assets, fixed assets, capital, depreciation or the interest paid were eliminated. In addition, only firms that had continuously operated over the period January 1, 2014 to December 31, 2017 were considered in the study. Further, observations of items from the balance sheet, and profit and loss statement showing signs contrary to reasonable expectations were removed.

3.4. DATA COLLECTION

This study used secondary or archival data (publicly available data) from audited financial reports and from Profile Data’s Sharemagic, Morningstar’s free web based database and Sharenet’s free web based database for the period 2014 to 2017. The advantages of secondary data may include: time and money saving, accessibility and availability, feasibility and the generation of new insights, especially to cover gaps and deficiencies and provides a basis for comparison from year to year when it may be the only means to research the past (Bryman & Bell, 2015; Zikmund et al., 2013). Audited financial reports are examinations of an entity’s financial statement and accompanying disclosures by independent auditors. From the audited financial reports, the following statements were examined: statement of financial position, statement of profit or loss and other comprehensive income, and the cash flow statement to assess the financial health of companies. As per the JSE's Listing Requirements, a company has to publish results twice a year and the results include information such as the statement of financial position, statement of profit or loss and other comprehensive income, and the cash flow statement which are all freely available for use by all stakeholders (JSE, 2018).

The financial statements used were the latest audited financial statements available before the company's failure. Unaudited financial statements were not utilised. Audited and unaudited financial statements contain the same types of financial information. An auditor nonetheless examines a company's financial data and reporting methods to determine accuracy and compliance with reporting standards which, for the JSE, are the International Financial Reporting Standards (IFRS). If the financial statements meet the IFRS standards, the auditor attaches a report to that effect to the company financial statements (Thomas, 2017). On the other hand, unaudited financial statements lack this testing and certification and may thus be materially misstated and consequently lack reliability (Thomas, 2017). It is for this reason that audited financial statements were used as a secondary source of data for this study.

To determine the failed companies on the JSE between 1 January 2014 and 31 December 2017, a list of all suspended companies between 1 January 2014 and 31 December 2017 was provided by Profiledata from Sharemagic and utilised. Further, all delistings that occurred on the JSE between 1 January 2014 and December 2017 as extracted from Profiledata's Sharemagic database was also utilised.

From this combined data set, it was determined which of these companies either:

i. Applied for or went into business rescue, and/or
ii. Applied for or went into liquidation, or

The determination was performed by researching each of the companies around the time of the suspension by using the Stock Exchange News Services. The JSE offers a service that provides the user with access to company announcements such as mergers, take-overs, suspensions, delisting's, rights offers, capital issues, cautionary notes, all of which have a direct impact on the movement in the market. This service is called the Stock Exchange News Service (SENS) (JSE, 2018).

3.5. DATA ANALYSIS

This data was loaded onto an Excel spreadsheet then analysed using Microsoft Excel 16. The entire population of 25 failed companies and each sector's control company were tested using the latest available audited financial statements.

Income Statement – now known as the Statement of Profit or Loss and Other Comprehensive Income (SPL),

i. Balance Sheet – now known as the Statement of Financial Position (SFP), and
ii. the Cash-Flow statements

The financial statements were extracted from Sharemagic, Morningstar, Sharenet and the individual companies' websites where they are freely available. For the entities that are still operational, the market capitalisation, as is needed to determine the Altman Z-score, was obtained from Sharemagic.

This data was transferred into Microsoft Excel with the Altman Z-score and the De la Rey K-scores calculated by applying the respective Altman Z-score and De la Rey K-score formulas. The data analysis was done through the use of Microsoft Excel. The following dates, which are crucial in the study, were obtained from Sharemagic and Sharenet:

iii. suspension dates,
iv. delisting dates, and
v. date on which audited annual financial statements are released and are available for use to all stakeholders.

These dates were then used to determine the latest available audited annual financial statements released on or before the suspension date to determine whether the Altman Z-score or de la Rey K-score models would have predicted such failure using such audited annual financial statements and how many days after the release of such audited annual financial statements did the company fail i.e. how early would these models have been able to predict the failure.

3.5.1. Altman Z (1968)

The Altman Z score is computed using the following formula as developed by Altman:

Z = 1.2A + 1.4B + 3.3C + 0.6D + 0.999E

Where:

A = Working Capital/Total Assets

B = Retained Earnings/Total Assets

C = Earnings before Interest and Taxes (Operating Profit)/Total Assets

D = Market Value of Equity (MVE)/Book Value of Total Debt

E = Sales/Total Assets

A - Working capital (WC)/Total Assets (TA)

This formula considers and rates the liquidity of the company with liquidity considered to be a contributing factor to financial distress or failure (Altman, 2000). The working capital was calculated as a company’s current assets less its current liabilities from the SFP of the company being analysed. The total assets were the total assets per the assets section on the SFP.

B - Retained earnings (RE)/Total Assets (TA)

Retained earnings in this case are a measure of a particular company’s profit reinvested in the same company over its life as a company (Altman, 2000) with the balance of the investment in the company being sourced through debt, such as loans. Altman (2000) cautioned that retained earnings’ figures could be distorted by, amongst other things, debt to equity conversion in which a particular debt of a company is converted, usually to the rand value equivalent of equity and dividend pay-outs.

Retained earnings over total assets as a ratio indicates the financial leverage of a company.

C - Earnings before Interest and Taxes (Operating Profit)/Total Assets (TA)

Operating Income/EBIT/Earnings Before Interest and Taxes is autonomous of any taxes or leveraging (debt) factors with the formula quantifying the true efficiency of a company's assets by measuring the earning power of these assets i.e. all the company's assets (Altman, 2000).

D - Market Value of Equity (MVE)/Book Value of Total Debt (Total Liabilities)

The Market Value of Equity (MVE) used was the market capitalisation of the company as determined by the JSE on the date of the financial year end corresponding with the financial statements. This was divided by the total book value of the company's debt in order to indicate or show how much the company's assets might have dropped in worth before the liabilities exceeded the assets and the company failed financially (Altman, 2000). For the failed companies, the share capital and share premium accounts were utilised as a proxy for the market value due to the scarcity of the market data being available. Share capital account on the balance sheet consists of all funds raised by a company in exchange for the shares of such company. This is accounted for at cost. A share premium account is typically listed on a company's balance sheet for money paid, or promised to be paid, by shareholders for shares over and above the cost of such shares (Investopedia, 2018).

As these were shares issued to the market, they served as a fair proxy for the market value of equity in the absence of a market capitalisation figure and this was utilised across the entire failed company population.

3.5.2. De la Rey K-score determination:

The De La Rey K-score is calculated using the following formula:

$$K = -0.01662A + 0.0111B + 0.0529C + 0.086D + 0.0174E + 0.01071F - 0.068811$$

Where:

K = overall index

A = (total outside financing / total assets) x 100

B = (income before interest and tax) / average total assets) x 100

C = total current assets and listed investments / total current liabilities

D = (income after tax / average total assets) x 100

E = (net cash flow / average total assets) x 100

F = (stock / inflation adjusted total assets) x 100

A - Total outside financing/Total Assets

This formula was used as a measure of the companies gearing or how much debt the company had taken on in comparison to using internal funds. This excluded preference shares when computing the total outside financing.

B - Income before interest and taxes/average total assets

This is similar to C in the Altman Z(EM) formula and measures the earning strength of a company's assets. Average assets are calculated as the average between the previous year and the current financial year (12 months) or the previous year plus the current year with the sum divided by two.

C - Total current assets and listed investments/total current liabilities

This is a modified liquidity ratio to measure the liquidity of the company with current assets modified to include listed investments, an inclusion that was deemed pertinent by De la Rey as most of these were classified under non-current assets despite their high liquidity as they traded on stock exchanges.

D - Income after Tax/Average Total Assets

This divides the Profit after Tax by the Average Total Assets. Average Total Assets were calculated as follows - (Current Financial Year Total Assets + Previous Financial

Year Total Assets) / 2. This ratio, Income after Tax/Average Total Assets, measured the net profit generating ability of a company's assets after tax.

E - Net Cash flow/Average Total Assets

This measures a company's assets' ability to generate cash by ignoring non-cash items such as depreciation and including non-income statement, but operational items such as changes in working capital. Average Total Assets were calculated as follows - (Current Financial Year Total Assets + Previous Financial Year Total Assets) / 2.

F - Stock/Inflation Adjusted Total Assets

Stock is the inventory on hand and this ratio measures how much of the company's assets are held as inventory. Reeves (2001) explained the figure at the end of the formula is the statistical point of separation between failed and non-failed firms and is seen as zero i.e. 0.06881.

3.6. CHAPTER SUMMARY

This chapter presented the research design and methodology process that was taken in achieving the main aim of study. It provided a detailed discussion of the research design, followed throughout the entire research journey. Furthermore, the sampling strategy, sample frame and sampling procedures were explained. The data collection methods or methods used for the study were discussed in detail, followed by the data analysis of the data and reports on the findings of the empirical research.

CHAPTER 4: PRESENTATION OF RESULTS

4.1. INTRODUCTION

The preceding chapter covered the research design and methodology process. A detailed description of the target population, the sample selection. as well as data collection and statistical analysis was provided. The fourth chapter of this thesis contains the presentation of the obtained data. The subsequent sections focus on the population of JSE listed failed companies; results of Altman Z-Score; and results of De La Rey K-score; the practical applicability of Altman's (1968) Z-score and De la Rey's (1981) K-score failure prediction models to failed JSE listed companies between the periods of 1 January 2014 to 31 December 2017. Moreover, most of the results in the current chapter are presented in a tabular format.

4.2. RESULTS PRESENTATION

4.2.1. Sample of JSE listed failed companies.

In table 4.1 are the 25 companies that were determined to have failed from the suspended and delisted JSE listed companies between 1 January 2014 and 31 December 2017.

Table 4.1: JSE listed failed companies.

#	Company name	Symbol	Short Name	Sector	Number of companies in Sector	As a % of total companies	Status
1	Awethu Ltd.	AWT	AWETHU	Beverages	1	4%	Failed
2	Chemical Specialities Ltd.	CSP	CHEMSPEC	Chemicals	1	4%	Failed
3	Protech Khuthele Holdings Ltd.	PKH	PROTECH	Construction & Materials	7	28%	Failed
4	Masonite (Africa) Ltd.	MAS	MASONITE	Construction & Materials			Failed
5	Africa Cellular Towers Ltd.	ATR	ACTOWERS	Construction & Materials			Failed
6	Sea Kay Holdings Ltd.	SKY	SEAKAY	Construction & Materials			Failed

7	Sanyati Holdings Ltd.	SAN	SANYATI	Construction & Materials			Failed
8	Pinnacle Point Group Ltd.	PNG	PINPOINT	Construction & Materials			Failed
9	Erbacon Investment Holdings Ltd.	ERB	ERBACON	Construction & Materials			Failed
10	StratCorp Ltd.	STA	STRATCORP	Financial Services	1	4%	Failed
11	Ububele Holdings Ltd.	UBU	UBUBELE	Food Producers	1	4%	Failed
12	William Tell Holdings Ltd.	WTL	WILLTELL	Industrial Engineering	1	4%	Failed
13	Alert Steel Holdings Ltd.	AET	ALERT	Industrial Metals and Mining	2	8%	Failed
14	Evraz highveld Steel and Vanadium Ltd.	EHS	EVRAZ	Industrial Metals and Mining			Failed
15	Central Rand Gold Ltd.	CRG	CENTRAL	Mining	6	24%	Failed
16	Platfields Ltd.	PLL	PLATFIELD	Mining			Failed
17	DiamondCorp plc	DMC	DIAMONDCP	Mining			Failed
18	Pamodzi Gold Ltd.	PZG	PZGOLD	Mining			Failed
19	Alliance Mining Corporation Ltd.	ALM	ALLIANCE	Mining			Failed
20	Miranda Mineral Holdings Ltd.	MMH	MIRANDA	Mining			Failed
21	BioScience Brands Ltd.	BIO	BIOSCI	Pharmaceuticals & Biotechnology	1	4%	Failed
22	Faritec	FRT	FARITEC	Software &	2	8%	Failed

	Holdings Ltd.			Computer Services			
23	Square One Solutions Group Ltd.	SQE	SQONE	Software & Computer Services			Failed
24	Quantum Property Group Ltd.	QPG	QPG	Travel & Leisure	2	8%	Failed
25	1time Holdings Ltd.	1TM	1TIME	Travel & Leisure			Failed
Total		**25**	**100%**				

Table 4.1 displays the 25 failed companies on the from JSE between 1 January 2014 and 31 December 2017 grouped by sector. It shows the percentage of failure by sector and status of failure.

4.2.2. Results of Altman

Table 4.2: Altman Z-Score Summary of Results

Details	**Z-score Score Range**	**Number of failed companies**	**As a Percentage of Population**	**Average days to failure**	**Average months to failure**	**Average Z-Score**	**Altman Z-Score Standard Deviation**	**Altman Z-Score Median**
Sample	**NA**	**25**	**100%**	**257**	**7.92**	**-0.14**	**3.88**	**1.02**
Almost certain will Fail	< 1.81	20	80%	250	8	-0.83		
Grey Area	between 1.81 and 2.99	4	16%	333	10	2.33		
Almost certain will succeed	> 2.99	1	4%	108	3	3.93		

Table 4.2 gives a summary of the results of the Altman Z-score failure prediction model on the twenty-five (25) failed companies between 1 January 2014 and 31 December 2017. The results show that the Altman Z-score model would have predicted that 20 of

the 25 companies were almost certain to fail on the day that their audited AFS were released with a Z-score of less than 1.81. The 20 companies were found to have an average of 250 days or eight (8) months between the release of their latest available audited AFS on which date the Altman Z-score is calculated to the suspension or delisting date, that is, the date of failure. The average Altman Z-score of these companies was -0.83.

The grey area or zone of ignorance in the Altman Z-score lies between 1.81 and 2.99. Should the Altman Z-score fall within this range, it cannot be determined as to whether a company will succeed or fail although great caution should be taken when making decisions pertaining to companies whose score falls within this area. About four (4) companies fell within the grey area with an Altman Z-Score of between 1.81 and 2.99. The four (4) companies were found to have an average of 333 days or ten (10) months between the release of their latest available audited AFS on which date the Altman Z-score is calculated to the suspension or delisting date, that is, the date of failure. The average Altman-Z score for these four companies in the grey area was 2.33.

Finally, one company had a score above 2.99 and was predicted to succeed and not fail. This company had 108 days or three (3) months between the release of its latest available audited AFS on which date the Altman Z-score is calculated to the suspension or delisting date, that is, the date of failure. This company had an Altman Z-score of 3.93.

The mean Altman Z-score for the 25 failed companies that failed between 1 January 2014 and 31 December 2017 was -0.14 with a Standard Deviation of 3.88 from the mean. The median Altman Z-score was 1.02.

4.2.3. Results of De La Rey

The results of the De la Rey K-score failure prediction model on the 25 failed JSE listed companies between 1 January 2014 and 31 December 2017 are shown in table 4.3.

Table 4.3: De la Rey K-score Summary of Results

Details	K-score Score Range	Number of failed companies	As a Percentage of Population	Average days to failure	Average months to failure	Average de la Rey K-score	de la Rey K-score Standard Deviation	de la Rey K-score Median
Population	**NA**	**25**	**100%**	**257**	**8**	**-0.11**	**2.15**	**-2.99**
Distressed	< -0.2	23	92%	263	8	-2.88		
Uncertain	between -0.2 and 0.2	1	4%	271	8	0.01		
Sound	> 0.2	1	4%	108	3	3.80		

The results show that the De la Rey K-score model would have predicted that 23 of the 25 companies were distressed and almost certain to fail on the day that their latest audited AFS were released. These companies had De la Rey K-score of less than -0.20. The 23 companies were found to have an average of 263 days or eight (8) months between the release of their latest available audited AFS on which date the De la Rey K-score is calculated to the suspension or delisting date, that is, the date of failure. The average De la Rey K-score of these distressed and almost certain to fail companies was -2.88.

The Uncertain Area or zone of ignorance in the De la Rey K-score model lies between a score of -0.2 and 0.2. Should the De la Rey K-score fall within this range, it cannot be determined as to whether a company will succeed or fail and great caution should be taken when making decisions relating to companies whose score falls within this area. One (1) company fell within the uncertain area or grey area, also know as the zone of ignorance, with a De la Rey K-score between -0.2 and 0.2. This company had 271 days between the release of its latest available audited AFS on which date the De la Rey K-score is calculated to the suspension or delisting date, that is, the date of failure. This one (1) company had a De la Rey K-score of 0.01.

Finally, one company had a score above 0.2 and was predicted to succeed and not fail. This company had 108 days or three (3) months between the release of their latest available audited AFS on which date the De la Rey K-score is calculated to their suspension from the JSE, that is, the date of failure. This company had a De la Rey K-score of 3.80.

The mean De la Rey K-score for all the 25 failed companies that failed between 1 January 2014 and 31 December 2017 was -2.50 with a Standard Deviation of 2.15 from the mean. The median Altman Z-score was -2.29.

4.2.4. Graphical presentation of Altman Z Score and De la Rey

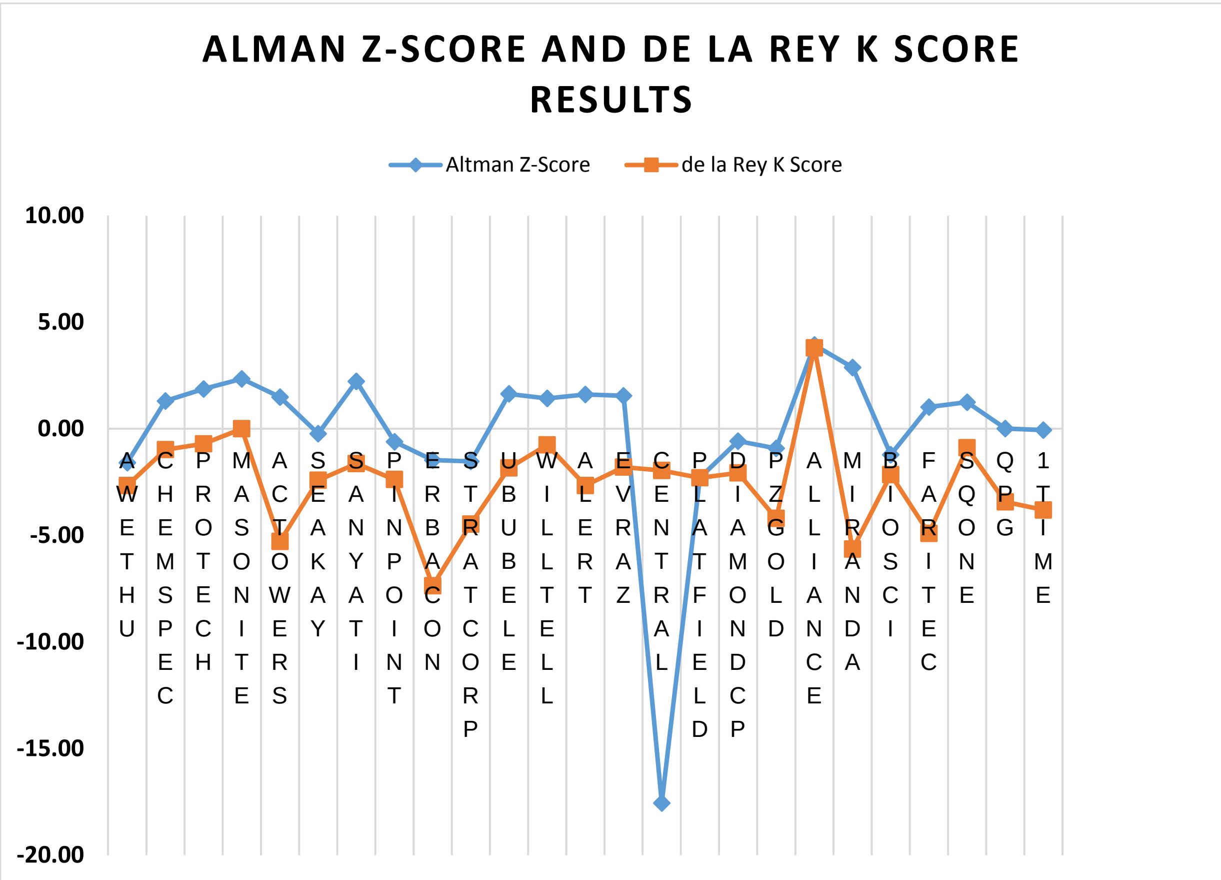

Figure 0.1: Altman Z Score and De la Rey line graph

Figure 4.1 is a line graph showing the Altman Z Score in comparison to the De la Rey K Score for the 25 failed companies from the JSE.

Table 4.4: Altman Z-Score and De la Rey K-score results

#	Company name	Short name	Altman Z-Score	de la Rey K Score
1	Awethu Ltd.	AWETHU	-1.5826	-2.6555
2	Chemical Specialities Ltd.	CHEMSPEC	1.3081	-0.9750
3	Protech Khuthele Holdings Ltd.	PROTECH	1.8706	-0.7004
4	Masonite (Africa) Ltd.	MASONITE	2.3461	0.0061
5	Africa Cellular Towers Ltd.	ACTOWERS	1.4931	-5.2818
6	Sea Kay Holdings Ltd.	SEAKAY	-0.2246	-2.4069
7	Sanyati Holdings Ltd.	SANYATI	2.2284	-1.6284
8	Pinnacle Point Group Ltd.	PINPOINT	-0.6062	-2.3758
9	Erbacon Investment Holdings Ltd.	ERBACON	-1.4652	-7.3585
10	StratCorp Ltd.	STRATCORP	-1.5231	-4.4688
11	Ububele Holdings Ltd.	UBUBELE	1.6422	-1.8321
12	William Tell Holdings Ltd.	WILLTELL	1.4283	-0.7508
13	Alert Steel Holdings Ltd.	ALERT	1.6151	-2.6555
14	Evraz highveld Steel and Vanadium Ltd.	EVRAZ	1.5489	-1.7966
15	Central Rand Gold Ltd.	CENTRAL	-17.5520	-1.9510
16	Platfields Ltd.	PLATFIELD	-2.2916	-2.2945
17	DiamondCorp plc	DIAMONDCP	-0.5739	-2.0642

18	Pamodzi Gold Ltd.	PZGOLD	-0.9145	-4.2014
19	Alliance Mining Corporation Ltd.	ALLIANCE	3.9330	3.7972
20	Miranda Mineral Holdings Ltd.	MIRANDA	2.8777	-5.6409
21	BioScience Brands Ltd.	BIOSCI	-1.2094	-2.1451
22	Faritec Holdings Ltd.	FARITEC	1.0243	-4.9006
23	Square One Solutions Group Ltd.	SQONE	1.2502	-0.8844
24	Quantum Property Group Ltd.	QPG	0.0177	-3.4228
25	1time Holdings Ltd.	1TIME	-0.0551	-3.8051
	Average (Mean)		**-0.14**	**-2.50**
	Median		**1.02**	**-2.29**
	Standard Deviation		**3.88**	**2.15**

Table 4.4 is a table showing the Altman Z Score in comparison to the De la Rey K Score for the 25 failed companies from the JSE.

4.3. CHAPTER SUMMARY

The primary aim of this study is to test the practical applicability of Altman's (1968) Z-score De la Rey (1981) K-score failure prediction models to failed JSE listed companies between the periods of 1 January 2014 to 31 December 2017. The chapter presented the data that was collected for the purpose of this research. Data analysis was undertaken on the data set through descriptive analysis.

CHAPTER 5: DATA ANALYSIS AND RESULTS INTERPRETATION

5.1. INTRODUCTION

This chapter contains the analysis of the data collected in order to address the research questions. The findings in this chapter, flowing from the analysis of the data, are discussed in this chapter. The discussion of the findings is situated within the context of the literature review in Chapter 2, as well as the methodology discussed in Chapter 3. The data sample, as discussed in chapter 3, comprises 25 failed companies that were listed on the JSE. The data was obtained from Sharemagic, Sharenet, Morningstar and the applicable company websites.

5.2. DATA ANALYSIS

The prediction results of the model to the sample of failed companies are discussed below. The empirical results are evaluated and presented using the sample containing only failed companies.

5.2.1. Altman's (1968) model

The chapter is devoted to the testing of Altman's (1968) Z-score model and De la Rey's (1981) K-score model to its practical prediction ability. The research objective was to determine the applicability of Altman's Z-score and De la Rey's K-score failure prediction models to JSE listed companies. The test of applicability of the models was done using a sample of 25 companies. These were all the failed companies on the JSE between 1 January 2014 and 31 December 2017 that were either suspended or delisted from the total population of the JSE suspended and delisted companies. The financial ratios developed by Altman were calculated and individual firms' Z-scores were derived and the results presented. The Altman's Z score equation was applied as follows;

Z = 1.2*T1 + 1.4*T2 + 3.3*T3 + 0.6*T4 + 0.999*T5 (Altman, 1968)

Where, according to Altman (1968);

T1 = Working Capital/Total Assets,

T2 = Retained Earnings/Total Assets,

T3 = Earnings before Interest and Taxes/Total assets,

T4 = Market Value Equity/book value of Total Liabilities,

T5 = Sales/Total Assets, and

Z = Overall Index.

The decision rule was that: Z<1.81 : almost likely to fail, for 1.81<Z>2.99: Grey Zone and Z>2.99: almost likely to succeed with no sign of bankruptcy at all.

5.2.2. De Le Rey model (1981)

De La Rey developed a model using financial information on twenty-six pairs of failed and non-failed South African listed companies, with the failed companies taken from the 1972 to 1979 period. Unlike Altman's Z-score model which used "Market value of Equity / Book value of Total Debt" as a variable, implying its use only on listed companies, the De La Rey model could be used for both listed and unlisted companies. By using Multiple Discriminant Analysis (MDA) and twenty-five variables, the following model was developed (Adapted from Naidoo, 2006:32):

K = -0.01662a + 0.0111b + 0.0529c + 0.076d + 0.0174e + 0.01071f - 0.068811 (De la Rey, 1981)

Where, according to De la Rey (1981);

a = Total Outside Funding / Total Assets x 100

b = EBIT / Average Total Assets x 100

c = (Total Current Assets + Listed Investments) /Total Current Liabilities

d = PAT / Average Total Assets x 100

e = Cashflow Profit after Tax / Inflation adjusted Total Assets x 100

f = Inventory / Inflation adjusted Total Real Assets x 100

A De la Rey K-score < -0.2 implies potential failure, with a De la Rey K-score > 0.2 implying a “Healthy” company. A zone of ignorance exists between a score of -0.2 and +0.20 implying that a company cannot be classified as either “Healthy” or “a candidate for potential failure” (De la Rey, 1981). The model was found by De la Rey (1981) to classify companies as either “Healthy” or “Likely to Fail” with a 96% overall accuracy one year prior to failure. This model forms part of the IRESS financial analysis service.

5.2.3. Sample of JSE listed failed companies

The quantitative data is represented by the Altman Z-Score and De la Rey K-score failure prediction model results. Table 4.1 in chapter 4 summarises the sample of recently failed JSE listed companies i.e. companies that failed from the population of companies that were either suspended or delisted from the JSE between 1 January 2014 and 31 December 2017. As can be observed in table 4.1, chapters 4, the majority, 28%, of the failed companies came from the construction and materials sector; followed by the mining sector with 24% and all other companies’ failures may be referred to the same table.

5.3. SUMMARY OF RESULTS AND INTERPRETTION

The analysis of financial variables is based on the Z-Score model developed by Altman (1968) and K-score model developed by De la Rey (1981).

5.3.1. Model based on financial variables – De la Rey K-score

According to Brummer (2015) the first failure prediction model to be developed in South Africa was the K-score model by De la Rey in 1981 which scored 94.5% of the financially sound companies and 98.6% of the failed or bankrupt companies out of a sample of 138 bankrupt and 255 financially sound companies. The average success rate was 96.6%.

In the analysis of the De la Rey K-score results, the zone of ignorance extends from -0.2 to + 0.2. This is also known as the uncertain area. Any company with a result below -0.2 has a high chance of failure unless corrective action is taken, while a score above +0.2 is regarded as being relatively safe according to De la Rey (1981). In Table 5.1, the number of observations as determined using the De la Rey K-score is summarised including some descriptive statistics.

Table 5.1: Results of the De la Rey K-Score failure prediction model

Details	K-score Range	Number of failed companies	As a Percentage of Population	Original Success Rate Achieved by De la Rey in 1981	Average prediction days to failure	Average prediction months to failure	Average de la Rey K-score score	de la Rey K-score Standard Deviation	de la Rey K-score Median
Sample	**NA**	**25**	**100%**		**257**	**8**	**-2.50**	**2.15**	**-2.29**
Distressed (likely to fail)	< -0.2	13	92%	98.6%	263	8	-2.88		
Uncertain (Grey Area)	between -0.2 and 0.2	1	4%		271	8	0.01		
Sound (Not likely to fail)	> 0.2	1	4%		108	3	3.80		

As it can be observed in table 4.1 in chapter 4, a sample of 25 companies was determined for the calculation of the De la Rey K-score. In table 5.1, in can be seen that the average amount of days between the availability of the latest audited AFS and the failure date, which is the suspension date, is 257 days or eight months for the whole sample. This means that the failure of these companies could on average have been predicted 257 days or 8 months before the date of failure which is the day that the failed company is suspended from the JSE. The failure could have been determined on the release of the latest available AFS from which the De la Rey K-score could have been determined and the applicable companies classified as likely to fail or not likely to fail. The mean or average De la Rey K-score of the sample was -2.50 with a standard deviation of 2.15 from the mean. The median De la Rey K-score for the sample of failed companies between 1 January 2014 and 31 December 2017 was -2.29.

As can be observed in table 5.1, it was discovered that 92%, or 23 of the 25 failed companies, were successfully categorised as distressed or likely to fail. One (1) company or 4% fell in the zone of ignorance while one (1) company or 4% was also incorrectly categorised as sound and likely to succeed.

Of the companies that were correctly classified as distressed and consequently likely to fail, the average number of days between the availability of the latest audited AFS and the date of failure is 263 days or approximately eight months. This means that the failure of these companies could on average have been predicted 263 days or 8 months before the date of failure which is the day that the failed company is suspended from the JSE. The average De la Rey K-score of these successfully placed observations was -2.88. Of those in the zone of ignorance, which was one company or 4%, it took 271 days or 8 months between the availability of the audited annual financial statements and the failure date. This company was also placed in the area of uncertainty by the Altman Z-score model.

Only one company with a score above 0.2 was incorrectly classified by the De la Rey K-score model as sound or likely to succeed or 4% of the sample. The average days between the availability of the latest audited annual financial statements and the failure date was some 108 days. De la Rey K-score of this company was 3.80 and the Altman Z-score model also incorrectly classified this company as likely to succeed.

It can thus be concluded that the model had a 92% success rate of being able to predict the failure of a JSE listed company that failed between 1 January 2014 and 31 December 2017 with such failure being predicted 263 days before the date of failure by the De la Rey K-score failure prediction model compared to De la Rey's 98.6% success rate in his 1981 study.

5.3.2. Model based on financial variables – Altman Z-Score

According to Naidoo (2005) Altman was the first person to develop an MDA company failure prediction model which he did in 1968 and this model was able to predict company failures 1 year prior to bankruptcy with a success rate of 95% compared to De la Rey's 98.6% failure prediction success rate.

Table 5.2: Results of the Altman Z-Score failure prediction model

Details	**Z-score Score Range**	**Number of failed companies**	**As a Percentage of Population**	**Original Success Rate Achieved by Altman in 1968**	**Average prediction days to failure**	**Average Prediction months to failure**	**Average Z-Score score**	**Altman Z-Score Standard Deviation**	**Altman Z-Score Median**
Population	**NA**	**25**	**100%**		**257**	**7.92**	**-0.14**	**3.88**	**1.02**
Almost certain will Fail	< 1.81	20	80%	95%	250	8	-0.88		
Grey Area	between +1.81 and 2.99	4	16%		333	10	2.33		
Almost certain will succeed	> 2.99	1	4%		108	3	3.93		

In the analysis of the Altman Z-score results, the zone of ignorance or grey area lies between 1.81 and 2.99. This is also known as the uncertain area. Any company with a result below 1.81 has a high chance of failure unless corrective action is taken, while a score above 2.99 is regarded as being relatively safe (Altman, 1968). In Table 5.2, the number of observations as determined using the Altman Z-score is summarised including some descriptive statistics.

As it can be observed in table 4.1 in chapter 4, a sample of 25 companies was determined for the calculation of the Altman Z-score. In table 5.5 in can be seen that the average amount of days between the availability of the latest audited AFS and the failure date, which is the suspension date, is 257 days or eight months for the whole sample. According to these results it means that the failure of these companies could on average have been predicted 257 days or 8 months before the date of failure which is the day that the failed company is suspended from the JSE. The failure could have been determined on the release of the latest available AFS from which the Altman Z-score could have been determined and the applicable companies classified as almost certain to fail or almost certain will succeed. The average or mean of the Altman Z-score of the sample was -0.14 with a standard deviation of 2.15 from the mean. The median Altman Z-score for the sample of failed companies between 1 January 2014 and 31 December 2017 was 1.02.

As can be further observed in table 5.2, it was discovered that 80%, or 20 of the 25 failed companies, were successfully categorised as almost certain to fail. This is compared to the 95% success rate achieved in Altman's 1968 study. Four (4) companies or 16% fell in the zone of ignorance while one (1) company or 4% was incorrectly categorised as sound and likely to succeed.

Of the companies that were correctly classified as distressed and consequently almost likely to fail, the average number of days between the availability of the latest audited AFS and the date of failure is 250 days or approximately eight months. This means that the failure of these companies could on average have been predicted 250 days or 8 months before the date of failure which is the day that the failed company is suspended from the JSE. This is similar to the results in the De la Rey K-score model which was able to predict failure 263 days before, some 13 days more that the Altman Z-score model. The average Altman Z-score of these successfully placed observations was -0.83. Of those in the zone of ignorance, which was four (4) company's or 16%, it took 333 days or 10 months between the availability of the audited annual financial statements and the failure date.

Only one company or 4%, like the De la Rey K-score model, was incorrectly classified by the Altman Z-score model as sound or almost certain will succeed. The average days between the availability of the latest audited annual financial statements and the failure date was some 108 days. The De la Rey K-score model also incorrectly classified this very company as likely to succeed.

It can thus be concluded that the model had an 80% success rate of being able to predict the failure of a JSE listed company that failed between 1 January 2014 and 31 December 2017 with such failure being predicted 250 days before the date of failure by the Altman Z-score failure prediction model.

5.3.3. Model based on financial variables - Control Companies

As discussed herein, the selected corresponding non-failed control companies within the same sector with similar operations were also categorised using the Altman Z-score and De la Rey K-score models in order to determine the reliability of these models as summarised in table 5.3:

Table 0.3: Control Companies – Summary of results of the Altman Z-score and De la Rey K-score failure prediction models

#	Company name	Symbol	Short Name	Sector	Status	Latest year end Audited AFS before Suspension	Altman Z-Score	Altman Z-Score category	De la Rey K-Score	De la Rey K-score category
1	Distell Group Holdings Ltd.	DGH	DISTELLG	Beverages	Non-failed	Not Yet listed on JSE (private company around comparative company failure date)	4.44	Almost certain will succeed	2.16	Sound
2	AECI Ltd.	AFE	AECI	Chemicals	Non-failed	24-Feb-15	3.83	Almost certain will succeed	1.81	Sound
3	Aveng Ltd.	AEG	AVENG	Construction & Materials	Non-failed	30-Jun-12	2.84	Grey Area	1.74	Uncertain

4	African Equity Empowerment Investments Ltd.	AEE	AEEI	Financial Services	Non-failed	31-Aug-16	2.77	Grey Area	2.18	Sound
5	Astral Foods Ltd.	ARL	ASTRAL	Food Producers	Non-failed	30-Sep-13	3.21	Almost certain will succeed	1.74	Uncertain
6	Bell Equipment Ltd.	BEL	BELL	Industrial Engineering	Non-failed	31-Dec-11	3.04	Almost certain will succeed	2.38	Sound
7	Kumba	KIO	Kumba	Industrial Metals and Mining	Non-failed	31-Dec-13	9.09	Almost certain will succeed	5.85	Sound
8	AngloGold Ashanti Ltd	ANG	ANGGOLD	Mining	Non-failed	31-Dec-12	8.68	Almost certain will succeed	1.69	Distressed
9	Adcock Ingram Holdings Ltd.	AIP	ADCOCK	Pharmaceuticals & Biotechnology	Non-failed	30-Sep-12	6.54	Almost certain will succeed	1.92	Sound
10	Adapt IT Holdings Ltd.	ADI	ADAPTIT	Software & Computer Services	Non-failed	28-Feb-09	6.83	Almost certain will succeed	3.25	Sound
11	City Lodge Hotels Ltd.	CLH	CITYLDG	Travel & Leisure	Non-failed	30-Jun-11	3.45	Almost certain will succeed	2.22	Distressed

The De La Rey K-score model classified 7 of the 11 companies, 64%, correctly as sound and likely to succeed with two (2) companies being placed in the uncertain area and two (2) or 18% being classified as distressed. This could mean that corrective measures were taken to prevent the failure of these companies and it is recommended that more research be performed to ascertain what seems to be a misclassification that these companies will fail by the De la Rey K-score failure prediction model.

The Altman-Z score correctly categorised nine (9) of the 11 companies correctly i.e. 82%. The remaining two (2) companies had scores that fell within the zone of ignorance.

5.4. CHAPTER SUMMARY

The De La Rey K-score model was able to correctly characterise 92% of the companies as likely to fail with 4% falling in the zone of ignorance with only one company being misclassified as likely to succeed. The Altman Z-score also had a high but relatively lower success rate when compared to the De la Rey K-score model at an 80% success rate in classifying companies as likely to fail. 16% of the results of the Altman Z-score model fell into the zone of ignorance or uncertainty. Only one company, or 4%, was incorrectly classified as likely to succeed. The results, while being of a tentative nature, indicate that better predictions concerning JSE-listed companies' financial distress and consequent failure may be obtained by using the De la Rey K-score failure prediction model as a whole and in comparison to the Altman Z-score model.

CHAPTER 6: SUMMARY, CONCLUSION AND RECOMMENDATIONS

6.1. INTRODUCTION

The preceding chapter provided the analysis and interpretation of the empirical results. This chapter presents the summary overview of the research by placing the objectives into context. The purpose of the study was to test the practical applicability of Altman's (1968) Z-score and De La Rey's (1981) K-score failure prediction models to failed JSE listed companies between 1 January 2014 to 31 December 2017. From the theory and the empirical research findings, recommendations are made, concluding with the benefits, limitations and implications for future research direction.

6.2. RESEARCH OBJECTIVES

This study has the following research objectives:

Objective 1: To test the practical applicability of Altman's (1968) Z-score and De la Rey's (1981) K-score failure prediction models to failed JSE listed companies between 2014 to 2017.

With the dependent variable being 'failed', the main objective is addressed by the analysis of the independent variable, based on the data analyses of the financial variables.

6.3. SUMMARY

The study aimed at establishing the applicability of Altman's Z-score and De La Rey's K-score failure prediction models to JSE listed companies by applying such models to JSE listed companies that failed between 1 January 2014 and 31 December 2017 and determining whether the Altman Z-score and De La Rey K-score failure prediction models would have been able to successfully predict the failure of these companies. The analysis of data towards the realisation of the research objective was conducted.

Using Altman’s Z-score model, the study found out that the Z-score for the failed companies indicated that 20 of the 25 failed companied would have successfully been predicted as companies that were almost likely to fail. The Altman Z-score failure prediction model's failure classification accuracy was 80%. The given results of Altman’s Z-score model were of benefit as it was an accurate predictor and thus can be used to predict the failure of JSE listed companies.

De La Rey’s K-score failure prediction model was found to be more accurate than Altman’s Z-score model. The De la Rey K-score failure prediction model successfully predicted the failure of 92% of the failed JSE listed companies between 1 January 2014 and 31 December 2017 compared to Altman’s Z-score model that achieved 80%. The De la Rey K-score failure prediction model was 12% more accurate than the Altman Z-score failure prediction model. Both models only misclassified 4% of the companies as likely to succeed. Although the results are not bad, the fine-tuning of Altman Z-score model might be of help.

Both the Altman Z-score and De la Rey K-score failure prediction models can be used to predict the failure of a JSE listed company with the De la Rey K-score model likely to produce more accurate results.

6.4. LIMITATION OF THE STUDY

The study further did not differentiate between the sector and sizes of the companies. This is because the companies which are quoted at the securities market will be accessible to a variety of capital sourcing in order to finance their operations. At the same time, the duration the company has been in operation would influence how it operates in the market as they are expected to have put in place mechanisms that would ensure that they compete effectively, unlike a new company that has not been in existence for a long period.

The competition in the industry and the new legislation has given rise to mergers and acquisitions and these would help companies to develop complementary earnings streams, realise opportunities for cost-saving synergies and strengthen their presence in the regional markets. However, these would impact on the true position of the company as there is pooling of resources by the companies.

6.5. RECOMMENDATIONS

This research suggests a few recommendations that have policy implications for decision makers. The study found out that the De la Rey K-score model successfully predicted 92% of the companies to fail compared to the Altman Z-score model which only predicted a relatively lower 80% to fail. Both models only misclassified 4% of the companies as likely to succeed. Based on these results, the use of the De la Rey K-score model to predict the failure of JSE listed companies is recommended.

It is further recommended as a future study that it be determined why the Altman Z-score model places more companies in the area of uncertainty compared to the De la Rey K-score model. It is also recommended to study why both the De la Rey K-score and Altman Z-score model are both still accurate in predicting the failure of JSE listed companies that are not manufacturing companies.

It is also recommended as a future study to determine the applicability of both the Altman Z-score and De la Rey K-score failure prediction models in predicting the success, and not the failure, of JSE listed companies.

A study on why 52% of the failed companies on the JSE were either in the construction and materials sector, with 28%, or the mining sector, with 24%, of the failures between 1 January 2014 and 31 December 2017 is also recommended.

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APPENDIX A: LIST OF FAILED JSE LISTED COMPANIES

#	Company name	Symbol	Shortname	Sector	# of companies in Sector	As a % of total companies	Status
1	Awethu Ltd.	AWT	AWETHU	Beverages	1	4%	Failed
2	Chemical Specialities Ltd.	CSP	CHEMSPEC	Chemicals	1	4%	Failed
3	Protech Khuthele Holdings Ltd.	PKH	PROTECH	Construction & Materials	7	28%	Failed
4	Masonite (Africa) Ltd.	MAS	MASONITE	Construction & Materials			Failed
5	Africa Cellular Towers Ltd.	ATR	ACTOWERS	Construction & Materials			Failed
6	Sea Kay Holdings Ltd.	SKY	SEAKAY	Construction & Materials			Failed
7	Sanyati Holdings Ltd.	SAN	SANYATI	Construction & Materials			Failed
8	Pinnacle Point Group Ltd.	PNG	PINPOINT	Construction & Materials			Failed
9	Erbacon Investment Holdings Ltd.	ERB	ERBACON	Construction & Materials			Failed
10	StratCorp Ltd.	STA	STRATCORP	Financial Services	1	4%	Failed
11	Ububele Holdings Ltd.	UBU	UBUBELE	Food Producers	1	4%	Failed
12	William Tell Holdings Ltd.	WTL	WILLTELL	Industrial Engineering	1	4%	Failed
13	Alert Steel Holdings Ltd.	AET	ALERT	Industrial Metals and Mining	2	8%	Failed
14	Evraz highveld Steel and Vanadium Ltd.	EHS	EVRAZ	Industrial Metals and Mining			Failed
15	Central Rand Gold Ltd.	CRG	CENTRAL	Mining	6	24%	Failed
16	Platfields Ltd.	PLL	PLATFIELD	Mining			Failed
17	DiamondCorp plc	DMC	DIAMONDCP	Mining			Failed
18	Pamodzi Gold Ltd.	PZG	PZGOLD	Mining			Failed
19	Alliance Mining Corporation Ltd.	ALM	ALLIANCE	Mining			Failed
20	Miranda Mineral Holdings Ltd.	MMH	MIRANDA	Mining			Failed
21	BioScience Brands Ltd.	BIO	BIOSCI	Pharmaceuticals & Biotechnology	1	4%	Failed

22	Faritec Holdings Ltd.	FRT	FARITEC	Software & Computer Services	2	8%	Failed
23	Square One Solutions Group Ltd.	SQE	SQONE	Software & Computer Services			Failed
24	Quantum Property Group Ltd.	QPG	QPG	Travel & Leisure	2	8%	Failed
25	1time Holdings Ltd.	1TM	1TIME	Travel & Leisure			Failed
	Total				*25*	*100%*	

APPENDIX B: FINANCIAL VARIABLES – DE LA REY K-SCORE

Details	K-score Score Range	Number of failed companies	As a Percentage of Population	Average days to failure	Average months to failure	Average de la Rey K-score	de la Rey K-score Standard Deviation	de la Rey K-score Median
Population	**NA**	**25**	**100%**	**257**	**8**	**-0.11**	**2.15**	**-2.99**
Distressed	< -0.2	23	92%	263	8	-2.88		
Uncertain	between -0.2 and 0.2	1	4%	271	8	0.01		
Sound	> 0.2	1	4%	108	3	3.80		

APPENDIX C: FINANCIAL VARIABLES – ALTMAN Z-SCORE

Details	Z-score Score Range	Number of failed companies	As a Percentage of Population	Average days to failure	Average months to failure	Average Z-Score	Altman Z-Score Standard Deviation	Altman Z-Score Median
Sample	**NA**	**25**	**100%**	**257**	**7.92**	**-0.14**	**3.88**	**1.02**
Almost certain will Fail	< 1.81	20	80%	250	8	-0.83		
Grey Area	between 1.81 and 2.99	4	16%	333	10	2.33		
Almost certain will succeed	> 2.99	1	4%	108	3	3.93		

APPENDIX D: FINANCIAL VARIABLES - CONTROL COMPANIES

#	Company name	Symbol	Short Name	Sector	Status	Latest year end Audited AFS before Suspension	Altman Z-Score	Altman Z-Score category	De la Rey K-Score	De la Rey K-score category
1	Distell Group Holdings Ltd.	DGH	DISTELLG	Beverages	Non-failed	Not Yet listed on JSE (private company around comparative company failure date)	4.44	Almost certain will succeed	2.16	Sound
2	AECI Ltd.	AFE	AECI	Chemicals	Non-failed	24-Feb-15	3.83	Almost certain will succeed	1.81	Sound
3	Aveng Ltd.	AEG	AVENG	Construction & Materials	Non-failed	30-Jun-12	2.84	Grey Area	1.74	Uncertain
4	African Equity Empowerment Investments Ltd.	AEE	AEEI	Financial Services	Non-failed	31-Aug-16	2.77	Grey Area	2.18	Sound
5	Astral Foods Ltd.	ARL	ASTRAL	Food Producers	Non-failed	30-Sep-13	3.21	Almost certain will succeed	1.74	Uncertain
6	Bell Equipment Ltd.	BEL	BELL	Industrial Engineering	Non-failed	31-Dec-11	3.04	Almost certain will succeed	2.38	Sound
7	Kumba	KIO	Kumba	Industrial Metals and Mining	Non-failed	31-Dec-13	9.09	Almost certain will succeed	5.85	Sound

8	AngloGold Ashanti Ltd	ANG	ANGGOLD	Mining	Non-failed	31-Dec-12	8.68	Almost certain will succeed	1.69	Distressed
9	Adcock Ingram Holdings Ltd.	AIP	ADCOCK	Pharmaceuticals & Biotechnology	Non-failed	30-Sep-12	6.54	Almost certain will succeed	1.92	Sound
10	Adapt IT Holdings Ltd.	ADI	ADAPTIT	Software & Computer Services	Non-failed	28-Feb-09	6.83	Almost certain will succeed	3.25	Sound
11	City Lodge Hotels Ltd.	CLH	CITYLDG	Travel & Leisure	Non-failed	30-Jun-11	3.45	Almost certain will succeed	2.22	Distressed