An assessment and comparison of bankruptcy prediction models in forecasting the financial distress of JSE-listed companies over a twenty-year period (2000 to 2020)

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Declaration

I declare that this is my own work and that it has not been submitted previously for any degree or examination. The findings and ideas of others have been incorporated into this research, in respect of which appropriate credit has been given.

Signed by candidate

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Abstract

This study aimed to test the reliability of various models in predicting the failure of JSE-listed companies. Spanning a period of twenty years between the years 2000 and 2020, a sample of 156 companies was considered, with variables extending across financial information, non-financial information, as well as macroeconomic indicators. The timespan considered for the assessment is particularly significant considering that it encompasses two periods of catastrophic negative market downturns. This includes the 2008 financial crisis and the impacts of the Covid-19 pandemic in 2020. Furthermore, the introduction of new international accounting standards in the latter part of this period, implemented to address issues of risk and transparency in financial reporting, had a marked impact on accounting ratios. Accounting ratios have traditionally been used as inputs in distress prediction models.

Considering this context, a study of the comparative performance of various models was undertaken, with the model set including multiple discriminant analysis, logit, probit, recursive partitioning and non-financial models. What was particularly noteworthy in this research was the inclusion of models developed by South African researchers in the model set.

In respect of the multiple discriminant analysis, logit and probit models, the results demonstrated a predictive accuracy rate below those surfaced in previous studies, with accuracy rates averaging between 55% and 70%. These models were cumbered predominantly by Type I errors.

The application of a model which included both financial and non-financial variables demonstrated more favourable results at an accuracy rate of 73%.

The recursive partitioning model, however, which comprehended a high ratio of cashflow-related variables, yielded the highest accuracy, at 83%. The model, with its cash focus and its unique approach of considering the cumulative impact of variables instead of basing the predictive outcomes on the performance of a single financial year, tended not to fall prey to the error-types prevalent in the other models in the model set.

The output of this research affirmed the importance of the traditional and rudimentary marker between distressed and non-distressed firms. That is, the abundance of cash or the lack thereof is the key differentiating mark between failure and success. The research also highlighted the importance of considering the cumulative impact of variables when forecasting the failure or

success of companies, instead of basing predictive outcomes on the performance of a single period. Furthermore, this research confirmed what had been established in previous studies. That is, the size of the firm is a significant predictor of bankruptcy.

This study also attempted to reassess the outcome of distress prediction models, by adjusting for the impact of changes in accounting. The impact on the predictive accuracy of the models by normalising for accounting changes, however, was inconclusive. This was mainly due to the extent of Type I errors across the multiple discriminant analysis, logit and probit models, in conjunction with the low prevalence of failed companies towards the latter part of the period considered in this research when changes in accounting standards were introduced. Further research is required in this area to understand the impact of accounting changes on traditional distress prediction models and potentially to revise these distress models, in order to yield higher predictive accuracies.

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Chapter 1: Research Background and Context

1.1 Introduction

Financial distress and corporate failure result in significant negative ramifications, not just for investors but for numerous stakeholders across the value chain. Cole, Johan and Schweizer (2021:1) note, that the impact of corporate failure is exacerbated when it happens concurrently with economic stress or when the failure is not limited to a specific firm but is industrywide. This in turn can result in the collapse of entire industries, reduce tax revenue, have negative impacts on the country’s economy, increase unemployment, as well as result in higher levels of poverty and crime (Cole, Johan and Schweizer, 2021:1).

In light of this, the development of reliable models for predicting financial distress and corporate failure is quintessential. Furthermore, Platt and Platt (2002:184) note, that a model that is able to anticipate financial distress provides management with a powerful, early warning tool that aids not just in identifying problems but provides management with the opportunity to rectify them before these problems mature into a crisis.

1.2 Problem statement

Since the mid-1960s and the introduction of the Altman Z-score as a predictive model for financial distress, a significant body of bankruptcy-related literature has been developed, surfacing alternative models for predicting financial distress and corporate failure. Like the Altman Z-score, a number of these models are largely rooted in accounting (Wu, Gaunt and Gray 2010:34) and much scrutiny has been placed on the reliability of these models, given the demise and failure of certain firms in the last twenty years, despite their historic accounting results[1]. To arrest the apparent shortcomings, especially of accounting-based models, alternative bankruptcy models have been developed, which incorporate additional elements spanning from market-related and macroeconomic variables to non-financial firm attributes (Wu, Gaunt and Gray 2010:34-35).

[1] Noted in this research are specific examples of significant corporate failures in the last twenty years, including the reasons for failure. The failures noted include the collapse of firms despite their display of strong historic accounting results. Please refer to Table 2.2 and section 2.2.4.

The problem is, however, that the ability of bankruptcy models to accurately predict corporate failure over specific time horizons (Wu, Gaunt and Gray 2010:35) and different economies (Altman et al., 2014:1), has not always yielded consistent results. In addition, some popular models noted in previous research, for example, Altman's Z-Score (1968) and Ohlson's O-Score (1980), were developed with a focus on particular industries. Moreover, the standards which guide how transactions are to be accounted for have not remained static over time. Given that predictive models tend to rely extensively on accounting information, historical models developed may not adequately deal with the changes in the basis of accounting.

There is therefore a need to investigate which financial distress predictive models[2] are best suited within the current setting, to guide various stakeholders on the most relevant and accurate predictive models in forecasting failure.

1.3 Research aims and objectives

Given the above considerations, this research aims to assess the reliability of various bankruptcy models, by assessing their ability to accurately predict the financial distress of firms over a twenty-year period (2000 and 2020), with reference to companies listed on the Johannesburg Stock Exchange (JSE).

This aim will be achieved by delivering on the following research objectives:

- Perform a comparative analysis of the predictive accuracy of financial distress models, by applying these models to financial and non-financial data of firms listed on the JSE over the period of 2000 to 2020. The firms selected for testing will include those that have failed[3], as well as a control group of non-failed firms.
- Review the impact of recent changes in International Financial Reporting Standards (IFRS), which have been introduced largely to allow for greater transparency in respect of the risk profiles of companies. As accounting information has been used extensively in traditional financial distress models, this assessment will include how these changes have impacted accounting results and financial ratios.

[2] References to "financial distress predictive models", "financial distress models" and "bankruptcy prediction models" or similar references, are used interchangeably in this research.

[3] Failure for the purposes of this research is defined in section 2.2

The timeframe considered in this research is particularly significant considering that it encompasses two periods of catastrophic negative market downturns. This includes the 2008 financial crisis and the impacts of the Covid-19[4] pandemic in 2020. In addition, the period under review includes the introduction of new international accounting standards in 2018 and 2019, which had a marked impact on accounting ratios.

1.4 Research questions

Considering the research aim and objectives, this study attempts to address the following research questions:

- Which financial distress predictive models are the most accurate in predicting financial distress in the current context and within the stated parameters of this research?
- How has the introduction of new financial reporting standards impacted accounting ratios and the accuracy of financial distress predictive models, in comparison to the results that surfaced in previous studies?

1.5 Scope and limitations of the research

The scope of this research is limited to JSE-listed companies and spans a twenty-year period, between the years 2000 and 2020. An extended period of assessment was considered to improve the chances of observing failed companies, given the low failure rate of listed companies. No limitations were placed on the industries that could be selected for testing.

The models reviewed in this research and the model set subsequently selected for comparative performance analysis, do not represent an exhaustive list of all bankruptcy models available in practice or those highlighted in previous studies. Furthermore, within this research undertaken, the technical aspects of the models are only addressed at a high level. The objective was to cover a broad range of model types, considering models commonly referenced in previous literature. In addition, the intention was to include models developed by South African researchers.

[4] Coronavirus disease 2019

1.6 Research data and methodology

The research design choice of this study is comparative in nature. That is, this research intends to demonstrate the comparative accuracy of prediction models. The research also places reliance on previous research undertaken in the area of financial distress and corporate failure, which is covered as part of the literature review. In addition, financial and non-financial information is drawn from reliable sources and is used as inputs to test the predictive ability of financial distress models selected as part of the model set.

1.7 Research outline

This study commences in Chapter 2 with the literature review, which is divided into three segments:

- The first segment provides an overview of financial distress and corporate failure and defines failure for the purposes of this research. This segment also seeks to summarise the causal factors for corporate failure and its far-reaching impacts, while focusing on corporate failure within the South African private sector.
- In light of the significant negative impacts of financial distress and corporate failure, the second segment provides an outline of the techniques and models that have been developed to forecast financial distress and discusses the research done in this area within the South African context. This segment includes a critique of the various techniques and models.
- As many of the financial distress models are based on accounting information, the third segment considers the response by regulators, specifically in the area of financial accounting, to address issues of risk and transparency in financial reporting. This segment also addresses the impact these changes have had on accounting information and accounting ratios.

Given the various models available and the changes in accounting, Chapter 3 puts forward the model set to be applied in this research and discusses the research methodology, the data selection and preparation process, as well as the restrictions and assumptions applied in the application of the data to the model set.

Chapter 4 details the prediction results of the model set. This chapter includes a comparative assessment of the outcomes of the various models, as well as the inferences and deductions made in reference to the results.

The research concludes in Chapter 5 with the key takeaways in respect of this research and potential avenues for further study in this area.

Chapter 2: Literature Review

2.1 Chapter overview

In this chapter, the literature review is covered in three segments.

The chapter commences with an overview of financial distress and corporate failure. This overview seeks to summarise the causal factors of corporate failure and its far-reaching impacts, highlighting the importance of detecting potential failure well in advance, not merely to safeguard against a poor investment decision but potentially to arrest the root cause in time to prevent catastrophic impacts. Corporate failure within the South African private sector is also discussed and what constitutes failure for the purposes of this research is defined.

Given the significant negative impacts of financial distress and corporate failure, a review of the various techniques and models that have been developed to predict financial distress and corporate failure is undertaken in the second segment of this chapter.

The third and final segment of the literature review considers the impact widespread failure has had on policymakers and regulators. As many of the financial distress prediction models are based on accounting information, this segment reviews the response by regulators in the area of financial accounting to address issues of risk and transparency in financial reporting.

2.2 Understanding financial distress and corporate failure

In its most simplistic form, financial distress reflects the circumstances in which a firm is unable to generate sufficient cash flows to meet its financial obligations (Steyn-Bruwer and Hamman, 2006:9). The Companies Act of South Africa (Companies Act 71 of 2008) extends this definition to include not only the factual event of being unable to meet financial commitments but the likelihood of being unable to meet obligations.

The Companies Act s128 (f) defines "financially distressed" as a company in respect of which:

(a) it appears to be reasonably unlikely that the company will be able to pay all of its debts as they fall due and payable within the immediately ensuing six months (i.e. commercially insolvent); or

(b) it appears to be reasonably likely that the company will become insolvent within the immediately ensuing six months (i.e. factually insolvent).

Elloumi and Gueyie (2001:16), echo the principles contained in The Companies Act by noting that a firm can be said to be in a state of financial distress when it has deteriorated to such a point that it is unable to meet its financial obligations. They note that the first signals of this distress are typically evident in the firm's inability to meet its commitments in respect of debt covenants, coupled with the omission or reduction of dividends (Elloumi and Gueyie, 2001:16). In essence, the distressed state is largely linked to a cash-poverty scenario, when cash resources are unable to meet current demands.

While the inability to meet current obligations and dividends omissions or reductions are key identifying marks of a distressed firm, symptoms of financial distress stretch well beyond these limitations. Stagnant or declining sales, poor profit performance, extended payment terms and growth in overdue debts, are all precursors to potential distress (Kubícková and Nulicek, 2016:36).

There are several sources of information that can assist in identifying the early warning signs of financial distress. A review and analysis of the firm's financial statements is by and large the most common reference point in this regard. Financial statements provide a platform for time series analysis (referencing current performance to prior periods), as well as cross-sectional analysis (measuring performance against other firms in the industry), allowing analysts to identify financial trends that typically point to distress (Welc, 2022:132). This analysis however generally extends beyond the constructs of financial ratios covering profitability, efficiency and liquidity. The extensive disclosure requirements incumbent upon firms, particularly those that are listed on the stock exchange, often allow for insights into corporate strategy, company-specific outlooks and major future projects, governance-related matters, management experience and skillset, as well as firm-specific performance drivers. However, despite the vast information embedded in a firm's financial statements and related disclosure, it is not without its limitations (Welc, 2022:132). Financial results are influenced to some degree by the accounting policies adopted, which not only makes time series analysis irrelevant when accounting policies are not adopted retrospectively but also sectional analysis, as firms across the same industry may apply different accounting policies (Welc, 2022:113-114). In addition, financial statements include areas of significant judgement and estimates, which are geared largely by the opinions of management (Welc, 2022:202).

Adding to the complexity of identifying a distressed firm, is that a financially distressed company may seek to avoid a voluntary declaration of financial distress given the risks associated with such a pronouncement. Chen and Merville (1999:277) note that firms can suffer significant losses when in financial distress, even if they don't default into bankruptcy. These risks include customers no longer buying the company's products in fear of no post-sale support or parts (Bisogno and De Luca, 2012:23), suppliers tightening terms or moving to a cash-based supply only, creditors cutting any further funding, an increase in the cost of capital (Cole, Johan and Schweizer, 2021:9) and employees leaving to avoid the backlash of retrenchments and reputational damage (Sutton and Callahan, 1987:406). These factors add to the burden of an already-stressed business and are partly the reason why management often engages in high-risk accounting transactions and off-balance-sheet business activity to mask pending financial distress (Hamilton and Micklethwait, 2006). This was evident in the now-infamous Enron debacle. In the report issued by the Permanent Senate Subcommittee concerning Enron, the report disclosed that the audit committee at the time stressed its concern to the Enron Board of accounting practices that pushed the limits and that they were "at the edge" of acceptable practice (Permanent Subcommittee of Investigations, 2002:12).

Linked to financial distress is corporate failure, which is often associated with the ultimate cessation of the firm's operations either through legal intervention by stakeholders or the voluntary declaration of bankruptcy by the firm (Cole, Johan and Schweizer, 2021:1). Cole, Johan and Schweizer (2021:1) extend the definition of corporate failure however beyond the termination of a company's operations to include failure to meet stakeholder objectives. Other studies have also broadened the failure definition to include the liquidation of a company, delisting from the stock exchange, as well as major structural changes of a company (Steyn-Bruwer and Hamman, 2006:10). Steyn-Bruwer and Hamman (2006:7) note that all circumstances that lead to a firm not being able to exist in its current form should be considered.

Bruno and Leidecker (2001:51-52) contend that while no two experts agree on the definition of business failure, definitions found in literature include the inability of the firm to meet responsibilities to employees, suppliers, communities and customers, as well the collapse or the reduction in the size of the firm.

For the purposes of this research, a company would be noted to have failed if the firm has entered liquidation (voluntary, provisionally or otherwise), is under business rescue, has dissolved or has delisted from the JSE for reasons tantamount to failure. In respect of reasons for delisting which are synonymous with failure, these could include failure to comply with

JSE requirements, suspension by the JSE and the general unwinding of the firm, amongst others. In some cases, firms may fall into more than one of the categories of failure.

2.2.1 The causes of corporate failure

While much research has been invested in predicting the distress, potential failure and longevity of firms, Holt (2013:50) notes that less focus has been centred on the causal agents of failure. Understanding the causes of failure, however, is important for all firms to consider. To this end, Bruno and Leidecker (2001:51) note, that the reasons why firms fail are probably more important to understand than the reasons why firms succeed.

The reasons for corporate failures are typically broad and vary from the very simple to the complex (Holt, 2013:51). The reasons for corporate failure range from management agency issues, fraud, failure of operation controls, poor governance, poor strategic decisions, ill-judged acquisitions and mergers, dominant CEOs[5], ineffective boards, latency in responding to market and customer changes, as well as independence issues (Hamilton and Micklethwait, 2006). Hamilton and Micklethwait (2006) further stress that while the blame list for corporate failure is long and can result from the actions of various stakeholders, including senior management, boards and audit committees, external auditors, rating agencies and regulators (including stock exchanges and banks) - at the heart of the blame list is greed.

Bruno and Leidecker (2001:54) reviewed failures of new ventures during the periods of the 1960s and 1980s and categorised the reasons for firm failure under the areas of product-related or market-related issues, financial issues, managerial or key employee issues and cultural or social-related issues. Over thirty percent of all major and minor causes of failure were attributed to product-related or market-related problems (Bruno and Leidecker, 2001:55). As it relates to product-related problems, issues generally stemmed from products entering too early or too late into the market, or firms being unable to develop a viable prototype based on the original product design (Bruno and Leidecker, 2001:54). Furthermore, product delivery was also curtailed in certain instances by poor strategies around distribution, which contributed towards the failure of the firm (Bruno and Leidecker, 2001:55).

In addition to product or market-related impediments, financial-related problems were also identified as a significant element for firm failure. Firm failure, particularly in the 1960s, was

[5] Chief Executive Officers

typically the result of under-capitalisation and the over-reliance on debt financing early in the life of the firm (Bruno and Leidecker, 2001:55).

Wang, Winton and Yu (2010:2255) noted how fraud by management, a common cause of corporate failure, is linked to the investor's beliefs about the prospects of the industry. That is, that management is more likely to commit fraud when investor confidence is high but is less likely to commit fraud when these beliefs are excessively high. They contend that when investor confidence is excessively high, the firm is generally able to obtain funding without having to manipulate its information to do so (Wang, Winton and Yu, 2010:2287).

Holt (2013:60), with reference to the construction industry in the United Kingdom, proposed that while there are numerous sub-causal agents (SCAs) for failure, the generic failure agents (GFAs) in order of frequency centred around managerial, financial and company characteristics, as well as macroeconomic factors.

Table 2.1 reflects Holt's (2013:62) assessment of the source of failure across the literature covered by his research. The results indicate, by rank, the generic failure agents for business failure, with managerial and financial components most prominent.

Table 2.1: Generic failure agent (GFA) by rank

	All literature	
Generic failure agent	**%**	**Rank**
Managerial	45	1
Financial	42	2
Macroeconomic	8	3
Company characteristic	5	4
	100	

Source: Holt (2013:62)

What Holt (2013) further highlights is that corporate failure is provoked by both qualitative and quantitative elements and that these elements are interlinked. For example, poor income control (a quantitative measure and a financial GFA) may be a product of a lack of financial knowledge (a qualitative measure and a managerial GFA). Figure 2.1 depicts the reciprocal and interrelated relationship between GFAs noted in Holt's research (Holt, 2013:62).

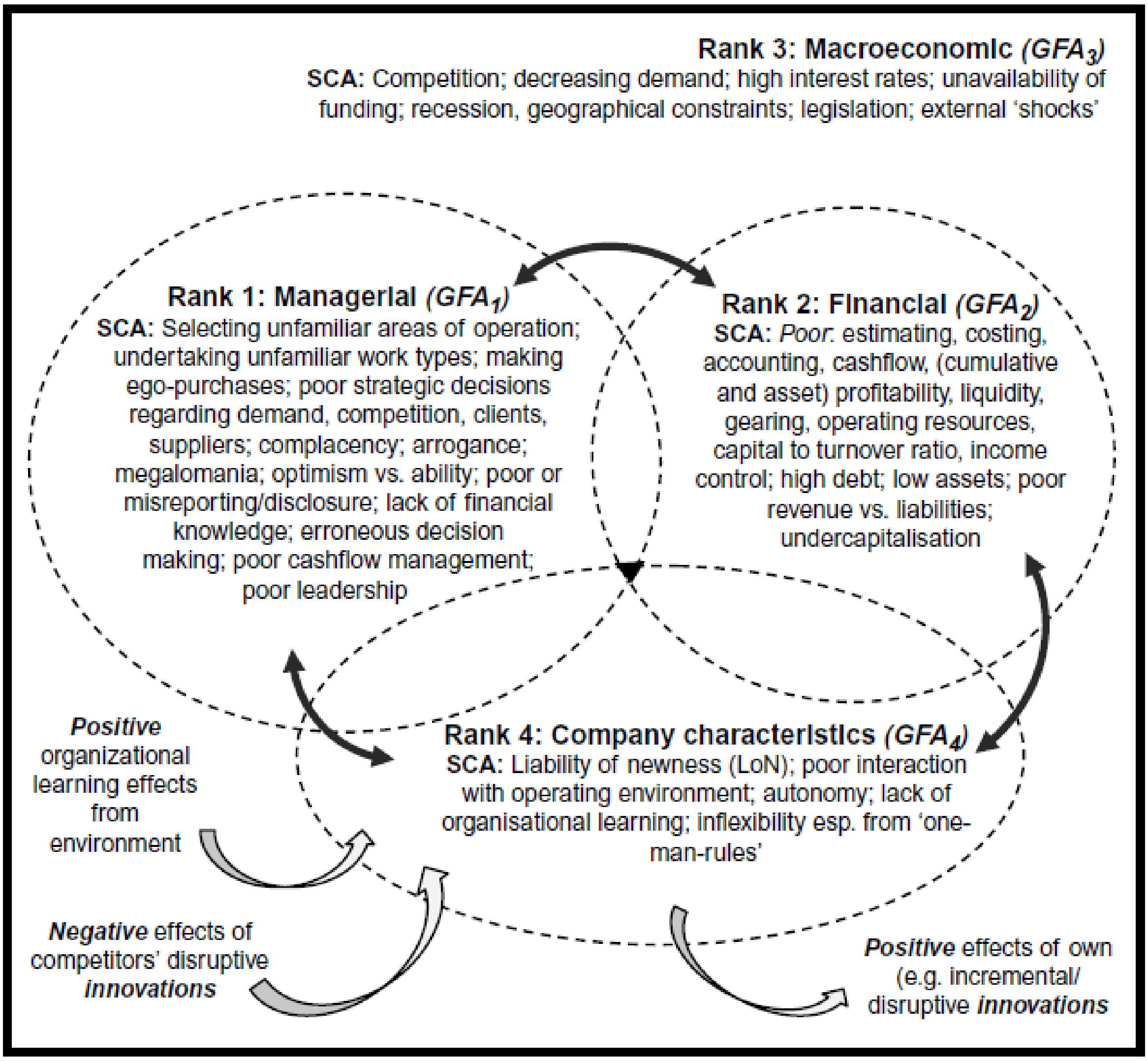

Figure 2.1: Holt's model of causal agents (GFAs and SCAs)

Source: Holt (2013:62)

As illustrated in Figure 2.1, the macroeconomic environment (GFA_3) effectively defines the universe within which the other generic agents (GFA_1: managerial, GFA_2: financial and GFA_4: company characteristics) and sub-causal agents operate (Holt, 2013:60).

These macroeconomic factors, while they are largely uncontrollable from a firm perspective, significantly influence both the proactive and reactive actions of management (Holt, 2013:63). Some of the macroeconomic factors such as competition, geographical-specific risks and the operating environment are known market factors to the firm and are managed within the firm's risk matrix. The GFA_3-universe (macroeconomic causes of failure), however, is also characterised by shock factors (Holt, 2013:63) such as sudden market collapses and recessions, which generally spark higher incidences of bankruptcy and ultimately corporate failure.

GFAs$_{1,2,4}$ (managerial, financial and company characteristics causes of failure) abide within the GFA$_{3}$-universe and are linked in a reciprocal matrix, exerting influence on one another (Holt, 2013:63). For example, management strategy influences the firm's financial attributes and reciprocally financial attributes influence the decisions taken by management. The extent of interaction and the reciprocal impacts between GFAs will vary from firm to firm (Holt, 2013:63).

The shaded triangle in the centre of the conceptual framework, denotes the combined susceptibly of a firm's GFAs, operating within its macroeconomic universe. Where GFAs$_{1,2,4}$ interact in an efficient and complimentary manner and the GFA$_{3}$ impacts are not adverse, the probability of failure is reduced. Where the converse is applicable, the probability of failure increases (Holt, 2013:63).

Understanding Holt's theoretical framework and the co-relationship between failure agents can be a powerful tool for management to avoid the pitfalls of failure. By adopting a proactive approach in view of the various GFAs and related SCAs, the firm can negate the undesirable effects described by Holt (2013). In light of Holt's research, it would be important to include markers that cover both quantitative and qualitative aspects in assessing potential financial distress, as both of these aspects can lead to failure.

2.2.2 The impacts of corporate failure

Corporate failure often has a far-reaching adverse impact, across a broad range of stakeholders.

While the entity's shareholders, management and employees arguably feel the impacts of dissolution most acutely given their proximity to the failure, creditors, government, banks, auditors, pensions funds and other institutions are also severely impacted (Cole, Johan and Schweizer, 2021:1). The financial ramifications can be startling, with ripple effects continuing across various streams for years thereafter (Cole, Johan and Schweizer, 2021:1).

Corporate failure as a result of bankruptcy is arguably the most severe form of failure. This type of failure carries with it a significant amount of costs to the firm, impacts other business stakeholders and potentially has a severe impact on the economy, depending on the size of the firm.

While corporate failure is a worldwide phenomenon, special focus has been given to corporate failure and its consequences in the United States of America (United States), given the relative size of its financial market to the rest of the globe and the availability of information related to the failure of firms in the United States.

In 2020, on the back of the adverse impacts of Covid-19, bankruptcy filings for public companies[6] in the United States reached its highest level in the last ten years (Douglas and Oellermann, 2021). Douglas and Oellermann (2021) noted that the amount of public company bankruptcy filings in 2020 was 110, compared to 64 in 2019. The combined asset value of the 110 public companies that filed for bankruptcy in 2020 was $292.7 billion, compared to $150 billion in 2019. This, however, is nothing compared to the impact experienced during the 2008 market crash, where the 138 public companies that filed for bankruptcy had prepetition assets valued at $1.2 trillion in aggregate (Douglas and Oellermann, 2021). Table 2.2 notes the 20 largest bankruptcies in the history of the United States and the reasons for the failure of the firm.

The cost of failure, however, is not only limited to the firm's asset value lost but also to other direct costs incurred through the bankruptcy process. These include costs associated with lawyer's fees, accounting costs, as well other professional fees incurred (Warner, 1977:338). Warner (1977:337) notes that on average the direct cost of bankruptcy for large firms amounts to one percent of the market value of the firm prior to bankruptcy.

Unfortunately for the firm, direct costs are not the only cost element of bankruptcy incurred over and above the asset value lost. There is the other area of indirect costs that also requires consideration. Bisogno and De Luca (2012:22) suggest that indirect costs denote the combined outcomes of suboptimal decisions made by various stakeholders during or preceding bankruptcy and that previous research notes that these costs are significantly higher than the direct costs that are associated with bankruptcy. However, as indirect costs represent opportunity costs associated with the event of bankruptcy, they are inherently difficult to estimate (Bisogno and De Luca, 2012:22). These costs include lost sales, forgone investment opportunities and the negative impacts stemming from the loss of supplier relationships and key members of management (Chen and Merville, 1999:277).

[6] Public companies are defined as firms which have publicly traded debt or shares (Douglas and Oellermann, 2021)

Table 2.2: The 20 largest bankruptcies in United States history

	Company	Number of employees impacted	Asset value lost, in billions (US $)	Reason for downfall
1	Lehman Brothers	26,200	691	2008 financial crisis
2	Washington Mutual	49,043	328	2008 financial crisis
3	Worldcom Inc.	30,000	104	$4bn accounting scandal
4	General Motors	88,000	82	Massive debt due to poor sales
5	CIT Group	unknown	71	Failed to find funding during the 2009 credit crunch
6	Pacific Gas and Electric Company	23,000	71	2017 and 2018 California wildfires
7	Enron	29,000	66	Fraud
8	Conseco	unknown	61	Failed acquisition strategy, federal investigation, plummeting stocks
9	MF Global	3,271	41	Traded in European sovereign bonds that failed, tried to liquidate with customer accounts
10	Chrysler	39,000	39	Massive debt due to poor sales

Table 2.2: The 20 largest bankruptcies in United States history (continued)

	Company	Number of employees impacted	Asset value lost, in billions (US $)	Reason for downfall
11	Thornburg Mortgage	400	37	Value of mortgage decline and unable to meet margin calls
12	Pacific Gas and Electric Company	20,000	36	Drought and reduced hydroelectric power forced PG&E to buy electricity at exorbitant rates
13	Texaco	55,000	35	Contract dispute with Pennzoil, costing $3bn
14	Financial Corporation of America	unknown	34	Savings and loan crisis in the late 1980s
15	Refco	<10	33	Accounting fraud
16	IndyMac Bancorp	11,000	33	FDIC takeover after mortgage market collapse
17	Global Crossing	10,000	30	Plummeting world economy
18	Bank of New England	17,299	30	Bad loans and heavy ties with creditors
19	General Growth Properties	unknown	30	Failed to find funds after aggressive growth and acquisition strategy funded by creditors
20	Lyondell Chemical	17,000	27	A decline in demand and volatility in material costs

Source: Desjardins (2019)

Cole, Johan and Schweizer (2021:1) note that these impacts of failure are further intensified when they are industry-wide or arise during a financial crisis. When this occurs, the negative impact can be felt across countries, resulting in increased unemployment, a reduction in tax revenue, coupled with higher levels of poverty and crime (Cole, Johan and Schweizer, 2021:1). In addition, these events can result in the collapse of entire industries or result in long-lasting reputational damage (Cole, Johan and Schweizer, 2021:1).

The reputational damage resulting from corporate failure however is not just limited to individual companies that fail but also to industry peers, who are viewed with equal suspicion. Cole, Johan and Schweizer (2021:1) note that the impact of corporate failure leads to the deterioration of trust of all market participants. Johnson (2008:116) notes that bankruptcy also carries with it negative social connotations. This cascades down to employees or management of failed firms who may not have been direct parties to the demise (Sutton and Callahan, 1987).

Large-scale failure has also in the past had an impact on policymakers and regulators, who have had to adjust the frameworks in which businesses operate and enhance corporate reporting requirements, in an attempt to address the causal issues of failure. This is evidenced by several legislative changes post the 2008 financial crisis, directed to particularly regulate the activities of the financial sector and to protect consumers (Ross, 2020). These included the issuing of Basel III in 2010, which amongst its various provisions, encompassed new requirements such as minimum liquidity buffers which are made available immediately after issues occur in the market, introducing leverage ratio requirements, as well as increasing the quality and quantity of capital requirements for financial institutions (Hattingh, 2018:36).

In the United States, amidst the additional measures taken up by the Federal Reserve, the most impactful legislative response came in the form of the Dodd-Frank Wall Street Reform and Consumer Protection Act (together often referred to as the Dodd-Frank Act) (Hattingh, 2018:16). The main thrust of these legislative policies was to prevent a market crisis by protecting the consumer from pernicious products offered by financial institutions, prescribing reserves given the credit risk carried by banks and like-entities, extending firmer requirements for credit rating agencies and subjecting bigger banks (identified by asset size), which are seen as quintessential to the US economy, with more stringent requirements (Hattingh, 2018:16-17). The Dodd-Frank Act also authorised the establishment of the Financial Stability Oversight Council (FSOC), with its primary focus on providing oversight of the financial risk in the non-banking sector (Hattingh, 2018:18-19).

Unlike the United States, there were no significant regulatory changes for South Africa immediately post the 2008 crisis. Almost fortuitously, the National Credit Act 34 of 2005 (NCA) became effective a year before the 2008 financial crisis. The NCA, the lack of exposure to foreign asset investment and the effective application of its inflationary-target framework by The South African Reserve Bank (SARB), helped South Africa to navigate the crisis relatively unscathed (Hattingh, 2018:30).

In the sphere of accounting, the IFRS Foundation and the International Accounting Standards Board (IASB), who are responsible for establishing accounting standards and principles, also introduced new accounting standards, such as IFRS 9 Financial Instruments and IFRS 16 Leases, to allow for more reliable and transparent reporting. The details of these changes and their impacts are addressed in section 2.4.

While regulatory changes are seen as a meaningful response to address some of the causal issues of the failure, like most regulatory reforms, these changes come with additional administrative burdens and increase the cost of doing business, leading to criticism by industry players. Finding a balance between meaningful regulations and creating speed bumps for businesses, is inherently complex.

Given the stark and broad ramifications of corporate failure, the ability to reliably predict and early-detect signs of failure is critical. While bankruptcy models have been developed to address this issue, models are cumbered with strengths and weaknesses, which makes the selection of which model to apply difficult (Aziz and Dar, 2006:18). In this study and within its definitive ambit, we will address the suitability of various prediction models. While these models are centred around predicting failure, the models do not extend the focus to the causal issues of the failure (Holt, 2013:50).

2.2.3 South Africa and corporate failure

Between the year 2000 and the end of 2020, an average of 1,449 South African companies (both private and public) liquidated every year (Statistics South Africa, 2021). These include companies that have undergone either compulsory or voluntary liquidation[7] and comprehend both listed and unlisted entities. Refer to Figure 2.2 and Figure 2.3 for the liquidation statistics in respect of companies over the period considered in this research.

The majority of these liquidations were in the financing, insurance, real estate and business services sectors, which included 13,188 firms over the period. This was followed by the trade, catering and accommodation sectors, with 7,725 liquidations. The statistics reflect a general downward trend in the number of annual liquidations, both overall and by-sector, with an upward tail in 2020, on the back of the Covid-19 pandemic and lockdown restrictions.

Incidentally, the drop in liquidations since 2011 coincided with the introduction of the revised Companies Act[8], which became effective on 1 May 2011. Amongst its numerous changes, the Act introduced a new chapter pertaining to business rescue procedures and compromises with creditors. This new chapter was introduced to assist companies in financial distress and extend to firms the opportunity to reorganise and restructure, in an effort to mitigate the risk of cessation (Du Preez, 2012:3). While there were over 30,000 company-related liquidations during the period from 2000 to 2020, only a marginal percentage of these would have been JSE listed entities.

[7] Per Statistics South Africa (Stats SA), "a compulsory liquidation takes place when the affairs of a company are wound up by order of the court. A voluntary liquidation on the other hand refers to when a company, by own choice, resolves to wind-up its affairs. Liquidation in this instance is defined as the winding-up of the affairs of a company when liabilities exceed assets and it can be resolved by voluntary action or by an order of the court".

[8] The Companies Act of South Africa (2008)

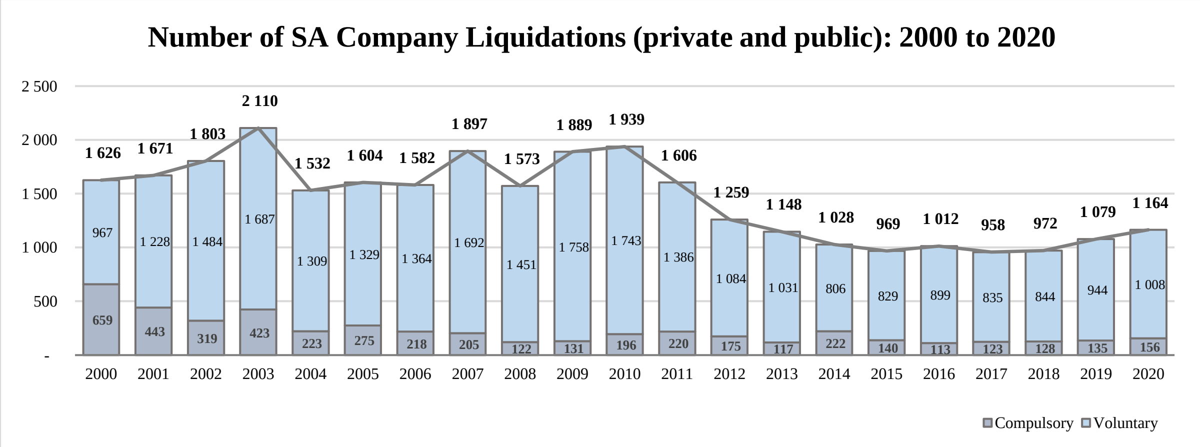

Figure 2.2: South African company (private and public) liquidation statistics – 2000 to 2020

Source: StatsSA (2021)

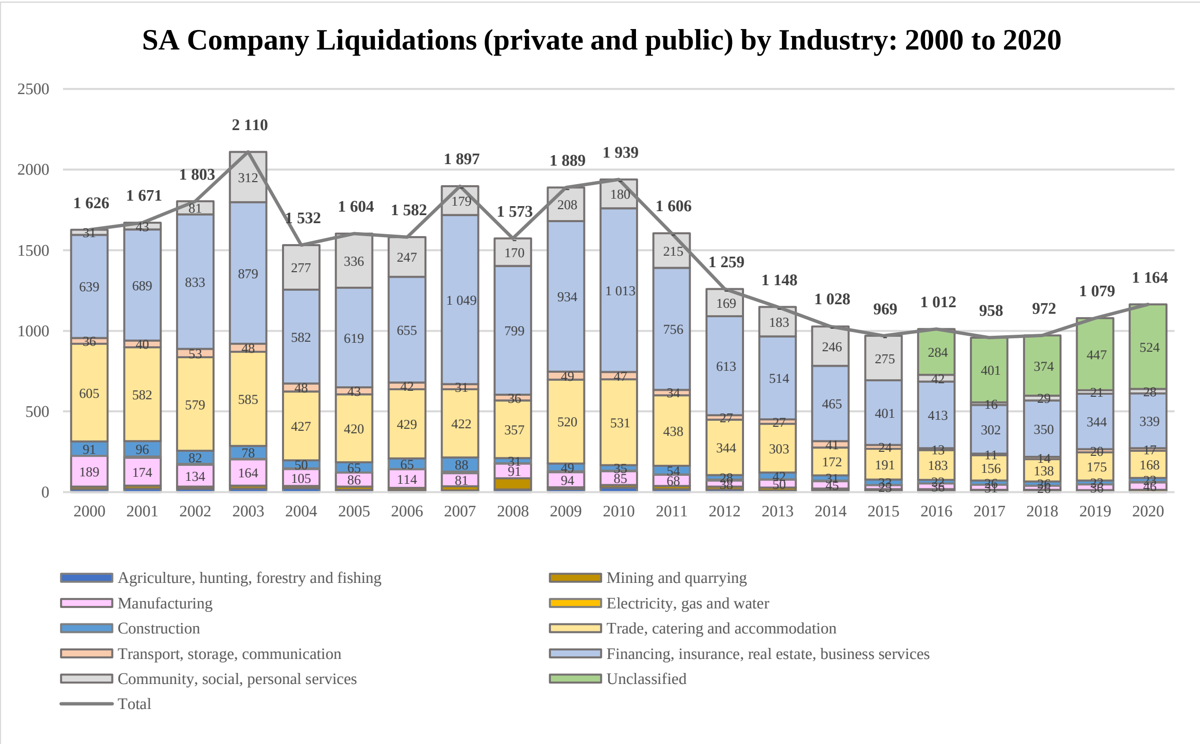

Figure 2.3: South African company (private and public) liquidation statistics by industry – 2000 to 2020

Source: StatsSA (2021)

While the average number of failures has declined per year over the last ten years, which includes the impacts of the Covid-19 pandemic and lockdown restrictions on businesses in 2020, the causal factors of failure in the private sector have been rather distasteful.

The past decade has seen South Africa riddled with allegations of corruption within the private sector (Business Insider SA, 2020). From Tongaat Hullet, who admitted to overstating its assets by over R3.5 billion (Business Insider SA, 2020), to Steinhoff who inflated its performance and assets by R250 million (Business Insider SA, 2020), JSE-listed companies have not been distanced from failure and the poor governance that has become so synonymous with state-owned entities. In both the Tongaat Hullet and Steinhoff cases it was established that failure was largely due to systemic and ongoing fraud by senior management (Open Secrets[9], 2020). Not all these lapses however have resulted in the termination of the company's operations.

In the South African context, bankruptcy prediction and the ability of firms to continue operating as a going concern have generally been guided by assurances provided by external auditors. In addition to the audit opinion expressed in respect of financial statements, the International Standard on Auditing (ISA) 570:6[10] requires that the auditor obtain evidence and conclude on the appropriateness of using a going concern basis of accounting in reporting the results of the firm. A risk assessment of the going concern assumption would be performed by the auditor, with financial ratios, analysis of the company performance and outlook, as well as an assessment of management's assumptions in this regard, typically forming the basis of such an assessment (ISA 570). The going concern assessment however doesn't necessarily act as an early detector for financial distress and failure, nor is the report of the auditors to be seen as a guarantee of such (ISA 570:7).

While auditors are required to express an opinion in respect of the firm's use of a going concern basis of accounting, in the past decade confidence in the veracity of the South African assurance industry has waned with major audit firms rocked by a myriad of governance and independence issues (Open Secrets, 2020) (Siphelele, 2020) (Business Insider SA, 2020).

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[9] "Open Secrets is a non-profit organisation which exposes and builds accountability for private sector economic crimes through investigative research, advocacy, and the law." (https://www.opensecrets.org.za/)

[10] ISA 570 relates to the auditor's responsibilities in its audit of a firm's financial statements as it relates to the firm as a going concern and the implications this has for the auditor's report.

2.2.4 Summary

The points covered in this segment highlight the importance of detecting potential failure well in advance, not merely to safeguard against a poor investment decision but potentially to arrest the root cause of distress in time, to mitigate its disastrous impacts.

Furthermore, the concerns surfaced in this chapter highlight the requirement for a more robust and independent prediction model for failure, that extends beyond accounting financial ratios, as the numbers cannot always be trusted. Given this fact, it is important to consider prediction models that encompass qualitative aspects (non-financial variables), as part of the potential model choice to be applied to the firm data considered in this research.

2.3 Models used in financial distress prediction

This segment provides an outline of the techniques and models that have been developed to forecast financial distress and corporate failure. Leaning on the research done by Aziz and Dar (2006), this section segments the bankruptcy models into three categories, namely, statistical models, artificially intelligent expert system models (AIES) and theoretical models, detailing their features and the characteristics of the sub-models that have been developed under these categories. Furthermore, this segment addresses the main bodies of research linked to these models, as well as the key learnings from their application. The analysis also includes a critique of the various techniques and models. A comparative review of different financial distress models, to guide the model set selection for this research, is also covered as part of the literature review.

The segment concludes by reviewing the research done in the South African context, considering not only the application of failure prediction models in the local arena but also the models developed in this space.

2.3.1 Statistical models

2.3.1.1 Introduction

Statistical models form the foundation of failure prediction studies and are by far the most popular category of prediction models employed in firm failure prediction research. These models follow classical modelling procedures and typically involve some degree of financial ratio analysis and coherently lean extensively on the financial statements of firms to drive their estimation of failure and success (Aziz and Dar, 2006:23-24).

In this category of bankruptcy models, the focus is given to the main model types developed in this area, namely, univariate, multiple discriminate, logit and probit models.

2.3.1.2 Univariate Model (Beaver, 1966)

The earliest noted work related to failure prediction, centred around the use of univariate and later multivariate analysis, to predict symptoms of distress. The analysis focused predominantly on financial ratios as an indicator of financial health, with inferences drawn mainly from the firm's financial accounting results (Aziz and Dar, 2006:20). The underlying rationale behind this technique was that if there are differences in the financial ratios displayed between the failing and non-failing firms, then these financial markers could be used to forecast firm failures (Aziz and Dar, 2006:20). This, however, required the merging of financial ratios commonly used in practice with statistical discipline, to create robust models to predict failure.

The forerunner in this model development was Beaver (1966), whose univariate model comprehended the primary use of financial ratios in predicting firm failure. Beaver (1966:71), for the purposes of his research, defined failure as the inability of the firm to meet its financial obligations as they mature. Considering a sample of seventy-nine firms that had failed across multiple industries between 1954 and 1964, Beaver applied thirty financial ratios, computing their outcomes for the five years preceding the failure of the firm. These failed firms were classified by industry and asset size and paired with non-failed firms of the same size and industry (Beaver, 1966:73).

While these ratios were selected based on their popularity (based on their frequency in literature), their success in previous research and cashflow criterion, Beaver eventually narrowed the ratio scope down to six variables due to their low error percentage when analysing the five years prior to failure (Beaver, 1966:78, 84). These six ratios comprised cash flow to total debt, net income to total assets, current plus long-term liabilities to total assets, working capital to total assets, the current ratio and no-credit interval (Beaver, 1966:80).

Beaver’s approach comprised computing the financial ratios, before engaging in a three-step approach, which included:

(i) a comparison of the mean value;
(ii) a dichotomous classification test; and
(iii) the analysis of likelihood ratios (Beaver, 1966:79).

In the comparison of the mean value step, Beaver computed the mean of the ratios for the failed and non-failed firms in each of the years before failure and compared their outcome in what he termed profile analysis (Beaver, 1966:79). Beaver noted that while the ratio distributions for non-failed firms were relatively stable over the period, the ratio distribution of failed firms deteriorated significantly as failure approached (Beaver, 1966:101).

In the dichotomous classification test, the financial ratios computed were used to predict the failure status of the firm, classifying firms as failed or non-failed in reference to a particular cutoff point (Beaver, 1966:83-84).

The final step related to the analysis of likelihood ratios, which involved an assessment of the probability of failure based on the financial ratio being observed (Beaver, 1966:83-84). Beaver concluded that the cash flow to total debt ratio was the overall best predictor, underscoring the extent to which a cash reservoir deters the likelihood of bankruptcy (Beaver, 1966:85). Beaver's research outcome suggested that the use of certain financial ratios could reasonably predict firm failure up to five years before bankruptcy. What Beaver's research however further pointed out was that the type of financial ratios used to predict failure is quintessential, as not all the financial ratios carry with them the same degree of accuracy (Beaver, 1966:101-102).

The application of a univariate measure for failure prediction however was not without its critics. Altman (1968:591) noted that a univariate analysis placed undue reliance on individual signals of impending problems, with the analysis presented in this fashion being susceptible to faulty interpretation and confusion. Altman (1968:591) illustrated this with reference to the notion that firms with poor profitability or with a poor solvency ratio may be regarded as bankrupt, even though these concerns may be mitigated as a result of the firm's liquidity position.

2.3.1.3 Multiple Discriminant Model (Altman, 1968)

Altman (1968:589) attempted to address the shortcomings of univariate models and the quality of ratio analysis as a technique in failure prediction, by employing a multiple discriminant analysis (MDA) methodology. Altman sought to employ this MDA technique to address the prioritisation of ratios when seeking to identify the probability of bankruptcy, what weights these ratios would carry and how the weights should be established (Altman, 1968:591). Limiting the sample to manufacturing corporations, Altman (1968:592) inferred that using MDA techniques carried an advantage over univariate models, as it considered an entire profile of characteristics common to relevant firms, as well as the interaction between them. In essence, these models represent the liner combination of certain discriminatory variables, which is used to derive a bankruptcy score (Aziz and Dar, 2006:20). This score is then in turn referenced to categorise firms into failed or non-failed groupings (Aziz and Dar, 2006:20).

In Altman's research (1968:592), this single discriminant score would be known as the Z-value or Z-score, which is derived from the function $Z = V_1 X_1 + V_2 X_2 + \ldots + V_n X_n$ where:

(i) $V_1, V_2, \ldots V_n$ = discriminant coefficients by the MDA model; and

(ii) $X_1, X_2, \ldots X_n$ = independent variables.

In this regard, the V_1 represents the discriminate coefficient calculated by the MDA model and X_1 represents the relevant financial ratio.

Altman's initial sample was composed of sixty-six companies, which were split into a bankrupt group and a non-bankrupt group, each consisting of an equal number of firms (Altman, 1968: 593). The thirty-three firms in the bankrupt group were identified based on their filing for bankruptcy under the United States Bankruptcy Act from 1946 to 1965. The mean asset size range of the firms selected was $6.4 million, with a range between $0.7 million and $25.9 million. Altman subsequently restricted the asset range to between $1 million and $25 million, due to the absence of comprehensive data available for small asset-size firms and the rarity of bankruptcy incidences for firms with large asset sizes (Altman, 1968:594).

Twenty-two potential financial ratios were initially considered by Altman as part of his evaluation (Altman, 1968:594). These financial ratios, which were selected based on their popularity in literature, their relevance to the study and which included a new tranche of ratios, were classified into five standard ratio categories covering the profiles of liquidity, profitability, leverage, solvency and activity (Altman, 1968:594). To derive a final profile of financial ratios, Altman adopted the following approach:

(i) He observed the statistical significance of various alternative functions, including the determination of the relative contributions of each independent financial ratio;
(ii) He considered the inter-correlations between the relevant financial ratios;
(iii) He observed the predictive accuracy of the various profiles; and
(iv) He applied judgment as part of the analysis (Altman, 1968:594).

Adopting this approach Altman finally established the discriminant function as follows:

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

where;

Z = overall index (Z-score)

X_1 = working capital / total assets

X_2 = retained earnings / total assets

X_3 = earnings before interest and taxes / total assets

X_4 = market value of equity / book values of total debt

X_5 = sales / total assets

Altman described the ratios included in his discriminant function as follows (Altman, 1968:594-595):

X_1 = working capital / total assets: This ratio, which was common in the study of corporate problems, measures the relativity of the net liquid assets of the firm to its total capitalisation. The working capital in this regard is described as the difference between the current assets and the current liabilities of the firm. Generally, loss-making firms will experience an adverse ratio. Altman noted this ratio to be the most valuable. This is in contrast to Beaver, who concluded that the cash flow to debt ratio as being the best single ratio predictor.

X_2 = retained earnings / total assets: This ratio, which was one of the new ratios introduced by Altman into the study of corporate failure, measured the relationship between the cumulative profits of the firm and its asset base. Generally, younger firms are expected to yield a lower ratio to mature firms, given the difference in the time frame for profit accumulation. However, this is contingent upon the industry and the firm's profit-making model. While the inclusion of this ratio could create a bias, leading to younger firms being classified as bankrupt relative to mature firms, the incidence of failure amongst firms in their earlier years in practice would support such a bias.

X_3 = earnings before interest and taxes / total assets: This ratio measures the productivity of the firm assets before the impacts of factors related to tax and debt leverage. The earnings before interest and taxes effectively represent the earnings available to meet the obligations to other stakeholders as they fall due. All things being equal, the lower the yield of earnings in relation to the firm's assets investment, the greater the risk of bankruptcy.

X_4 = market value of equity / book values of total debt: This measure, which includes the combined market value of all shares, measures the extent to which the firm's assets can fall before the firm becomes technically insolvent.

X_5 = sales / total assets: This ratio measures the ability of the assets to generate sales. Sales, while often being touted as the firm's measure of success, can also just be a vanity measure if the firm is unable to generate sufficient margin therefrom. For example, high sales growth can be generated on the back of significant rebates being passed to customers, which dents margin performance and ultimately the firm's earnings and net cash flows. Altman noted that based on its statistical insignificance, the measure would not have been included. However, it was included due to its unique relationship to other variables in the model.

The prevalence of the firm to distress was based on the firm's Z-score output, with reference to the following zonal markers:

(i) Where the Z-score was greater than 2.99, the firm was categorised into a "non-bankrupt" sector (safe zone);
(ii) Where the Z-score was greater than 1.81 but less than 2.99, the firm was categorised into a "zone of ignorance" or "gray area" (grey zone); or
(iii) Where the Z-score was less than 1.80, the firm was categorised into a "bankrupt sector" (distressed zone) (Altman, 1968: 606).

While Altman's research contributed significantly to the realm of bankruptcy prediction, it was not absent from critique. Altman's sample size was relatively small and was only focused on the manufacturing industry. Aziz and Dar (2006:23) note however that the small sample problem would be inherent in most bankruptcy predictive studies, as public firms don't generally go bankrupt.

Altman also recognised the limitations of his model in its potential application to out-of-sample firms. Altman (1968:600) noted that while the subset of the variables he had defined was effective for the initial sample, there was no guarantee that the results would yield the same for the general universe of firms.

The suitability of the coefficients applied in the Z-score function has also been questioned in later studies. Grice and Ingram (2001), who tested the time-specific accuracy of the Altman Z-score, as well as its performance outside the realm of manufacturing firms, noted the need to re-estimate the coefficients of the original model to derive a more accurate predictive outcome.

2.3.1.4 Logit Model (Ohlson, 1980)

Logit (or logistic) models, like univariate and multiple discriminant analysis, lean on the financial information of a firm to model the probability of failure. The output of the model is a probability, that is a product of explanatory variables applied (Aziz and Dar, 2006:20). In its application in respect of bankruptcy prediction, a probability of 0.5 would imply that a firm has an equal chance of failing or succeeding. Where 1 is set to denote bankruptcy, the closer the probability is to 0, the progressively lower the chance of the firm becoming bankrupt (Aziz and Dar, 2006:20).

Ohlson (1980), is noted to be a pioneer in respect of the use of logit analysis in bankruptcy prediction. While MDA had been the most popular technique at the time in the arena of corporate failure, Ohlson applied the econometric methodology of conditional logit analysis in his research, to avoid the common pitfalls of the MDA technique. These problems included:

(i) Limitations to the scope of the investigation under the MDA model, as certain statistical requirements are imposed on the distributional properties of the predictors. As an example, the variance-covariances matrices are required to be the same across the groupings of failed and non-failed firms and the requirement for normally distributed predictors limits the use of dummy independent variables (Ohlson, 1980:111-112);

(ii) Limited intuitive interpretation is possible under the MDA model as the output of the technique is a score. Ohlson suggests "for decision problems such that a misclassification structure is an inadequate description of the payoff partition, the score is not directly relevant" (Ohlson, 1980:112); and

(iii) MDA models are cumbered with matching problems, with asset size and industry criteria for matching being regarded as arbitrary. Ohlson noted that it is not clear from MDA models what is lost or gained from such a matching exercise or whether matching matters at all (Ohlson, 1980:112).

According to Ohlson, applying conditional logit analysis avoids these pitfalls associated with the MDA model and distils bankruptcy prediction to a simple statement, namely, "given that a firm belongs to some prespecified population, what is the probability that the firm fails within some prespecified time period?" (Ohlson, 1980:112).

Ohlson adopted the same basis as Altman in identifying failed firms, being the filing for bankruptcy by the firm under the United States Bankruptcy Act. The population boundaries applied by Ohlson restricted the population for testing to companies from the industrial sector whose shares were publicly traded from 1970 to 1976. Ohlson used this criterion mainly for practical reasons given the availability of data, with certain industries (transportation, utilities as well as financial services firms) excluded from the population due to their structural difference and the bankruptcy environment (Ohlson, 1980:114).

In establishing his logit model, Ohlson (1980) conducted three sets of computations, namely:

- (i) The first of these models predicted bankruptcy within one year of the event;
- (ii) The second model predicted bankruptcy within two years of the event; and
- (iii) The third model predicted bankruptcy within one or two years of the event.

Beginning with an initial sample of 105 failed firms, a sample of 2,058 non-failed firms, which suited the criterion set forth by Ohlson, were also selected.

In determining the probability of failure, Ohlson developed the following probabilistic model for bankruptcy (Ohlson, 1980:118-119):

$$P = (1 + \exp\{-\beta' X\})^{-1}$$

where:

P = the probability of bankruptcy; $0 \leq P \leq 1$

β = vector of unknown parameters

The logit function maps the value of $\beta' X$ to a probability bounded between 0 and 1

X = represents the financial variables (vector of predictors) below:

SIZE = log (total assets/GNP price-level index). The index assumes a base value of 100 for 1968.

TLTA = total liabilities divided by total assets

WCTA = working capital divided by total assets

CLCA = current liabilities divided by current assets

OENEG = 1, if total liabilities exceed total assets, 0 otherwise

NITA = net income divided by total assets

FUTL = funds provided by operations divided by total liabilities

INTWO = 1, if net income was negative for the last 2 years, 0 otherwise

CHIN = $(NI_t - NI_{t-1}) / (|NI_t| + |NI_{t-1}|)$, where NI_t is the net income for the most recent period. The denominator acts as a level indicator. The variable is thus intended to measure the relative change in net income. The (|) symbol indicates that the absolute value of the variable is to be used.

The coefficients of the different ratios were grouped as follows:

Positive: TLTA, CLCA and INTWO; Negative: SIZE, WCTA, NITA, FUTL and CHIN and Indeterminate: OENEG

For the purposes of this research, the first model applied by Ohlson described below, will be considered for inclusion in the model set (Ohlson, 1980:121):

$$O = -1.32 - 0.407SIZE + 6.03TLTA - 1.43WCTA + 0.0757CLCA - 1.720ENEG - 2.37NITA - 1.83\mathrm{FUTL} + 0.285INTWO - 0.521CHIN$$

Ohlson’s research indicated that four financial statement factors were statistically significant in forecasting the probability of bankruptcy. The first of these was the size of the firm (as measured by the size element in the model); the second, the extent to which the firm is leveraged (as measured by the TLTA element in the model); the third, the firm’s performance (as measured by the NITA element in the model); and the fourth, being the firm’s liquidity (as measured by the WCTA and CLCA elements in the model) (Ohlson, 1980:123). Ohlson would later underscore that the size of the firm was the most important predictor of bankruptcy (Ohlson, 1980:122). This conclusion is echoed in other later studies. Beaver, McNichols and Rhie (2010:18) for example noted that ceteris paribus, larger firms have a lower probability of bankruptcy.

While Ohlson’s model for predicting bankruptcy within one year yielded the correct classification 96.12% of the time (Ohlson, 1980:120), Ohlson’s overall error rates were much larger than those that surfaced in Altman’s 1968 study, as well as other studies using data from periods prior to 1970.

The predictive powers however contained in Ohlson’s model seemed to be robust across the estimation procedure and although at higher error rates than other studies, Ohlson’s application of a logit methodology was noted as a more vigorous approach to bankruptcy prediction. Ohlson acknowledged that the presence of market-related data would have enhanced the predictive power of his model (Ohlson, 1980:111).

2.3.1.5 Probit Model (Zmijewski, 1984)

Probit models (derived from the combination of probability and unit), as is the case for logit models, fall within the scope of conditional probability analysis and have very similar characteristics to its logit model counterpart. Similar to logit models, probit models aim to estimate the probability of a prescribed event occurring. The fundamental difference between the probit and logit models is their use of link functions. That is, the probit regression uses an inverse normal link function, whereas the logistic regression uses a logit link function in their respective probability assessments.

Even though probit analysis was formulated in the 1930s, it first appeared in the realm of bankruptcy prediction in 1977 in Hanweck's research covering failure prediction in the banking sector. While Hanweck took the first steps in the application of probit analysis in failure prediction, it is the work of Zmijewski (1984) that is most widely used in this area of probability analysis (Suresh et al., 2022:98)

Zmijewski argued that researchers in the area of financial distress prediction based their predictive analysis on non-random sampling, which could result in biased parameters and probability estimates if the appropriate estimation techniques were not applied. These biases Zmijewski noted were a choice-based sample bias (a result of researchers "oversampling" distressed firms) and a sample-selection bias (a result of a "complete data" criterion for sample selection) (Zmijewski, 1984:59).

According to Zmijewski, the oversampling (which led to a choice-based bias) was a result of an extremely low-frequency rate of public firms that experienced characteristics of financial distress, thus leading researchers to compensate for the imbalance in the dataset between firms and non-distressed firms due to this underrepresentation of distressed firms. The complete data criterion (which led to a sample-selection bias) was a result of data for financial distress firms often not being available (Zmijewski, 1984:59).

Zmijewski supported his view of these biases being common in previous studies by referencing 17 studies conducted (including his own), illustrating how samples were collected. He noted that as it related to the sample selection, "all 17 studies estimated models on the "known" population of distressed firms subject to a complete data criterion, with 12 of the 17 studies using a matched-pairs design for collecting the non-distressed sample" (Zmijewski, 1984:60).

He further noted in reference to the sample composition, that when examining the distressed firm sample frequency (i.e. the number of distressed firms divided by the total number of firms in the sample) that the majority of the studies used a 50% rate, with only three studies using rates less than 40%. Zmijewski thus concluded that the previous studies estimated models on non-random samples, which have composition considerably different from the composition of the population (Zmijewski, 1984:60). Refer to Table 2.3 for a summary and comparison of the sample and data selection procedures of the studies reviewed by Zmijewski.

Zmijewski determined to address these apparent methodical issues that were prevalent in typical financial distress prediction models by applying his probit model on six sets of data, where the distress/non-distressed firm ratio was varied from 1:1 to 1:20 (this is unlike the 1:1 distress/non-distressed matching criterion common in previous research). As in previous studies, financial distress was defined as the act of filing for bankruptcy (Zmijewski, 1984:63,67-68).

Zmijewski's probit model (1984:65-66) described the probability of bankruptcy where a firm is observed to file a petition for bankruptcy (B = 1) when B*, an underlying response variable, exceeds zero:

$$P\ (B = 1) = P\ (B^* > 0)$$

$$B^* = a_0 + a_1 ROA + a_2 FINL + a_3 LIQ + u$$

$$P\ (B^* > 0) = P\ (-\ u < a_0 + a_1 ROA + a_2 FINL + a_3 LIQ)$$

where:

$P(.)$ = probability of (.); B = 1 if bankrupt, 0 otherwise

ROA = net income to total assets (return on assets)

$FINL$ = total debt to total assets (financial leverage)

LIQ = current assets to current liabilities (liquidity)

u = a normally distributed error term

For the purposes of this research, the coefficients applied by Zmijewski in his 40:800[11] sample, which yielded the highest accuracy, will be considered for inclusion in the model set (Zmijewski, 1984:69). This is defined as:

$$X = -4.336 - 4.513ROA + 5.679FINL + 0.004LIQ$$

Applying the model to Zmijewski's original composition of 96 distressed firms to 3,880 non-distressed firms, yielded a high overall accuracy rate of 98% (or an overall error rate of 2%) (Zmijewski, 1984:71). Significantly, based on the overall error rate, the model performed better than Beaver, Altman and Ohlson's models. However, Zmijewski's error rate in determining distressed firms was higher than in previous studies. Refer to Table 2.3 for a comparison of error rates (accuracy) of the 17 research studies reviewed by Zmijewski.

To assess the impacts of the choice-based bias, Zmijewski selected six samples, each containing 40 bankrupt firms but increasing the non-bankrupt firms in each estimation sample. This allowed for a distribution of samples with a large bias to a small degree of bias and a comparative assessment of the results across the sample spectrum (Zmijewski, 1984:68). Zmijewski concluded that while bias is indeed prevalent and the elimination of the bias is possible, that the bias did not affect the statistical inferences or the overall classification rates for the financial distress model and the samples tested (Zmijewski, 1984:77).

In assessing the sample selection bias, Zmijewski incorporated the use of a bivariate probit assessment, which incorporated the impact of missing data on the estimates of bankrupt probabilities. Similar to the assessment of the choice-based bias, while addressing the sample selection bias influenced probability estimates, it did not affect the statistical inferences or the overall classification rates (Zmijewski, 1984:76-77).

[11] This refers to the ratio between the number of bankrupt versus non-bankrupt firms in the sample

Table 2.3: Summary of the sample and data collection procedures used in Zmijewski's financial distress research

Research Study	Sample Selection			Sample Composition			Classification Error Rates[4]		
	Complete Data Criterion	Population of Distressed Firm Used	Matched Pairs Sample	Number of Firms: *D*[1]	Number of Firms: *ND*[2]	Sample Frequency Rate[3]	*D*[1]	*ND*[2]	Overall
Beaver (1966)	Yes	Yes	Yes	79	79	.500	NR	NR	.10
Altman (1968)	Yes	Yes	Yes	33	33	.500	.06	.03	.05
Wilcox (1971; 1973)	Yes	Yes	Yes	52	52	.500	NR	NR	.06
Deakin (1972)	Yes	Yes	Yes	32	32	.500	.03	.03	.03
Blum (1974)	Yes	Yes	Yes	115	115	.500	NR	NR	.08
Elam (1975)	Yes	Yes	Yes	48	48	.500	NR	NR	NR
White and Turnbull (1975)	Yes	Yes	No	34	2,303	.015	.53	.01	.02
Alman et al (1977)	Yes	Yes	No	53	58	.477	.06	.09	.07
Deakin (1977)	Yes	Yes	No	63	80	.441	.12	.01	.06
Ketz (1978)	Yes	Yes	Yes	75	100	.429	.33	.04	.07
Van-Frederiklust (1978)	Yes	Yes	Yes	20	20	.500	.05	.10	.08
Norton and Smith (1979)	Yes	Yes	Yes	30	30	.500	.11	.03	.07
Dambolena and Khoury (1982)	Yes	Yes	No	46	46	.500	.09	.01	.06
Ohlson (1980)	Yes	Yes	Yes	105	2,058	.049	NR	NR	.04
Emery and Cogger (1982)	Yes	Yes	Yes	52	52	.500	NR	NR	.10
Zavgren (1982)	Yes	Yes	Yes	45	45	.500	NR	NR	.18
Zmijewski (1983)	**Yes**	**Yes**	**No**	**96**	**3,880**	**.025**	**.83**	**.01**	**.02**

Source: Zmijewski (1983:71)

[1] D – distressed firms;

[2] ND – non-distressed firms

[3] Number of distressed firms/total number of firms in the sample. The Pearson correlation coefficient between the distressed firm sample frequency rate and the distressed and non-distressed classification error rate – .932 and .428, significant at the 0.1 and >.10 levels, respectively

[4] Error rates are the proportion of firms incorrectly classified reported in the respective studies for one year prior to financial distress

2.3.1.6 Hazard Model (Shumway, 2001)

Shumway (2001:101) proposed a discrete-time hazard logit model to predict firm bankruptcy, incorporating not just accounting ratios but also market variables. A key feature of Shumway's model was its ability to predict bankruptcy given the entire period of information being considered. That is, Shumway's model considered all the information of the firm at every point in time over the years being observed, to assess the firm's bankruptcy risk (Shumway, 2001:102). This was in contrast to other static logit models that only incorporated the firm's performance for a single fiscal year for each observation (Wu, Gaunt and Gray 2010:34-35).

Shumway (2001:101-102) considered static models to be inappropriate in accurately predicting bankruptcy, given the nature of bankruptcy information. Shumway noted that this single period or static model ignored the fact that firms change through time, resulting in bankruptcy probabilities that are biased, inconsistent and incorrect inferences being made. In addition, he noted that the application of a static model introduced selection bias into estimates.

Shumway (2001:102-103), argued that hazard models are preferable over static models and carry the following distinct advantages. Firstly, hazard models addressed the problems of static models by explicitly accounting for the impacts of time. Secondly, unlike static models, hazard models adjusted for the period at risk of bankruptcy, by considering periods before the actual declaration of bankruptcy. Thirdly, hazard models surface the changing health of the firm over the period by incorporating time-varying co-variates (variables that change over time). These include the incorporation of macroeconomic variables that vary year after year. Lastly, with the incorporation of more information and market-related data points, the results of hazard models are superior and perform better than static models, out of sample.

In establishing his best-performing model, Shumway (2001:103) incorporated market variables which included market size, past stock returns, as well as the standard deviation of stock returns. These variables were coupled with accounting metrics, which included the ratio of net income to total assets and the ratio of total liabilities to total assets. Shumway further assumed that bankruptcy could occur at any time (t) over the period being observed and varying from other research, defined failure as the time when a firm leaves the sample for any reason (Shumway, 2001:104).

Selecting a sample of 300 bankruptcies between 1962 and 1992, Shumway (2001) considered variables used by Altman and Zmijewski as part of his comparative scenarios of probability. Shumway (2001:123) concluded that half of the accounting ratios used in previous distress prediction models were poor predictors and that the inclusion of previously neglected market-related variables is strongly related to bankruptcy prediction. Combining the proposed market-related data with the two accounting ratios proposed by Shumway resulted in a model that by his estimation was "quite accurate" in respect of out-of-sample tests (Shumway, 2001:123).

2.3.2 Artificial Intelligent Expert System Models (AIES)

2.3.2.1 Introduction

Artificially Intelligent Expert System (AIES) models, like statistical models, focus on the symptoms of failure and conclude on a firm's probability of failure or success based on the financial accounts of the firm. The use of AIES models is a product of technological advancement and these models are heavily dependent on the use of computer technology for model development (Aziz and Dar, 2006:19).

AIES models carry with them some significant advantages over other model categories, with Aziz and Dar (2006:26) noting that models in this category outperform statistical and theoretical models in their prediction accuracy.

In this section, the main branches of AIES models (based on their prevalence in past studies) are covered, namely artificial neural networks and recursive partitioning.

2.3.2.2 Artificial neural networks

Artificial neural networks (ANNs), as a technique for the prediction of firm failure, were introduced in 1990 and dominated the literature on firm failure in the second half of that decade (Balcaen and Ooghe, 2004:12).

These ANNs comprise computer systems and networks that can assess the risk of firm failure (the output of the technique) based on a vector of inputs (independent variables) and training values (dependent variables). As data is fed into the system, the processing elements called neurons can identify patterns in the data and transform this input data into meaningful output. The ability of the system to analyse and assess data inputs is established via a training algorithm, which then directs the identification of patterns (e.g. indicators of failure and success) within a data set. Typically, a training sample is used with a varied set of weights, until an appropriate mapping for the system is derived (Balcaen and Ooghe 2004:11-12).

In the arena of ANNs, several training algorithms can be applied, which inform how data patterns are identified by the model. According to Balcaen and Ooghe (2004:13), the most popular training algorithm applied in the construction of ANNs is back-propagation algorithms.

Back-propagation algorithms, applied in the development of distress models, involve the assessment of input neurons against a required output. Inputs are run through a network and compared to the desired output, with errors identified through the exercise used to adjust the weights in the connection, working backwards through the network. This input-versus-output assessment is repeated until the network (model) is trained to understand the relationship between the inputs to the model and the output (Balcaen and Ooghe, 2004:13). Several disadvantages are however associated with the use of back-propagation algorithms. These include the fact that the approach involves high computational intensity and there is a need for specific expertise to run the model (Balcaen and Ooghe, 2004:13). Fahlman and Lebiere (1989:524) further note, that given the training approach of back-propagation algorithms, that the process tends to be slow.

The use of another category of training algorithms, namely cascade-correlation algorithms, is said to overcome the shortfalls associated with the popular back-propagation algorithms. According to Fahlman and Lebiere (1989:524), cascade-correlation algorithms learn much faster, as it requires no back-propagation of the errors identified through the various elements of the network. Furthermore, this faster learning approach is facilitated by beginning with a minimal network, that trains and adds new hidden units one by one, instead of adjusting the weights within a fixed topology, as is the case for back-propagation algorithms (Fahlman and Lebiere, 1989:524).

According to Aziz and Dar (2006), the application of ANN techniques delivers excellent results across various failure prediction studies, but while having several advantages over other prediction methods, is also cumbered with several shortcomings. These advantages and disadvantages are summarised in Table 2.4.

Table 2.4: Advantages and disadvantages of ANN models

Advantages	Disadvantages
– Has the ability to analyse complex patterns in an expedient manner, with a high level of accuracy – It is not subject to restrictive statistical assumptions – Able to learn from examples without the need for any pre-programmed information – Input data does not need to conform to linearity. The non-linear approach is considered a significant advantage over other models – Allows for the use of qualitative data inputs – Able to handle unstructured ("noisy") data – Can overcome the issue of autocorrelation – Considered to be more flexible than other methods with the ability to effectively handle small sample sizes	– Requires data of high quality and careful selection of the variables in the training sample is needed, as ANN models are highly sensitive to the "garbage-in, garbage-out" problem – ANN models do not surface the significance of each variable in the final classification and the weights that are derived cannot be interpreted – ANN models are typically at risk of over-fitting[12], which impacts the model's application for out-of-sample data – Requires a large training sample to train the network sufficiently

Source: Balcaen and Ooghe (2004:14-15)

[12] "Overfitting is a modelling error in statistics that occurs when a function is too closely aligned to a limited set of data points." When overfitting is prevalent, the model tends to only be applicable in respect of the data set that was used in its construction and does not perform well when other data sets are applied to it (Twin, 2021).

2.3.2.3 Recursive partitioning

Recursive partitioning is a method of classification, which utilises a decision tree to correctly classify members of a population, based on a set of independent variables (Cassim, 2016:5). The decision tree would typically be hierarchical, consisting of a series of if-then conditions (known as tree nodes), which in the realm of failure prediction ultimately leads to a terminal node, classifying a firm as failed or non-failed (Steyn-Bruwer and Hamman, 2006:9).

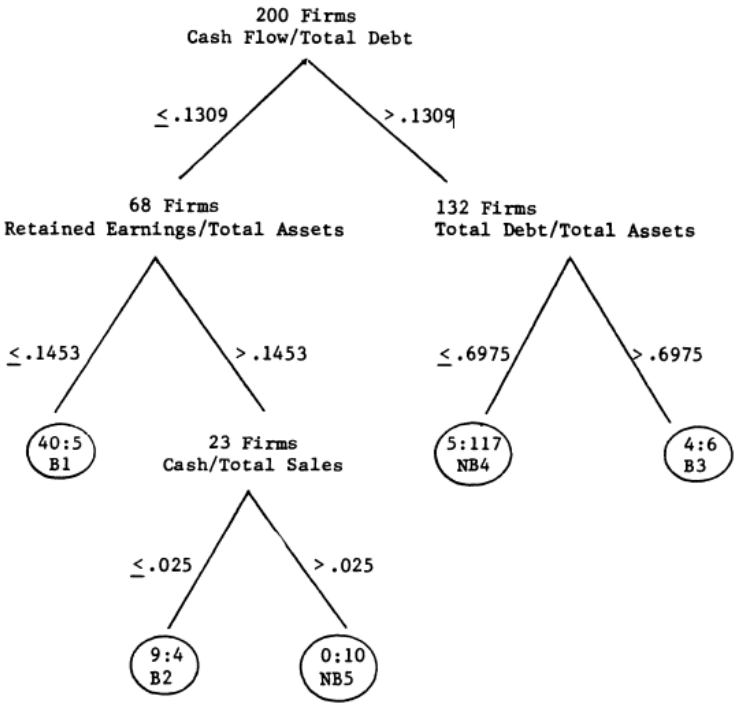
Key in deriving the correct classification is the establishment of independent variables that act as discriminators for the various observations at the decision point. Connected to this is also the setting of an appropriate value of the independent variable, to correctly classify the observation (Steyn-Bruwer and Hamman, 2006:9). Algorithms are often used to determine these key aspects of the decision tree.

Frydman, Altman and Kao (1985) applied this methodology in their research, presenting at the time a new classification procedure, which they had termed Recursive Partitioning Algorithm (RPA). The objective of their research covered a comparative analysis between this technique and discriminant analysis. Frydman, Altman and Kao (1985:270), described the RPA as a "computerised, nonparametric classification technique based on pattern recognition", which had characteristics of both univariate and multivariate methods. The model, which resulted from RPA, was in the form of a binary classification tree, which assigned objects into selected groups (Frydman, Altman and Kao, 1985:270). Refer to Figure 2.4 which describes a binary classification tree constructed by a RPA, based on the financial data of 200 firms.

In this particular case (refer to Figure 2.4), the sample begins with 200 firms which are classified as bankrupt (B) or non-bankrupt (NB), based on financial data. For example, a firm with a cash flow to debt ratio $\leq$ .1309 (68 firms) is siphoned to a node where an assessment that considers the ratio of retained earnings to its total assets is performed. Where this ratio of retained earnings to total assets is $\leq$ .1453, the firms (45 firms) are denoted as bankrupt. However, in this case, only 40 firms were factually bankrupt, with 5 firms being misclassified.

A two-step approach was adopted by Frydman, Altman and Kao (1985) in establishing the classification rules for their binary classification tree. The first step involved the grouping of the termination nodes in such a way as to minimise the cost (risk) of misclassification (also known as the re-substitution risk). The second step involved minimising the cross-validation[13] risk.

Figure 2.4: RPA classification tree



Source: Frydman, Altman and Kao (1985:272)

Balcaen and Ooghe (2004:10) note that binary classification trees are usually complex trees which tend to overfit the data. The selection of a tree with the appropriate complexity of the tree is therefore important. This is achieved by minimizing the cross-validation risk and by a trade-off between complexity and the re-substitution risk. Based on their research, RPA was

[13] Cross-validation is a method used in statistics when assessing and comparing learning algorithms. The method involves data being segregated into two parts, with one segment applied to train a model and the second segment utilised to validate the model. The goal of such an assessment is to obtain the correct ratio to derive an accurate setting of the model and to derive accurate performance outside of the sample when exposed to new data. (Refaeilzadeh, Tang and Liu, 2009)

found to outperform discriminant analysis. The application of recursive partitioning in the South African context is discussed in section 2.3.4.3.

Applying this method carries with it several advantages and disadvantages. These are summarised in Table 2.5.

Table 2.5: Advantages and disadvantages of RPA models

Advantages	Disadvantages
– Given the non-parametric[14] application/approach, there are no requirements for strong statistical data – The model can handle incomplete and qualitative data – Able to handle non-systematic errors in the data – Considered user-friendly and simple	– The decision tree requires specification of prior probabilities and misclassification costs (risks). "The ‘prior probabilities’ are the probabilities of belonging to the failing and the non-failing group in the total population. The “misclassification costs” are the costs of a Type I and a Type II error."[15] – Decision tree models assume that the failing and non-failing grouping of firms are distinct, nonoverlapping and distinguishable. This is however not always the case in practice. – The models cannot compare firms within the same risk category

Source: Balcaen and Ooghe (2004:11-12)

[14] Non-parametric refers to the statistical technique in which the data doesn’t need to fit a normal distribution in order for it to be analysed (Grant, 2021).

[15] A Type I error refers to the incorrect classification of a failed company as a non-failed company, while a Type II error refers to the incorrect classification of a non-failed company as a failed company.

2.3.3 Theoretical models

2.3.3.1 Introduction

Alternative models for bankruptcy prediction, outside the realms of classical statistical models, have also been developed. These models include balance sheet decomposition measures, gambler's ruin theory, as well as cash management and credit risk theories, amongst many others. Aziz and Dar (2006:19) note that these models tend to focus on the qualitative causes of failure are typically multivariate in nature and while being theoretical, draw on statistical techniques to support the theoretical argument put forward as an alternative perspective on bankruptcy prediction.

In this section, a summary of some of the alternative models available in the realm of distress prediction is provided, highlighting their main characteristics and underlying theoretical arguments.

2.3.3.2 Balance sheet decomposition models

Balance sheet decomposition models (BSDM) essentially examine changes in the firm's balance sheet and mark significant changes as potential indicators of financial stress. The underlying theory suggests that firms attempt to maintain an equilibrium in their financial structure and that significant changes in their financial structure indicate the firm's lack of control and their inability in maintaining that equilibrium, which is then noted as a symptom of financial distress. (Aziz and Dar, 2006:22).

Lev (1973), in his research related to decomposition measures, described this equilibrium theory by borrowing from the experience of the human organism. Lev (1973:56), states: "A major characteristic of all living organisms is homeostasis – an equilibrium maintained by a self-regulatory mechanism. When such an equilibrium e.g., a human body temperature of 98.6 degrees[16] is disturbed, forces are set in motion to restore it. It has been suggested by organization theorists and economists, that the behavior of business organizations can also be characterized by homeostasis in which optimal (equilibrium) relationships among the various inputs and outputs are determined and efforts are made to maintain them against disturbances. Thus, for any given level of activity, for example, there exist optimal relationships between

[16] Normal body temperature is described here in degrees Fahrenheit

labor and capital inputs, inventory and sales, cash and short-term securities, debt and equity capital."

Firms however are not static organisms and their goal is not necessarily to maintain a financial position but rather to grow. Furthermore, balance sheets by their very nature are subject to variances as a product of profit and cash flows, which are the primary objectives of firms. In addition, monitoring changes in a firm's balance sheet is not uncommon. Exception reporting by analysts and other users of the financial statements forms part of the general analytical review procedures they perform to identify performance and risk trends (Lev, 1973:56).

Lev (1973:56) suggests, however, while acknowledging that balance sheets are subject to planned and unplanned changes and that traditional financial statement analysis encompasses a review of changes over time, that when considering various periods, this approach is inefficient.

Lev argues that a decomposition analysis is a more efficient and convenient method of identifying whether a firm has been subject to significant changes and identifying where the change can be found (Lev, 1973:56). This can then be used as a tool to identify distress when comparing the results to other benchmarks, such as industry averages.

Despite appearing to be quite a rudimentary approach, based on the review of previous studies performed by Aziz and Dar (2006:26), balance sheet decomposition models yield a predictive accuracy of 88% on average.

2.3.3.3 Gambler's ruin theory

Gambler's ruin theory involves the application of conditional probability methods in the area of financial distress. The theory applied under this model suggests that the firm is a gambler that has a certain amount of capital (denoted as K). This capital (K) is subject to random positive changes (expressed as a probability, p) or negative changes ($1 - p$). These positive and negative changes are denoted by Z. The firm enters bankruptcy when $K + Z < 0$ (Scott, 1981:327-328). Effectively, the result encompasses the compounded probability of a firm running out of capital (i.e. bankruptcy).

K can be defined with reference to the accounting value, market value or liquidation value of the firm's capital. Another key assumption in this model is that the firm is cut off from the open market to raise funding and must fund any losses through the selling off of its assets (Scott, 1981:327-328).

Given these assumptions, the model may be best applied in scenarios where firms cannot raise new capital or are not in a position to borrow funds easily. In some cases, these restrictions may already be indicators of distress. These types of restrictions represent one of the weaknesses of the model, as they are not necessarily indicative of practical realities. Furthermore, another weakness noted with this model is that while it represents the compounded probability of a firm running out of cash, it assumes that cash flow results from a sequence of independent trials and disregards the opportunities available for management to intervene during a negative spell (Scott, 1981:323).

Scott (1981:328) defined the model linked to this theory as follows:

$$Z - \mu_z / \sigma_z < -(\mu_z + K) / \sigma_z$$

where:

K = capital

Z = change in K

μ_z = mean

σ_z = standard deviation

Interestingly, in the review performed by Aziz and Dar (2006:26) of previous studies, the gambler's ruin theory yielded the highest predictive accuracy, at 94%. Their research, however, only considered one research study (representing 1.1% of the total studies reviewed), which applied the gambler's ruin theory (Aziz and Dar, 2006:27).

2.3.3.4 Cash management theory

Cash-related models address the fundamental element of bankruptcy, being the cash management of the firm and its ability to meet obligations as they become due. Where there is an imbalance between the cash inflows and cash outflows generated by a firm, this leads to distress and ultimately failure (Aziz and Dar, 2006:22). In addition to the imbalance of cash flows, the type of cash flows between healthy and distressed firms generally differ, which allows for a discriminant measure to segregate between these two types of firms in the market.

For example, a healthy firm would have steady cash flows generated from operational activities and pay higher taxes, on the back of higher profits (Aziz, Emanuel and Lawson, 1988:428). Inversely, distressed firms may see a higher degree of cash inflows being derived from financing activities and lower tax liabilities, given their lower profit levels (Shamsudin and Kamaluddin, 2015:772).

The models generated in this ambit of financial distress prediction, utilise cash-based financial ratios and statistical techniques to drive models that compute cash flow indicators (positive or negative) as markers for distress.

Aziz, Emanuel and Lawson (1988) for example used Lawson's (1971) cash flow identity, applying MDA and logit techniques to a sample of firms covering the period of 1971 to 1982, to assess the accuracy of a cashflow-based model as a predictor of distress. The components were calculated for one to five years prior to the bankruptcy occurrence date.

Lawson's cash flow identity is described as follows (Aziz, Emanuel and Lawson, 1988:420):

$$(k_j - h_j) - (A_j + R_j - Y_j) - H_j - t_j = (F_j + N_j - M_j) + (D_j + B_j)$$

where:

$(k_j - h_j)$ denotes operating cash flow in year j represented by cash collected from customers, k_j, and operating cash outflow, h_j;

$(A_j + R_j - Y_j)$ stands for net capital investment, represented by replacement investment, A_j, growth investment, R_j, and the proceeds from assets displaced, Y_j in year j;

H_j denotes liquidity change in year j;

t_j stands for all taxes assessed on the corporation that is paid in year j;

F_j represents period j interest payments;

N_j is medium and/or long-term debt raised or retired in year j;

M_j is short-term debt raised or repaid in year j;

D_j represents dividends paid to shareholders in year j; and

B_j is equity capital raised or repaid in year j.

Aziz, Emanuel and Lawson's (1988) models produced an overall prediction accuracy as high as 92.8%, one year before bankruptcy, to 80.9%, five years before bankruptcy.

2.3.3.5 Credit risk theory

Credit risk theories are linked to the Basel I and Basel II accords and consider the risk that any borrower (the firm) will default on their obligation (Aziz and Dar, 2006:22). The financial distress models in this category lean on economic theories of corporate finance, with risks being published by credit bureaus and rating agencies (Aziz and Dar, 2006:22).

Based on the review of previous studies performed by Aziz and Dar (2006:26), credit models yield a predictive accuracy of 91% on average.

2.3.3.6 Other qualitative models

Other theoretical models related to financial distress prediction, have considered non-financial data as a basis for distress prediction.

2.3.3.6.1 Delays in reporting, director resignations and appointments and director shareholding

Court's (1991) research considered the significance of certain firm-specific, non-financial variables in failure prediction. Applying logit regression, Court (1991) developed a model for predicting failure centred around three main non-financial variables, namely, the delay by the firm in publishing its annual financial statements, the resignation and appointment of directors and director shareholdings. Court demonstrated that his failure prediction model, based solely on non-financial variables, produced more accurate results than traditional models containing only financial ratios (Court, 1991:3). Court (1991), in an enlarged sample, subsequently included financial variables alongside the non-financial variables. The financial variables added to the three main three non-financial variables included:

- i) Profit before interest after tax / total assets;
- ii) Market value of equity / book value of debt; and
- iii) Owners' equity / total capital employed

The inclusion of financial metrics improved the predictive ability of the model “dramatically” (Court, 1991:10). Court concluded by recommending that the accuracy of financial ratio-based prediction models could be improved by including non-financial variables (Court, 1991:10).

2.3.3.6.2 Firm diversification

Rose (1992) proposed a model which considered firm diversification as a barrier to bankruptcy. Rose (1992:67-68) proposes in his model that increasing the number of independent divisions of a firm (i.e. diversifying the firm) reduced variance in the income of the firm and reduced the likelihood that the firm will be unable to meet its obligations. This in turn reduces its exposure to the risk of bankruptcy.

2.3.3.7 Comparative review of financial distress models

To draw to summation the various distress prediction models discussed, reference is made to the research undertaken by Aziz and Dar (2006).

Aziz and Dar (2006) undertook an extensive literature review and comparative analysis of different financial distress models and methodologies, considering empirical findings across ten different countries. Their analysis, which covered 89 published works, attempted to resolve the problem of model choice by considering the prevalence, characteristics and accuracy of various prediction models from past studies (Aziz and Dar, 2006:18).

The product of their research was a unique ranking system, the first of its kind, to guide the selection of model choice (Aziz and Dar, 2006:18). Furthermore, Aziz and Dar (2006:18) concluded, that while the predictive accuracies of different models seem to be generally comparable, AEIS models performed marginally better than statistical and theoretical models.

Please refer to Figure 2.5, Figure 2.6 and Table 2.6, which respectively detail the prediction accuracy (by category and individual model type) and ranking of the various models, considered in their research.

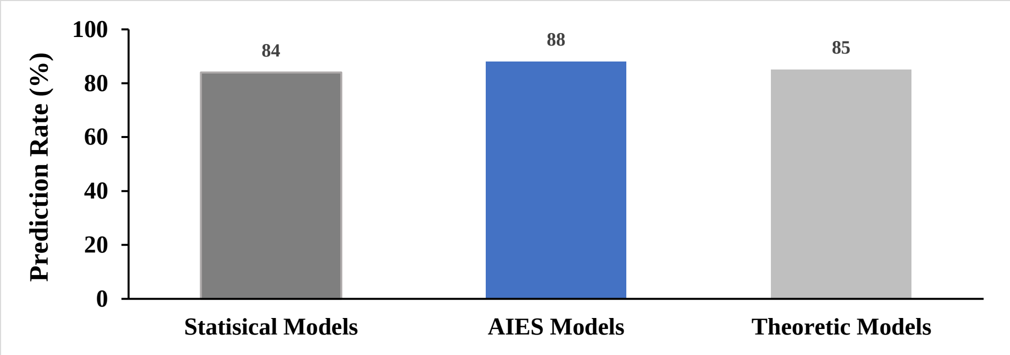


Figure 2.5: Overall category predictive accuracies

Source: Aziz and Dar (2006:27)

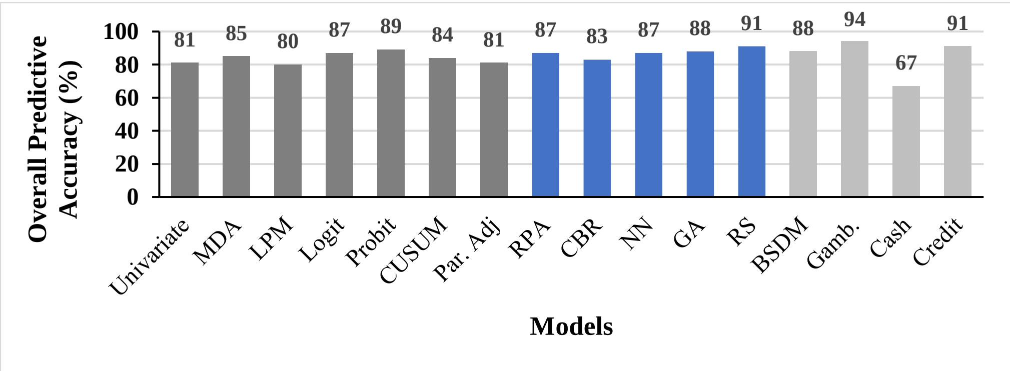


Figure 2.6: Individual model type predictive accuracies

Source: Aziz and Dar (2006:26)

Table 2.6: Overall and individual model type predictive accuracies

Model Type	***Number of applications in past studies (f)***	***Geometric mean of % prediction rates (X)***	***fX***	***Weighted variance (WV), using GM***	***Weighted standard deviation (WSD), using GM***	***Adjusted standard deviation (WSD/f)***	***Ranks (using WSD/f)***
Univariate.	3	81.0918	243.2754	86.02245	9.274829	3.092	9
MDA.	25	85.13469	2128.367	74.09812	8.608027	.344	1
LPM.	3	80.45573	241.3672	162.9942	12.76692	4.256	11
Logit.	19	86.6655	1646.645	78.9162	8.883479	.468	2
Probit.	2	88.85944	177.7189	74.8978	8.654352	4.327	12
CUSUM.	2	83.99405	167.9881	6.331802	2.516307	1.258	4
Par Adj.	1	81	81	81	NA	NA	NA
RPA.	5	86.37933	431.8966	131.4196	11.46384	2.293	7
CBR.	2	83.48653	166.9731	12.2752	3.503598	1.752	6
NN.	7	87.39402	611.7582	126.1244	11.23051	1.604	5
GA.	4	88.44349	353.7739	86.57967	9.30482	2.326	8
RS.	3	90.78846	272.3654	102.8432	10.14116	3.380	10
BSDM.	4	87.70087	350.8035	18.5042	4.301651	1.075	3
Gamb.	1	94	94	NA	NA	NA	NA
Cash.	3	67.01017	201.0305	557.8339	23.61851	7.873	14
Credit.	2	90.80198	181.604	133.1242	11.53795	5.769	13
Total	**86**	**1363.206**	**7350.567**				

Source: Aziz and Dar (2006:27)

2.3.4 South Africa: Development of financial distress prediction models

2.3.4.1 Introduction

While studies in the South African context have typically covered the application of models crafted in other bodies of research, several models have been developed in South Africa.

2.3.4.2 Models developed by South African researchers

Garbers and Uliana (1994) highlighted numerous multivariate failure prediction models developed in South Africa, including those by De La Rey (1981) and Clarke, Hamman and Smit (1991).

Garbers and Uliana (1994:38) note that De la Rey's model is probably the best-known South African model and had an accuracy rate of 96% in its classification of failed and non-failed firms. Del La Rey's multivariate model, similar to other classical statistical models, leaned primarily on financial ratios.

The model was set out as follows (Garbers and Uliana, 1994:38):

$$k = -0.01662a + 0.0111b + 0.0529c + 0.086d + 0.0174e + 0.01071f - 0.068811$$

where:

k = discriminant value (where k is negative, this signals potential failure)

a = total outside funding / total assets x 100

b = earnings before interest and tax (EBIT) / average total assets x 100

c = (total current assets + listed investments) / total current liabilities x 100

d = profit after tax / average total assets x 100

e = cash flow profit after tax / inflation-adjusted total assets x 100

f = total stocks / inflation-adjusted total assets x 100

Clarke, Hamman and Smit (1991) developed a model specifically for use by a South African financial institution and in particular for privately owned industrial operations (Garbers and Uliana, 1994:39). The definition of distress in the model centred on the inability of the related firm (borrower) to honour scheduled loan repayments (Garbers and Uliana, 1994:39).

Using financial metrics, Clarke, Hamman and Smit (1991), set out the following model (Garbers and Uliana, 1994:39):

$$Z = -11.907 + 1.524\, ASS + 0.506\, ASSTO + 1.606\, SF/ASS + 2.226\, WC/ASS + 5.136\, CF/INT$$

where:

Z = discriminant value (where firms having Z scores of above 0 are classified as non-failed and those with Z scores of below 0 are classified as failed)

ASS = log (total assets / production price index)

ASSTO = turnover / total assets

SF/ASS = shareholders' funds / total assets

WC/ASS = net working capital / total assets

CF/INT = EXP [(NPAT + dep.) / total assets] / EXP [interest / total assets]

The model achieved an overall prediction accuracy of 85% including both Type I and Type II errors (Garbers and Uliana, 1994:39).

2.3.4.3 Distress prediction models applied in the South African context

Research undertaken by Steyn-Bruwer and Hamman (2006) in respect of failure prediction in the South African context, sought to address deficiencies of bankruptcy models noted in previous studies by applying recursive partitioning (specifically the classification tree algorithm). Comprehended in their research, which assessed JSE-listed industrial companies between June 1997 and May 2002, was a provision for different economic cycles, with different models being developed for periods of growth and recession (Steyn-Bruwer and Hamman, 2006:7). The study also challenged the ambit of what was regarded as corporate failure in previous studies and extended the definition of failure beyond bankruptcy to include delisting and major structural changes (Steyn-Bruwer and Hamman, 2006:7).

Among the 15 independent variables used in developing their failure prediction models, more than 50% were related to cash flow. Steyn-Bruwer and Hamman (2006:9) incorporated this cash focus as they noted that while the causal reasons for financial distress may vary, failure ultimately was due to a lack of cash being available to meet obligations as and when they fall due. While the models developed as part of this research addressed many of the deficiencies that were prevalent in previous studies, the accuracy of the predictions was not notably more successful (Steyn-Bruwer and Hamman, 2006:17).

In 2009, Muller, Steyn-Bruwer and Hamman revisited the 2006 work completed by Steyn-Bruwer and Hamman (2006), to test whether certain modelling techniques were more accurate than others in their prediction of financial distress. The modelling techniques comprehended in the study spanned multiple discriminant analyses, recursive partitioning, logit analysis and neural networks (Muller, Steyn-Bruwer and Hamman, 2009). Unique to this study was the introduction of the "Normalised Cost of Failure" which accounted for the cost of Type I and Type II errors surfacing in the application of the model.

The research covered the same period as the 2006 study by Steyn-Bruwer and Hamman, with the period between 2003 and 2006 being used to mark companies that failed. The definition of failure applied to this study was also consistent with Steyn-Bruwer and Hamman's 2006 work.

Incorporating the "Normalised Cost of Failure", the research notably concluded that logit analysis and neural networks provided the best failure predictive accuracy when applying the related models to South African data from 1997 to 2002 (Muller, Steyn-Bruwer and Hamman, 2009:21).

2.3.5 Summary

This segment provided significant insights in steering the model set choice to be applied to the firm data and period considered as part of this research.

What is particularly noteworthy is the research by Muller, Steyn-Bruwer and Hamman (2009), given its focus on South African companies listed on the JSE and which addressed the performance of various distress models.

The research covered in this paper expands upon these building blocks by considering the impacts of significant accounting changes (in section 2.4), post the periods comprehended in the literature review and concludes on the model set to be applied (in Chapter 3) given the regulatory accounting changes and inferences by made by past distress research.

2.4 Regulatory response – The impacts in the accounting arena

Widespread failure in the past has had an impact on policymakers and regulators, who have had to adjust the frameworks in which businesses operate and enhance corporate reporting requirements, in an attempt to address the causal issues of failure and allow for greater transparency. As many of the financial distress models are based on accounting information, this segment reviews the response by regulators, specifically in the area of financial accounting, to address issues of risk and transparency in financial reporting. A particular focus is given to IFRS 16 Leases, IFRS 9 Financial Instruments and IFRS 15 Revenue from contracts with customers, which were introduced in recent years and have had a fundamental impact on the reporting of financial results and accounting ratios. Given that these accounting standards became applicable during the latter part of the period covered by this research, it will be crucial for these impacts to be considered when evaluating the comparative results of accounting-based financial distress prediction models.

2.4.1 IFRS 16: Leases

2.4.1.1 Overview of IFRS 16

IFRS 16 Leases (IFRS 16) was issued by the IASB in January 2016 and replaced the International Accounting Standard (IAS) 17 Leases (IAS 17) for reporting periods beginning on or after 1 January 2019. These standards of financial reporting address the accounting treatment of lease arrangements for both the lessee and lessor, with IFRS 16 introducing a significant shift in accounting for lease transactions, as well as introducing substantially more disclosure requirements.

The new leases standard (IFRS 16) establishes a detailed model for identifying lease arrangements and sets out the accounting treatment for both the lessee and lessor (Deloitte, 2016:3). IFRS 16 effectively applies a control criterion, in contrast to a risk and rewards model under IAS 17 (IAS 17:7) for the identification of leases and distinguishes between leases and service contracts based on whether there is an identified asset controlled by the lessee to the contract (IFRS 16:9, B9-B33) (Deloitte, 2016:3).

2.4.1.2 Changes in accounting treatment of leases and its implications

For lessors, the changes introduced by IFRS 16 versus that under IAS 17 were not regarded as significant, with the areas impacted limited primarily to additional requirements in respect of lease modifications (IFRS 16:79-80), subleases (IFRS 16:70) and lease disclosure (IFRS 16:89-97) (Deloitte, 2016:3).

For lessees, however, IFRS 16 brought with it significant changes. To appreciate the significance of the change, an understanding of the IAS 17 accounting implications for lessees is essential.

Under IAS 17, the classification of leases as a finance lease or an operating lease and its subsequent accounting treatment, hinged primarily on whether significant risks and rewards were transferred by the lessor to the lessee as part of the lease arrangement. To assist with the classification and in the determination of whether significant risks and rewards were transferred by the lessor as part of the arrangement, IAS 17 set forth certain criteria to aid the assessment, which is detailed in IAS 17:10-11.

Where one or more of the criteria were satisfied, the lease was classified as a finance lease and the lessee was required to recognise an asset and a corresponding liability in its balance sheet at the commencement of the lease. The asset and the liability were measured at the lower of the fair value of the asset and the present value of the minimum lease payments (IAS 17:20). Where available, the present value would be derived by considering the rate implicit in the lease or where this was not possible, the firm’s incremental borrowing rate would be applied, considering the nature and lifespan of similar assets held (IAS 17:20). Subsequently, the firm would apportion its lease payments between the capital portion of the lease liability and any applicable finance charge, with the leased asset being depreciated over the shorter of the lease period or the useful life of the asset (IAS 17:25-28).

Where the requirements of IAS 17:10-11 were not met, however, the lease would be classified as an operating lease, which carried with it significantly different accounting implications than that applicable for finance leases. In these scenarios, the firm was required to primarily recognise the lease payments made over the term of the lease in the income statement (as a rental expense), on a straight-line basis (IAS 17:33). While this may give rise to assets and liabilities being recognised in the balance sheet due to differences between the actual lease payments and the lease expense recognised during a particular financial year, the accounting standards effectively allowed for the firm to carry assets and liabilities off the balance sheet. This distorted the actual leverage of certain firms, as well as misrepresented the asset base that generated income for the firm. This was a concern for users of financial statements, particularly in respect of firms with significant operating leases. IFRS 16 was introduced primarily to address this concern.

For firms applying IFRS 16 as a lessee to a contract, practically all leases which convey the right to control the use of an identified asset results in the recognition of the related assets and liabilities of the contract in the firm's balance sheet. These are recognised in the form of a right-of-use (ROU) asset (reflecting the right to control the asset held under the lease arrangement) and a corresponding lease liability (reflecting the obligation of the lessor in the arrangement), at the commencement of the lease (IFRS 16:9,22). The initial and subsequent treatment is similar to the treatment of finance leases under IAS 17.

The treatment of leases as operating leases (as classified under IAS 17), where lease payments are expensed in the income statement, is restricted to a narrow scope of lease types under IFRS 16. This is limited to short-term leases (i.e. leases that run for 12 months or less), variable lease components and leases in respect of which the underlying assets to the lease are regarded as low value (IFRS 16:5-8, 38). What is regarded as "low-value" is not authoritatively defined in the standard but the IASB has provided an indicative new-asset value of US$ 5,000 or less, as part of the Basis for Conclusions (BC) on IFRS 16 Leases (BC on IFRS 16: BC100).

While IFRS 16 brought with it significant accounting changes for lessees, the new standard had no impact on the underlying economic model of the firm and its general order of business operations, the cash flows generated or paid by the firm or fundamental business indicators such as turnover and margin. The introduction of IFRS 16 did however have a significant impact on key performance metrics. These include metrics such as earnings before interest, tax, depreciation and amortisation (EBITDA) and gearing ratios, due to depreciation and interest charges replacing traditional operating lease expenses in the income statement and the introduction of ROU assets and lease liabilities to the balance sheet. With financial ratios being a key input in many distress prediction models, the IFRS 16 implications require consideration, especially in comparing financial information pre and post its introduction. This, however, will be influenced to some extent by the firm's method of transition in adopting the requirements of IFRS 16.

2.4.1.3 Transitioning options to IFRS 16 and its implications

IFRS 16 essentially allowed two transition methods in the migration from IAS 17 and the adoption of the requirements of IFRS 16. These options effectively involved a trade-off between cost and comparability (Bascom et al., 2018:1). That is, the option and expedients that simplify and reduce the costs of the transition to the new standard, also tended to reduce the comparability of financial information (Bascom et al., 2018:1). Conversely, the transition options that were complex and costly, resulted in more comparable information as it relates to accounting periods before and after the introduction of IFRS 16.

Upon transition, per the provisions of IFRS 16, the lessee was permitted to:

i) Adopt IFRS 16 retrospectively; or

ii) Follow a modified retrospective approach (Bascom et al., 2018:11).

Under the retrospective approach, the company would apply the IFRS 16 retrospectively in accordance with IAS 8 Accounting Policies, Changes in Accounting Estimates and Errors. That is, a firm would:

i) Apply the standard to its entire lease portfolio, as applicable, in respect of which it is the lessee to the arrangement;

ii) Restate its prior financial information;

iii) Recognise an adjustment in equity at the beginning of the earliest period presented; and

iv) Makes the disclosures required by paragraph 28 of IAS 8: Accounting Policies, Changes in Accounting Estimates and Errors (IAS 8), as a result of the change in accounting policy (Bascom et al., 2018:12).

The restatement of prior financial information is the component of this method of adoption that would be most useful to the stakeholders of the firm and allow for comparability of results pre and post the introduction of the standard. Adopting this approach, however, is inherently complex and required the firm to have extensive and detailed information about its leasing transactions. This would include historical information about lease payments and discount rates, as well as the historical information that management would have used to make the various judgements and estimates that are necessary to apply the lessee accounting model (Bascom et al., 2018:13).

Under a modified retrospective approach, however, the firm was only required to apply the standard from the beginning of the date of adoption. To do this, the firm would:

i) Measure lease assets and lease liabilities as at the beginning of the current financial period, applying the rules included in the new standard;
ii) Not have to restate its prior-period financial information;
iii) Recognise an adjustment in equity at the beginning of the current period; and
iv) Make additional disclosures specified in the new standard and is exempt from certain disclosures usually required by paragraph 28 of IAS 8 on a change in accounting policy (Bascom et al., 2018:13,20-25).

The key benefit of this approach is a reduction in the cost and simplicity of transition as there is no requirement to restate comparative financial information and it is possible to apply a modified retrospective approach using only current period information (Bascom et al., 2018:14). The principal disadvantage is a reduction in the comparability of the firm's financial information.

Given that this research comprises financial periods before and post the introduction of IFRS 16, the impacts of the standard will have to be comprehended, being sensitive to the firm's application of IFRS 16 given the various options and expedients available.

2.4.2 IFRS 9: Financial Instruments

2.4.2.1 Overview of IFRS 9

IFRS 9 Financial Instruments (IFRS 19) was issued by the IASB in July 2014 and replaced IFRS 39 Financial Instruments – Recognition and Measurement (IFRS 39), for reporting periods beginning on or after 1 January 2018.

IFRS 39, which became applicable on 1 January 2005, had been the subject of a potential revision for several years due to its complexity, its departure from the reality of how firms were managed and mainly because of its provisions allowing for the deferral of credit losses (impairment) on financial assets to quite late in the credit cycle (PwC, 2017:5).

The deferral of the impairment of financial assets permitted under IFRS 39 required rethinking, given the scrutiny it came under in the aftermath of the 2008 financial crisis (PwC, 2017:5). This scrutiny was indeed justified. The provisions of IFRS 39 effectively limited the recognition of losses to the point in time at which these losses were incurred and did not provide the user of the firm's financial statements adequate insight into the risk attached to the financial assets, as these risks became apparent too late in the financial statements of the firm. IFRS 9, amongst other things, sought to address this issue (PwC, 2017:5).

The fundamental changes brought by IFRS 9 centred around the following areas:

i) The classification and measurement of financial instruments;
ii) The impairment of financial assets; and
iii) Disclosure requirements for financial instruments.

2.4.2.2 The classification and measurement of financial instruments

The focus of IFRS 9, under this particular area of change, was for all financial assets to be classified and measured at fair value, with any changes in the underlying value of the financial asset to be recognised in the income statement of the firm. These financial assets would be classified under the category of fair value through profit or loss (FVPL). Only under certain limited scenarios were financial assets to be classified at amortised cost or as fair value through other comprehensive income (FVOCI). In the case of FVOCI classification, changes in the value of the financial asset would be recognised through equity and reflected in the statement of other comprehensive income. The decision as to whether assets were to be classified as FVPL, amortised cost or FVOCI was essentially based on two criteria, namely, the firm's business model for managing assets and whether the financial instrument's contractual cash flows represented solely payments of principal and interest (SPPI) (PwC, 2007:6-12).

The focal objectives behind this classification criterion in IFRS 9 were to decomplexify the treatment of financial assets (PwC, 2007:7), for financial assets to be reflected at their true value (PwC, 2007:6) and for changes to the value of the majority of assets to be reflected in an area of the financial statements that is of primary focus for the users of the thereof, namely the income statement (PwC, 2007:6). While this model brought with it the simplicity and transparency that was being sought in this area of accounting, it did create the potential for extreme volatility in the firm's income statement (PwC, 2007:6). Many financial distress models, especially those that consider the income statement-based performance of a firm as a key predictor of distress, would have to comprehend the implications of IFRS 9, particularly when evaluating comparative years, pre and post its introduction.

2.4.2.3 The impairment of financial assets

The manner in which impairment losses were considered was one of the key changes introduced by IFRS 9. IFRS 39's incurred loss approach was replaced by a forward-looking expected credit loss (ECL) model under IFRS 9 (PwC, 2017:7).

Under IFRS 9's ECL model, a firm was required to calculate the allowance for losses against its assets by comprehending the cash shortfalls it could potentially incur in the future under various default scenarios (PwC, 2017:8). These shortfalls would be discounted, multiplied by a probability assigned to the occurrence of each of the default events and summed (PwC, 2007:8). The losses, which essentially represented the credit risk associated with the financial assets, were expected to yield a much higher expected losses than the bad debt provisions previously carried under IFRS 39.

This new approach did bring with it, however, an area of significant judgement into the financial results of firms. While the principles of IFRS 9 require an unbiased evaluation of outcomes and their future probabilities (PwC, 2007:31-32), practically these don't exist. Evaluations are steered largely by the assumptions made by management and the future is inherently unpredictable. Nevertheless, the objective of this approach by the IASB was to bring into the financial statements a degree of prudency and relative conservativeness in the measurement of financial assets to avoid blindsiding the users of the financial statements to risks.

2.4.2.4 Disclosure requirements for financial instruments

In addition to the new classification, measurement and impairment principles, IFRS 9 brought with it significant disclosure requirements, specifically focused on the credit risk associated with financial instruments. Firstly, IFRS 9 brought with it amendments to IAS 1 Presentation of Financial Statements (IAS 1) and required separate-line disclosure on the face of the income statement in respect of IFRS 9 elements. These included separate lines for impairment losses and reversals, as well as certain gains and losses arising from the derecognition or reclassification of financial assets (PwC, 2007:35).

Further to the front-end disclosure of financial assets on the face of the income statement, firms were also required to provide extensive disclosure related to the credit risk associated with classes of financial assets (PwC, 2007:38).

2.4.2.5 Transition to IFRS 9 and its impacts

The general requirement of IFRS 9, required the retrospective application of the standard (as if the provisions of the standard had always been in place) at the date of initial adoption, in harmony with the provisions of IAS 8 (PwC, 2007:39). However, this did not necessarily require a restatement of the results in prior financial periods. Firms could simply account for the difference between the carrying amounts of financial instruments under IAS 39 versus that under IFRS 9 directly in opening retained earnings or some equivalent, at the date of initial adoption (PwC, 2007:39). This effectively means that the cumulative effect of past differences would be accounted for in the single financial period.

This approach in the transition did however mean that previous financial statement results would not carry the individual impacts of IFRS 9, leading to a distortion in comparison with future periods, post-application.

2.4.3 IFRS 15: Revenue from contracts with customers

2.4.3.1 Overview of IFRS 15

IFRS 15 Revenue from contracts with customers (IFRS 15), which became effective on 1 January 2018, superseded IAS 11 Construction Contracts (IAS 11) and IAS 18 Revenue (IAS 18). The new standard (IFRS 15) addressed the accounting treatment of all revenue arising from contracts with customers, with a few exceptions. In a general sense, IFRS 15 had less of a material impact on the accounting results of firms than IFRS 16 and IFRS 9. This is in reference to the fact that IFRS 15 did not necessarily change the amount of revenue recognised but rather impacted the timing and the profile of the revenue. Furthermore, the change primarily affected firms that had a sale and a service component as part of a single revenue contract. These impacts are discussed further in section 2.4.3.2.

IFRS 15 essentially established a five-step model to account for revenue arising from contracts with customers and required that revenue be recognised at an amount that reflects the consideration which the firm expected to be entitled to in exchange for transferring goods or services to a customer (IFRS 15:47). This five-step model replaced the risk and rewards model of IAS 18 and included an assessment of the following steps in the recognition of revenue:

i) Identifying the contract with the customer;
ii) Identifying the performance obligations in the contract;

iii) Determining the transaction price;
iv) Allocating the transaction price to the performance obligations; and
v) Recognising revenue as each performance obligation was satisfied (Kien, 2017).

2.4.3.2 Impacts of IFRS 15

In the formation of IFRS 15, the IASB was seeking to provide a more robust framework for the recognition of revenue, something which was noted as lacking under IAS 18 and to allow for better comparability across industries in terms of revenue (Kien, 2017).

The expectation was that the industries that would be materially impacted by the new revenue standard would be those that have contractual arrangements that include both a sale and a service component as part of the transaction price (Kien, 2017). These would include for example telecommunication companies, that sell subsidised handsets and a telecommunication service over a contractual period, as part of a single transaction price offer. How to allocate the transaction price between these two components and determining when the performance obligations are met across the two elements, are some of the complexities introduced by IFRS 15 (Deloitte, 2014:2). This would potentially result in deferring revenue, which was typically recognised earlier under IAS 18, as well as change the revenue profile. The key takeaway is not that the amount of revenue had necessarily changed but rather that the timing of its recognition and profile could change. This may however impact certain ratios in a particular financial year.

2.4.3.3 Transitioning to IFRS 15

As with other transitions, IFRS 15 permitted full retrospective adoption, with a restatement of prior results report or a modified retrospective adoption approach, with the cumulative effect on past periods being recognised in opening equity on the date of adoption of the standard (IFRS 15:C3). As seen in the adoption of other new standards, there is a trade-off between complexity and comparability under these different transition methods.

2.4.4 Summary

The introduction of IFRS 16 and IFRS 9 present marked differences in the treatment of leases and financial assets, respectively, with profound impacts on both the income statements and balance sheets of firms. IFRS 15, in a general sense, was less impactful on the income statements of firms. Given that these accounting standards became applicable during the latter part of the period covered by this research, it will be quintessential for these impacts to be considered when evaluating the accounting results and ratios and assessing the comparative results of accounting-based financial distress prediction models.

Chapter 3: Research Methodology

3.1 Introduction

This chapter builds on what was established in Chapter 2 and commences by addressing the model set to be applied to the data selected for testing, as well as the rationale for the model set selection. The research methodology is then addressed, with the considerations regarding the data, the assumptions applied and data gaps discussed.

3.2 Selecting the model set

The research design choice of this study is comparative in nature. That is, the research intention is to demonstrate the comparative accuracy of prediction models applied to JSE-listed companies during the years 2000 to 2020. The inclusion of different explanatory variables and different econometric techniques are therefore required to highlight the predictive accuracy of different models in the South African company context. The intention is to lean on the different methods discussed in Chapter 2 and apply as many different model types as practically possible.

Given the regulatory accounting changes discussed, the inclusion of accounting-based models would be meaningful. The general prevalence of accounting ratios applied in the models discussed in Chapter 2, as well as the popularity of accounting ratios in practice as a base assessment of firm distress, makes the inclusion of these model types attractive. Furthermore, the general accuracy of these model types in past studies, the relative availability of inputs as disclosed in publicly available financial statements and the ease of its application, support the use of this model category.

While the inclusion of accounting-based models is well supported, the shortcomings of relying only on accounting results have also been discussed in Chapter 2. To this end, model types that include market-related data and non-financial data must be considered. While applying market-related data may be feasible, the incorporation of non-financial metrics, however, such as those incorporated by Court (1991) (see section 2.3.3.6.1) or firm diversification as suggested by Rose (1992) (see section 2.3.3.6.2), may not be practically possible. This will be tested as part of the data collection process.

Finally, given the local focus and the relatively high accuracy of the models developed by South African researchers discussed in section 2.3.4.2, the models noted are included in the model set.

With these considerations in mind, the following model set was selected:

i) Altman Z-score (1968) – MDA model (accounting-based, including market input)
ii) De La Rey (1981) – MDA model (accounting-based, including macro factor input) (*South Africa*)
iii) Clarke, Hamman and Smit (1991) – MDA model (accounting-based, including macro factor input) (*South Africa*)
iv) Ohlson (1980) – Logit model (accounting-based, including macro factor input)
v) Zmijewski (1984) – Probit model (accounting-based)
vi) Steyn-Bruwer and Hamman (2006) – Recursive partitioning (*South Africa*)
vii) Court (1991) – Non-financial and financial variables (*South Africa*)

A summary of each model is described in Table 3.1 below.

Gambler's ruin theory has been omitted from consideration due to its relatively low prevalence in previous studies (Aziz and Dar, 2006:16). Shumway's hazard model (as addressed in section 2.3.1.6) was excluded based on the unavailability of historical market-related inputs. Cash management theory (as addressed in section 2.3.3.4) and a balance sheet-focused model (as addressed in section 2.3.3.2) have also been excluded from the model set as the variables included in the other models selected extensively cover these elements. Artificial neural networks (as addressed in section 2.3.2) have been omitted for practical reasons and credit risk measures (as addressed in section 2.3.3.5) have been excluded as these measures are generally obtainable from credit bureaus and like-agencies. Rose's firm diversification model (as addressed in section 2.3.3.6.2) was excluded, as the data denoting independent divisions of JSE-listed companies and their respective income, is not readily available.

Table 3.1: Model set overview

Model	Formula	Description
i) Altman Z-score (1968) ***MDA model***	$\mathbf{Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5}$ Where the Z-score is greater than 2.99, the firm is categorised into a "non-bankrupt" sector (safe zone) Where the Z-score is greater than 1.81 but less than 2.99, the firm is categorised into a "zone of ignorance" or "gray area" (grey zone) Where the Z-score is less than 1.80, the firm is categorised into a bankrupt sector (distressed zone)	**Z** = overall index (Z-score) $\mathbf{X_1}$ = working capital / total assets $\mathbf{X_2}$ = retained earnings / total assets $\mathbf{X_3}$ = earnings before interest and taxes / total assets $\mathbf{X_4}$ = market value of equity / book values of total debt $\mathbf{X_5}$ = sales / total assets
ii) De la Rey (1981) ***MDA model*** *(South Africa)*	$\boldsymbol{k = -0.01662a + 0.0111b + 0.0529c + 0.086d + 0.0174e + 0.01071f - 0.068811}$ Where ***k*** is negative, this signals potential failure	***k*** = discriminant value (k-score) ***a*** = total outside funding / total assets x 100 ***b*** = earnings before interest and tax (EBIT) / average total assets x 100 ***c*** = (total current assets + listed investments) / total current liabilities x 100 ***d*** = profit after tax / average total assets x 100 ***e*** = cash flow profit after tax / inflation-adjusted total assets x 100 ***f*** = total stocks / inflation-adjusted total assets x 100

Model	Formula	Description
iii) Clarke, Hamman and Smit (1991) ***MDA model*** *(South Africa)*	**Z = -11.907 + 1.524 *ASS* + 0.506 *ASSTO* + 1.606 *SF/ASS* + 2.226 *WC/ASS* + 5.136 *CF/INT*** Where firms having Z scores of above 0 are classified as non-failed and those with Z scores of below 0 are classified as failed	***Z*** = discriminant value (Z-score) ***ASS*** = log (total assets / production price index) ***ASSTO*** = turnover / total assets ***SF/ASS*** = shareholders' funds/ total assets ***WC/ASS*** = net working capital / total assets ***CF/INT*** = EXP [(NPAT + dep.) / total assets] / EXP interest / total assets]

Model	Formula	Description
iv) Ohlson (1980) ***Logit model***	**P = (1 + exp {— *β*' *O*})-1** **P =** default probability, where >50% denotes default ***O* = – 1.32 – 0.407*SIZE* + 6.03*TLTA* – 1.43*WCTA* + 0.0757CLCA – 1.720*ENEG* – 2.37*NITA* – 1.83*FUTL* + 0.285*INTWO* – 0.521*CHIN***	***O*** = discriminant value (O-score) **SIZE** = log (total assets/GNP price-level index). The index assumes a base value of 100 for the starting year of the review **TLTA** = total liabilities divided by total assets **WCTA** = working capital divided by total assets **CLCA** = current liabilities divided by current assets **OENEG** = 1, if total liabilities exceed total assets, 0 otherwise **NITA** = net income divided by total assets **FUTL** = funds provided by operations (income from operation after depreciation) divided by total liabilities. **INTWO** = 1, if net income was negative for the last 2 years, 0 otherwise **CHIN** = (Nit — Nit—1) / (|Nit| + |Nit—1|), where Nit is the net income for the most recent period
v) Zmijewski (1984) ***Probit model***	**X = – 4.336 – 4.513*ROA* + 5.679*FINL*+ 0.004*LIQ*** Where firms having X scores of above 0 are classified as non-failed and those with X scores of below 0 are classified as failed	***X*** = discriminant value (X-score) ***ROA*** = net income to total assets (return on assets) ***FINL*** = total debt to total assets (financial leverage) ***LIQ*** = current assets to current liabilities (liquidity)

Model	Formula	Description
vi) Steyn-Bruwer and Hamman (2006) ***RPA***	Classification tree, based on 15 independent variables	**LogTA/GDP** = log of total assets standardised by means of the GDP deflator **LF:TL** = the closing balance of cash divided by the closing balance of total liabilities **E:TL** = the closing balance of equity divided by the closing balance of total liabilities **AR:S** = the closing balance of accounts receivable divided by the revenue for the year **WC:TA** = the closing balance of (inventories + accounts receivable – accounts payable) divided by the closing balance of total assets **P:S** = the profit for the year divided by the revenue for the year **CFO:S** = the cash flow from operating activities divided by the revenue for the year **P3:S** = the cumulative profit for the last three years divided by the cumulative revenue for the last three years **CFO3:S** = the cumulative cash flow from operating activities for the last three years divided by the cumulative revenue for the last three years **CFO:TL** = the cash flow from operating activities divided by the closing balance of total liabilities

Model	Formula	Description
		CFI:TL = the cash flow from investing activities divided by the closing balance of total liabilities **CFF:TL** = the cash flow from financing activities divided by the closing balance of total liabilities **CFO3:TL** = the cumulative cash flow from operating activities for the last three years divided by the closing balance of total liabilities **CFI3:TL** = the cumulative cash flow from investing activities for the last three years divided by the closing balance of total liabilities **CFF3:TL** = the cumulative cash flow from financing activities for the last three years divided by the closing balance of total liabilities

Model	Formula	Description
vii) Court (1991) ***Non-financial and financial variables*** *(South Africa)*	Non-financial and financial variables	Profit before interest after tax / total assets Market value of equity / book value of debt Owner's equity / Total capital employed Director appointments and resignations Director appointments and resignations / number of directors Change in director shareholding Director shareholding The delay in publishing the financial statements in the year of failure Change in delay in publishing the financial statements

3.3 Data selection and preparation

3.3.1 Introduction

As noted in Chapter 2, for the purposes of this research, a company would be noted to have failed if it has entered liquidation (voluntary, provisionally or otherwise), is under business rescue, has dissolved or has delisted from the JSE for reasons tantamount to failure. In respect of reasons for delisting which are synonymous with failure, these could include failure to comply with JSE requirements, suspension by the JSE and the general unwinding of the firm, amongst others. In some cases, firms may fall into more than one of the categories of failure.

In identifying failed companies for the period under review, reference was made to information available by Who Owns Whom: African Business Information[17] and information sourced from the JSE. Accounting and market variables, exchange rates and non-financial data to be applied to the various models were sourced from the IRESS Expert database, Thomson Reuters and published annual financial statements. Macroeconomic data such as historical inflation, Product Price Index (PPI), Gross Domestic Product (GDP) and Gross National Product (GNP), were obtained from macrotrends[18].

3.3.2 Period for sample selection and related considerations

In identifying firms to be considered for testing, a period spanning from the year 2000 to 2020 was considered. An extended period was selected to improve the chances of observing failed companies, given the low failure rate of listed companies.

There are a few aspects to consider in respect of the timeline that may influence the outcome of testing. These include:

i) The period under review encompasses two periods of catastrophic negative market downturns. These include the 2008 financial crisis and the impacts of the Covid-19 pandemic in 2020.

[17] Who Owns Whom (WOW) is an independent research organisation that provides South African business and economic environment data. Subscribed information is obtainable at https://www.woweb.co.za/

[18] macrotrends.net collates information from the World Bank

ii) The introduction of new international accounting standards in 2018 and 2019, had a marked impact on accounting ratios. In particular, this would include IFRS 9 and IFRS 16.

3.3.3 Data restrictions and general assumptions

In the assessment of the failed companies to be included in the sample selected for testing, reference was made to the availability and quality of data for these companies. Due to distress factors facing certain firms, failed companies often tend to be subject to missing data points as a result of not producing or releasing annual financial statements (no audited financial information is available), delisting (information is no longer publicly available) or suspension of trading (limited market-related information is available). To overcome the issue of missing data, one could outright exclude the company or the specific data points or provide an equivalent, substitute data point. Key to note in reference to Zmijewski's research is that adjusting for missing data may not necessarily affect the statistical inferences or the overall classification rates (Zmijewski, 1984:76-77).

In consideration of the above and in selecting the sample of companies for the purposes of this research, the following general principles were applied:

i) Failed companies with extensive missing data were omitted from the sample;
ii) Failed companies with less than three years of data available in the lead-up to their year of failure, were excluded from the sample;
iii) Failed companies with more than three years of data but with data only available beyond the year preceding the year of failure, were excluded from the sample;
iv) The period of assessment was limited to five years before the year of failure;
v) For non-failed companies, the five years leading to the year 2020 were considered to comprehend the period of significant accounting changes; and
vi) Where a key data point was missing within the sample selected, a substitute, equivalent data point was included, where possible.

Specific considerations related to the models selected for this research are addressed in section 3.3.4.

3.3.4 Specific considerations and assumptions applied to models

3.3.4.1 Altman Z-score (1968) – MDA model

The following specific assumptions were applied in the application of the Altman Z-score to the sample of companies selected for testing:

i) The application of the Altman Z-score requires the inclusion of the market value of equity (market capitalisation) of the firm being assessed. Where this data was not available due to suspended trading or other reasons, the book value of equity was used to substitute for this data point. Where the market value of equity was not available and the book value of equity was negative as a result of a sustained period of losses, the variable was substituted at a zero value;
ii) While there may be other interpretations for what represents working capital, the definition as applied by Altman, being current assets less current liabilities, was applied in the application of the model (Altman, 1968:594);
iii) The book value of total debt required for inclusion in the model was considered to be the book value of total liabilities recorded in the annual financial statements; and
iv) Entities were noted as failed if their Z-score was less than 1.80. Companies in the "grey zone" were not considered to have failed.

3.3.4.2 De La Rey (1981) – MDA model

The following specific assumption was applied in the application of De La Rey's MDA model to the sample of companies selected for testing:

i) In reference to the inflationary marker to be applied to variables that require to be reflected at an inflationary adjusted amount, the annual inflation for the financial year under review was applied.

3.3.4.3 Clarke, Hamman and Smit (1991) – MDA model

The following specific assumption was applied in the application of De La Rey's MDA model to the sample of companies selected for testing:

i) In reference to the PPI marker to be applied to the total assets variable in the model, the annual PPI for the financial year under review was applied.

3.3.4.4 Ohlson (1980) – Logit model

The following specific assumptions were applied in the application of Ohlson's O-score to the sample of companies selected for testing:

i) The application of Ohlson's O-score requires the inclusion of the GNP index as part of the firm size in the formula. The year 1995 was assigned at a base value of 1, with subsequent periods through to 2020 reflecting adjustments off the 1995 base. As GNP is typically expressed in US Dollars and to assess the change in the index normalised for exchange rate fluctuations, an average annual US Dollar to South Africa Rand (USD:ZAR) exchange rate was applied to convert the GNP figure to a Rand value across the period;

ii) The profit after tax value was used for the net income variable required in the model; and

iii) The model requires consideration as to whether the firm under review was subject to a net loss for two consecutive years. In the last or outer year of testing, the previous year's net income was considered to be zero.

3.3.4.5 Zmijewski (1984) – Probit model

The following specific assumption was applied in the application of Zmijewski's probit model to the sample of companies selected for testing:

i) The profit after tax value was used for the net income variable required in the model.

5.3.4.6 Steyn-Bruwer and Hamman (2006) – Recursive partitioning

The following specific assumptions were applied in the application of Steyn-Bruwer and Hamman's model to the sample of companies selected for testing:

i) Steyn-Bruwer and Hamman's model requires the consideration of the cumulative impact of certain variables, comprehending in certain circumstances a period of up to three years. These include for example cumulative cash flows and profits over a three-year period. As the assessment for this research was limited to five years before the year of failure and due to the availability of data, where data for the two years prior to the year being considered in the testing was not available, the formula was calibrated accordingly; and

ii) In setting up the decision tree algorithm, where years of performance were not available for failed firms in the five years considered, these years were removed from the data frame.

3.3.4.7 Court (1991) – Non-financial and financial variables

The following specific assumptions were applied in the application of Court's model to the sample of companies selected for testing:

i) Court's model requires non-financial variables such as the number of directors or dates on which the financial statements were approved. Where these data points were not available, the data was not substituted and the company, while being comprehended in other models, was excluded from testing when applying this model;
ii) The ratio of appointments and resignations to the total number of directors was derived based on the net movements in the number of directors, year on year;
iii) The book value of total debt required for inclusion in the model was considered to be the book value of total liabilities recorded in the annual financial statements; and
iv) The total capital employed required for inclusion in the model was determined by subtracting current liabilities from total assets.

3.3.5 Sample selection

The application of the principles noted in sections 3.3.3 and 3.3.4 in deriving the sample for testing, resulted in the inclusion of 78 failed companies. No limitations were placed on the industries selected for testing. A controlled group of non-failed companies of the same number was included in the sample, resulting in a total of 156 companies in the dataset. In reference to Zmijweksi's research and his assessment of a "choice-based bias" in the sample selection, the application of a 1:1 ratio in this testing sample between failed and non-failed firms should not affect the statistical inferences or the overall classification rates (Zmijewski, 1984:77).

The control group selected represents companies listed on the JSE at the time of this research, which has not formally entered into liquidation or business rescue procedures. The control group selection process considered the related economic sector, industry group, industry and sub-industry of the failed entities. The list of companies included in the dataset has been included in Appendix 2. To further enhance model insights, industry information and reasons for failure have been considered.

3.4 Summary

The model set selected, the period considered and the non-discriminate approach in terms of industries selected for testing allows for a broad performance assessment of different distress models, which have historically had high accuracy rates. Given the characteristics of the period considered in this research and the changes in accounting standards in the latter part of this time frame, it is expected that the models will yield accuracy rates different from previous studies. This, however, allows for an assessment in respect of the relevance of these models given the change in the landscape.

The research results, analysis and inferences made are presented in Chapter 4.

Chapter 4: Research Results

4.1 Introduction

The research results are presented in this chapter in the following manner:

i) The chapter begins with a synopsis of the characteristics of the dataset applied to the models identified in Chapter 3;

ii) A comparative assessment is then undertaken, comprehending the performance of the various models;

iii) The performance of specific models is then addressed, with the analysis and inferences in respect of the results discussed;

iv) The relevant models are then flexed, normalising the data inputs for changes in accounting, revisiting certain factors and reassessing the model outcomes; and

v) The chapter concludes with an overall reflection on the results given the aim of this research.

4.2 Characteristics of the dataset

4.2.1 Failed companies

The 78 failed companies included in the sample span several economic sectors and industries. The prevalence of specific sectors and industries, across the period under assessment, is reflected in Table 4.1. The failed companies in the sample show a high frequency in the Financials, Industrial, Basic Materials and Technology sectors.

The concentration of the years of failure is depicted in Table 4.2, with nearly half of the failed companies in the sample failing in the first 5 years of the period under review.

Table 4.1: Failed companies by economic sector, industry group and industry

Economic Sector	Number of Companies by Economic Sector	Industry Group	Industry	Number of Companies by Industry
Basic Materials	14	Basic Resources	Industrial Metals and Mining	1
			Mining	12
		Chemicals	Chemicals	1
Consumer Goods	6	Automobiles and Parts	Automobiles and Parts	1
		Food and Beverage	Beverages	1
			Food Producers	4
Consumer Services	7	Media	Media	1
		Retail	General Retailers	6
Financials	21	Financial Services	Financial Services	14
		Insurance	Life Insurance	2
		Real Estate	Real Estate Investment and Services	5
Health Care	2	Health Care	Health Care Equipment and Services	1
			Pharmaceuticals and Biotechnology	1
Industrials	16	Construction Materials	Construction Materials	3
		Industrial Goods and Services	Industrial Engineering	3
			Industrial Transportation	4
			Support Services	6
Technology	11	Technology	Software and Computer Services	11
Utilities	1	Utilities	Electricity	1
Total	**78**			**78**

Table 4.2: Failed companies – periods of failure

Period	Number of failed companies	% of the failed company sample
2000 to 2004	38	49%
2005 to 2009	14	18%
2010 to 2014	17	22%
2015 to 2020	9	12%
Total	**78**	**100%**

The reasons for failure as depicted in Table 4.3, include a major portion of companies that have entered liquidation and companies that have wound up or have deregistered. As noted in the definition of failure, companies that delisted for reasons tantamount to failure have also been included in the sample of failed companies. Other reasons for failure include specific instances of companies which experienced significant losses and are no longer trading or dormant.

Table 4.3: Failed companies – reasons for failure

Reasons for failure	Number of failed companies	% of the sample
Business rescue	8	10%
Liquidation, winding up or deregistration	51	65%
Failure to comply and suspension	15	19%
Other	4	5%
Total	**78**	**100%**

The models applied in this research lean on over 20 accounting-related data points per year, in addition to the market and non-financial data inputs. These data points, including an overview of the data across the failed companies in the sample, are depicted in Appendix 3 and Appendix 4, respectively. A key observation in this regard is the difference in the mean values of the key markers used in the models between that of the failed companies in the sample and the non-failed companies (Appendix 5).

4.2.2 Non-failed companies

The 78 non-failed companies, which act as the control group in the sample, represent companies listed on the JSE at the time of this research, which has not formally entered into liquidation or business rescue procedures. The selection process considered the related economic sector, industry group, industry and sub-industry of the failed entities, to ensure matching with the failed group of companies, as far as practically possible. The one sector not matched, of which only one company is included in the list of failed companies in the sample, is the Utilities sector (and the related Electricity industry). There was no non-failed JSE-listed company matching this criterion at the time of this research. The exclusion of this grouping is considered to be immaterial, given its low prevalence in the failed group of companies. The specific sectors and industries selected as part of the non-failed grouping are reflected in Table 4.4.

An overview of the data across the non-failed companies in the sample is depicted in Appendix 5. The data for the non-failed companies comprehended the five years between 2020 and 2016. The inclusion of this period for the non-failed companies was to allow for the assessment of significant changes in accounting, which were instituted from 2018, as well as for practical reasons, considering data accessibility related to the non-failed companies selected for testing.

Table 4.4: Non-failed companies by economic sector, industry group and industry

Economic Sector	Number of Companies by Economic Sector	Industry Group	Industry	Number of Companies by Industry
Basic Materials	14	Basic Resources	Industrial Metals and Mining	1
			Mining	11
		Chemicals	Chemicals	2
Consumer Goods	7	Automobiles and Parts	Automobiles and Parts	1
		Food and Beverage	Beverages	1
			Food Producers	3
		Personal and Household Goods	Personal Goods	1
			Tobacco	1
Consumer Services	7	Media	Media	1
		Retail	General Retailers	5
		Travel and Leisure	Travel and Leisure	1
Financials	21	Banks	Banks	1
		Financial Services	Financial Services	13
		Insurance	Life Insurance	2
			Non-life Insurance	1
		Real Estate	Real Estate Investment and Services	1
			Real Estate Investment Trusts	3
Health Care	2	Health Care	Health Care Equipment and Services	1
			Pharmaceuticals and Biotechnology	1

Table 4.1: Non-failed companies by economic sector, industry group and industry (continued)

Economic Sector	Number of Companies by Economic Sector	Industry Group	Industry	Number of Companies by Industry
Industrials	16	Construction Materials	Construction Materials	5
		Industrial Goods and Services	Electronic and Electrical Equipment	2
			General Industrials	1
			Industrial Engineering	3
			Industrial Transportation	1
			Support Services	4
Technology	11	Technology	Software and Computer Services	11
Total	**78**			**78**

4.3 A comparative assessment of the model set

Steyn-Bruwer and Hamman's RPA model yielded the highest predictive accuracy of the models applied to the dataset, with Court's model, which incorporates non-financial variables, outperforming the balance of the model set. The MDA models tended to perform comparatively poorly versus the outcomes noted by Aziz and Dar's (2006) research. The models were particularly susceptible to Type I errors.

The specific outcome for each model is further addressed in section 4.4

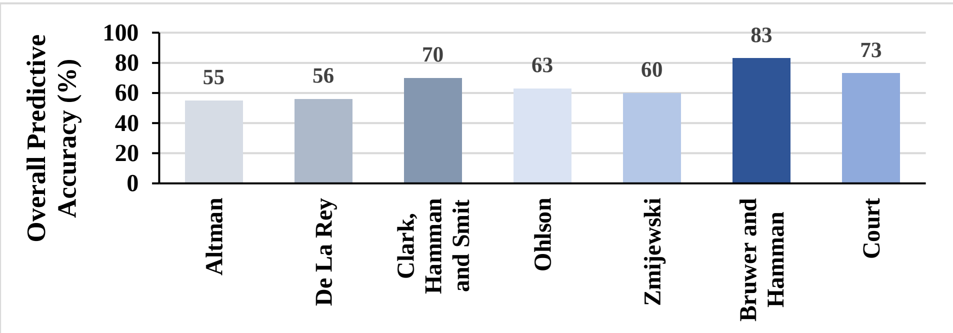


Figure 4.1: Comparative performance of the model set under the testing parameters

4.4 Specific model prediction results

4.4.1 Altman Z-score (1968) – MDA model

When applying the data in the sample and the original coefficients considered in the Altman Z-score model, the model performed relatively poorly versus the outcomes in Altman's original research (Altman, 1968:600). The overall prediction accuracy within the confines of this research was 55%. The accuracy and the error rates of the model are reflected in Figures 4.2 to 4.5.

As expected, the model showed improved accuracy in correctly classifying failed firms, closer to the year of failure. Overall, the average prediction accuracy in the classification of failed firms was 58% when considering the two years prior to failure, with a reduced accuracy rate of 52% over the five-year period. As the non-failed firms included a year impacted by the restrictions of Covid-19 lockdowns, the accuracy rates were significantly lower for the 2020 financial year. However, whilst the model performed better when this anomaly was removed from consideration, the overall performance of the model was still poor, with an average accuracy of 61% in correctly classifying non-failed firms.

When considering the performance of the model across specific sectors in relation to the failed companies in the sample, it was noted that when considering the year before failure, the Consumer Goods sector performed the worst, with an accuracy rate of only 33%. In contrast, the Health Care and Utilities sector saw an accuracy rate of 100% but the representation of these companies in the sample is relatively low. There was no strong correlation when considering the sector performance of non-failed firms, with the Financials sector showing low accuracy at an average of only 24%. Incidentally, the Health Care sector reflected the highest accuracy at an average of 80%.

As noted in section 2.3.1.3, the suitability of the coefficients applied in the Z-score function has been questioned in previous studies (Grice and Ingram, 2001), including a requirement to re-estimate the coefficients of the original model to derive a more accurate predictive outcome for non-manufacturing firms. An attempt was made to improve the predictive accuracy of the model by adjusting the coefficients while keeping the variables, as well as the success and failure factors, constant. The exercise yielded no significant increase in the performance of the model, rendering the conclusion that the Altman Z-score, under these specific testing parameters, is not the most suitable model for accurately predicting firm failure.

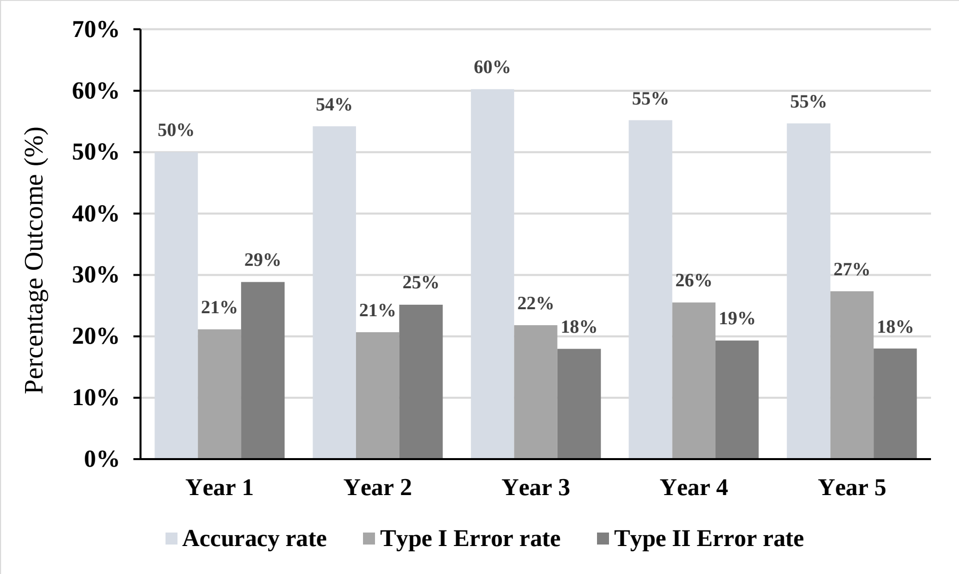


Figure 4.2: Overall predictive accuracy of the Altman Z-Score

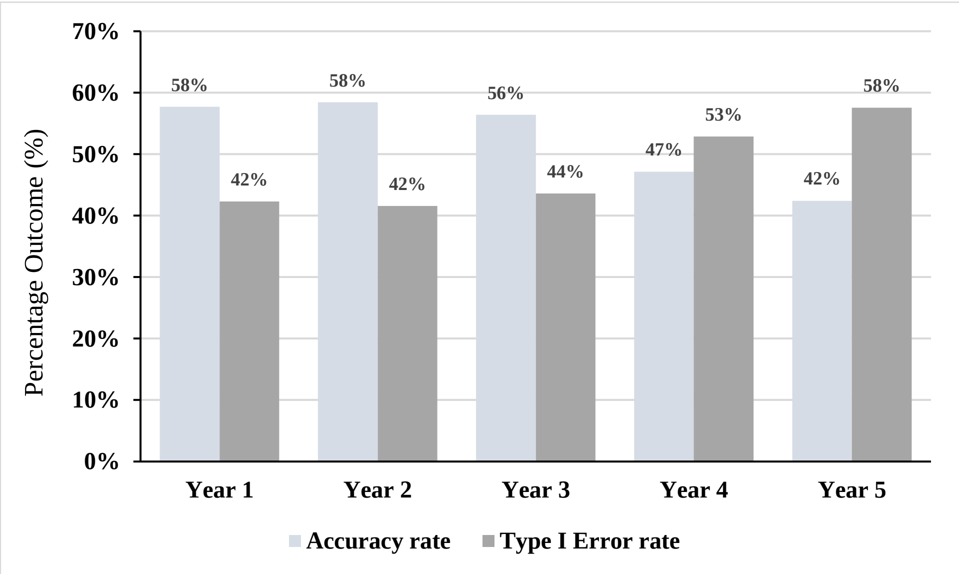


Figure 4.3: Predictive accuracy of the Altman Z-Score in correctly classifying failed firms

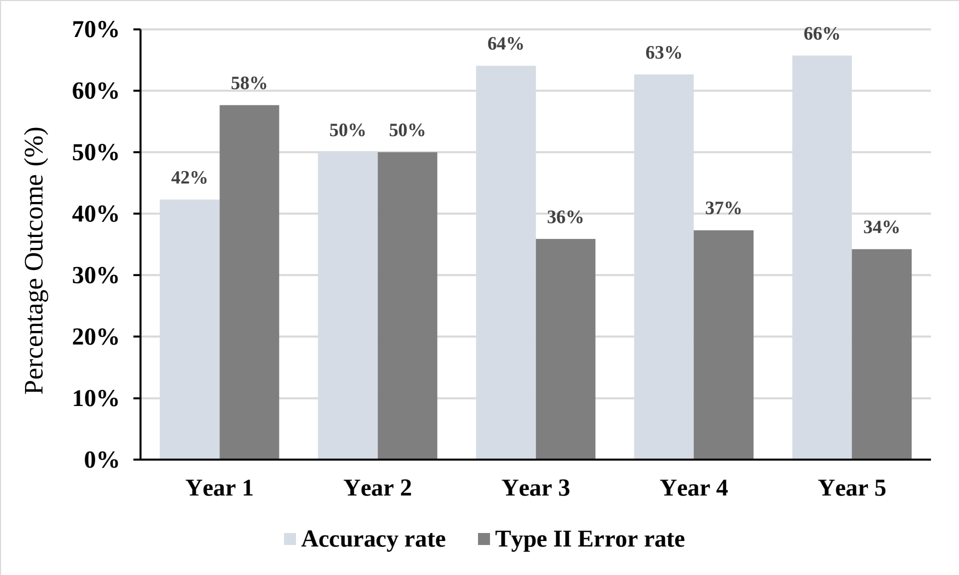


Figure 4.4: Predictive accuracy of the Altman Z-Score in correctly classifying non-failed firms

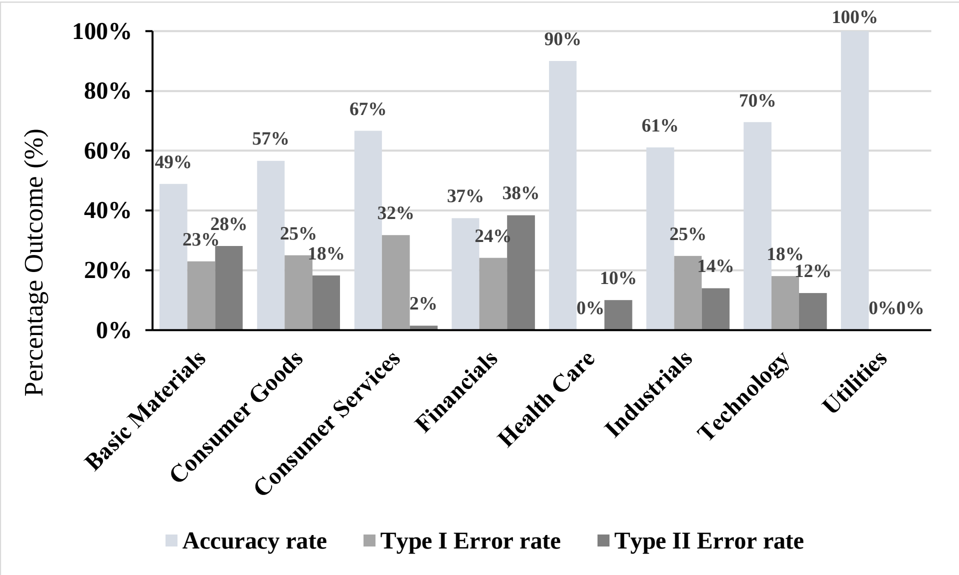


Figure 4.5: Overall predictive accuracy of the Altman Z-Score by economic sector

4.4.2 De La Rey (1981) – MDA model

When applying the data in the sample and the original coefficients considered in De La Rey's model, the model performed very poorly, especially in its classification of failed firms. The overall prediction accuracy within the confines of this research was 56%. The accuracy and the error rates of the model are reflected in Figures 4.6 to 4.9.

In respect of failed companies, whilst the model performed better when considering the years closer to failure, the rates were alarmingly low. The average prediction accuracy in the classification of failed firms was 21% when considering the two years before failure, with a reduced accuracy rate of 13% over the five years considered. In contrast, in respect of non-failed firms, the model reflected a high prediction accuracy of 98%. The model however is cumbered with Type I errors averaging 87% over the period of testing.

Given the overall prediction accuracy and skewed error types, the sector-specific performance was not meaningful for consideration.

Under the parameter of testing applied in this research, De La Rey's K-score model did not perform well in predicting the failure of firms.

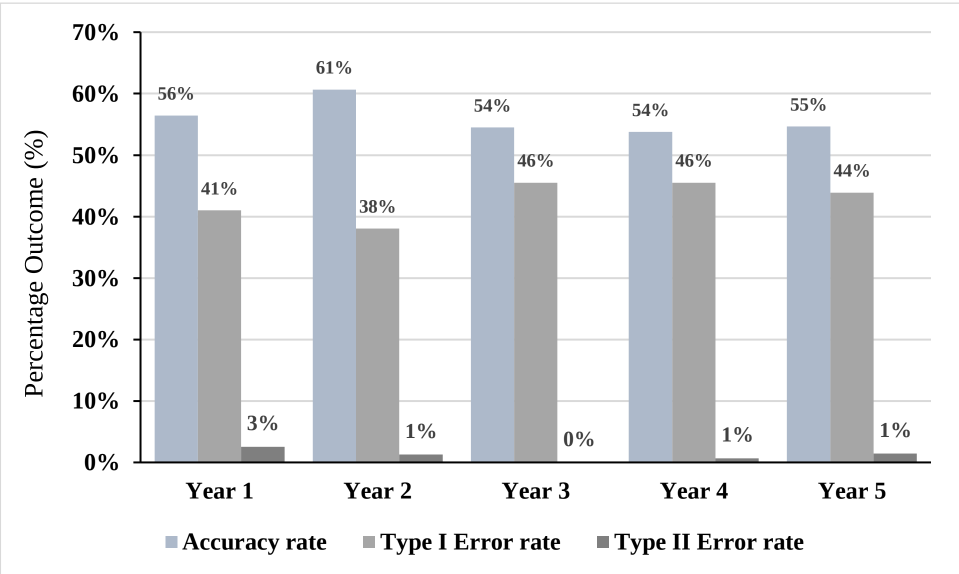


Figure 4.6: Overall predictive accuracy of the De La Rey K-Score

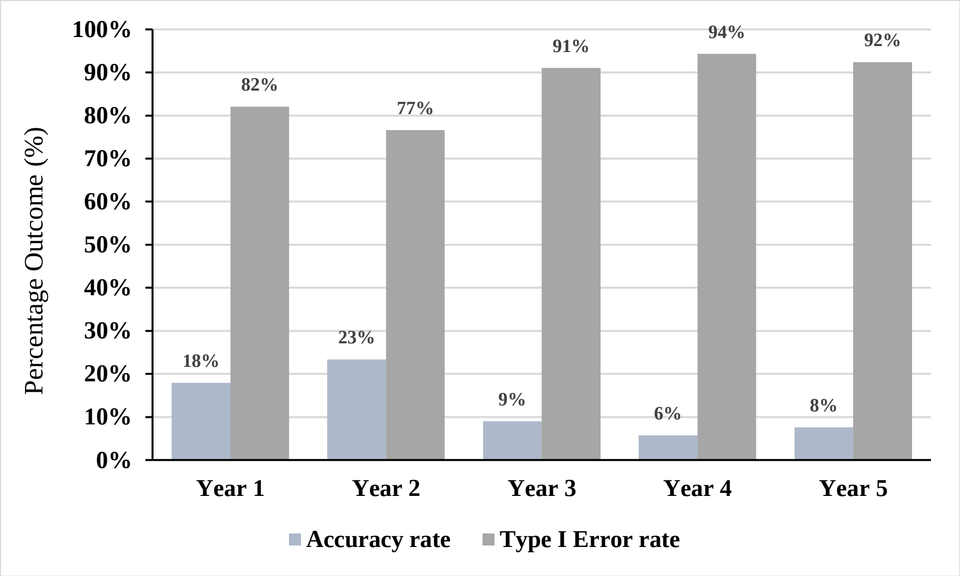


Figure 4.7: Predictive accuracy of the De La Rey K-Score in correctly classifying failed firms

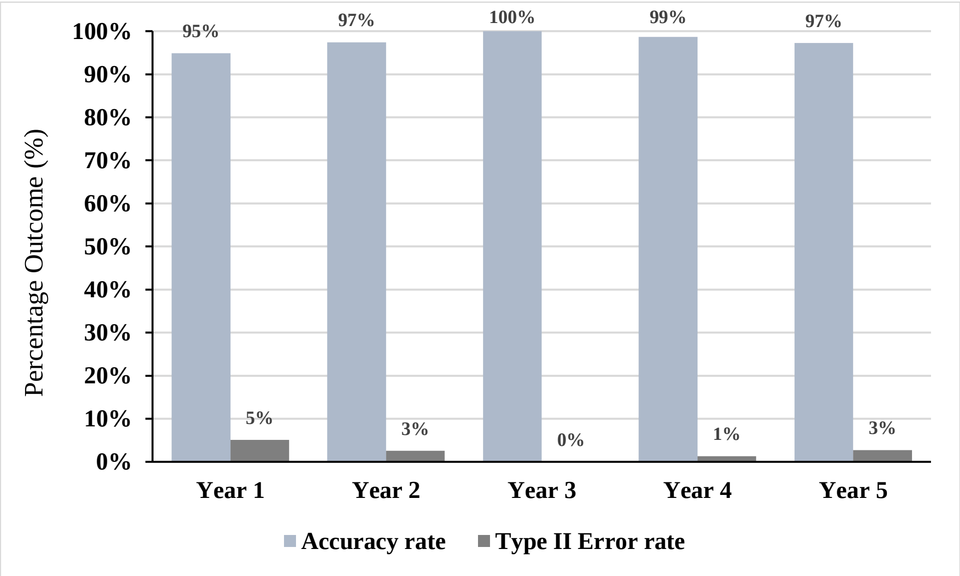


Figure 4.8: Predictive accuracy of the De La Rey K-Score in correctly classifying non-failed firms

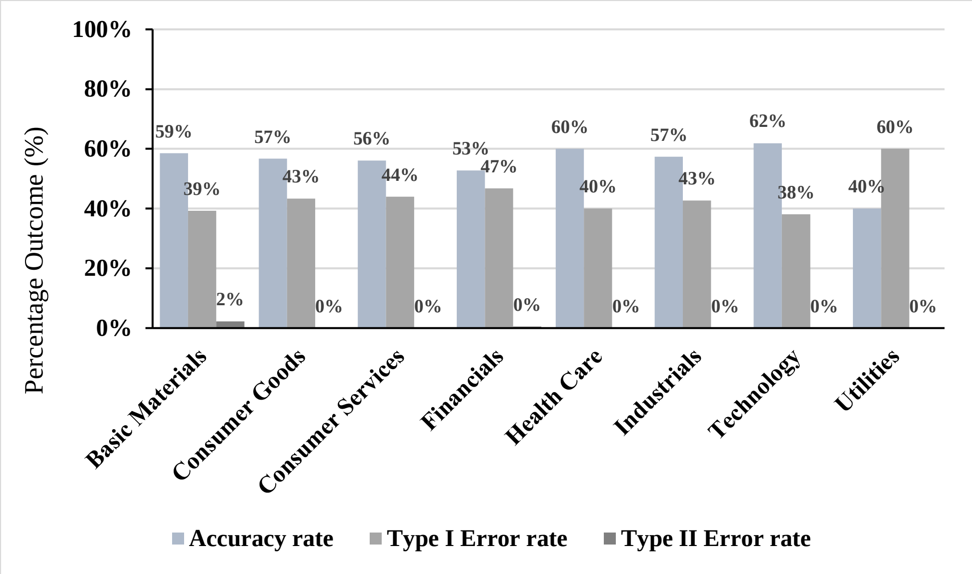


Figure 4.9: Overall predictive accuracy of the De La Rey K-Score by economic sector

4.4.3 Clarke, Hamman and Smit (1991) – MDA model

When applying the data in the sample and the original coefficients considered in Clarke, Hamman and Smit's Z-score model, overall the model performed the best of the MDA models considered in this research, with an overall prediction accuracy of 68%. This is in comparison to Altman's Z-score prediction of 55% and De La Rey's K-score model output of 56%. The accuracy and the error rates of the model are reflected in Figures 4.10 to 4.13.

In line with expectations, the model performed better when considering the years closer to failure, with a 50% accuracy in the year prior to failure. The model was prone to Type I errors resulting in an average prediction accuracy in respect of failed firms of 47% over the period of testing. For non-failed firms, the model reflected a high prediction accuracy of 89%. When the 2020 Covid-impacted year is removed from consideration, the prediction accuracy improved to 91%.

Ignoring the Utilities and Health Care sectors, which have a low prevalence in the sample, the performance of the accuracy rates in the Technology and Consumer Goods sectors were particularly noticeable, with accuracy rates of 76% and 74% respectively. If these accuracy rates were applicable out-of-sample, the model may be deemed suitable for these economic sectors.

Given the relatively favourable outcome versus other MDA models in this research, the suitability of the coefficients applied in Clarke, Hamman and Smit's Z-score was reassessed in an attempt to improve the overall predictive accuracy of the model. The exercise, which resulted in an adjustment of all coefficients in the model, yielded some benefit, increasing the overall predictive accuracy to 70%, with a drop in both Type I and Type II errors, particularly in years 1 and 2. The Technology and Consumer Goods sectors did however see a 3% to 5% drop in accuracy rates, whilst other sectors improved. The new coefficients are reflected in the updated formula as follows:

$$Z = -11.907 + 2.45\,ASS + 1.15\,ASSTO + 0.81\,SF/ASS + 0.60WC/ASS + 1.57\,CF/INT$$

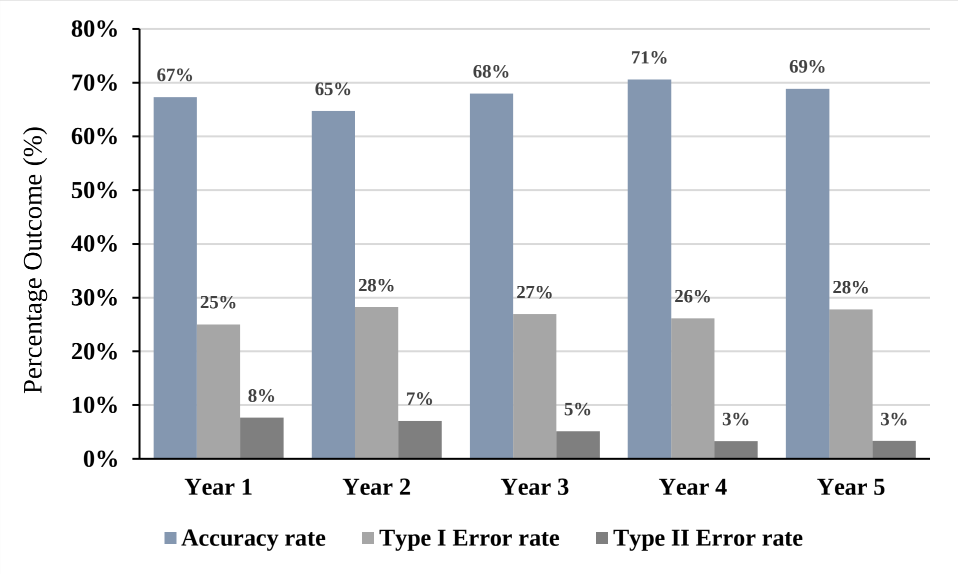


Figure 4.10: Overall predictive accuracy of the Clarke, Hamman and Smit Z-Score

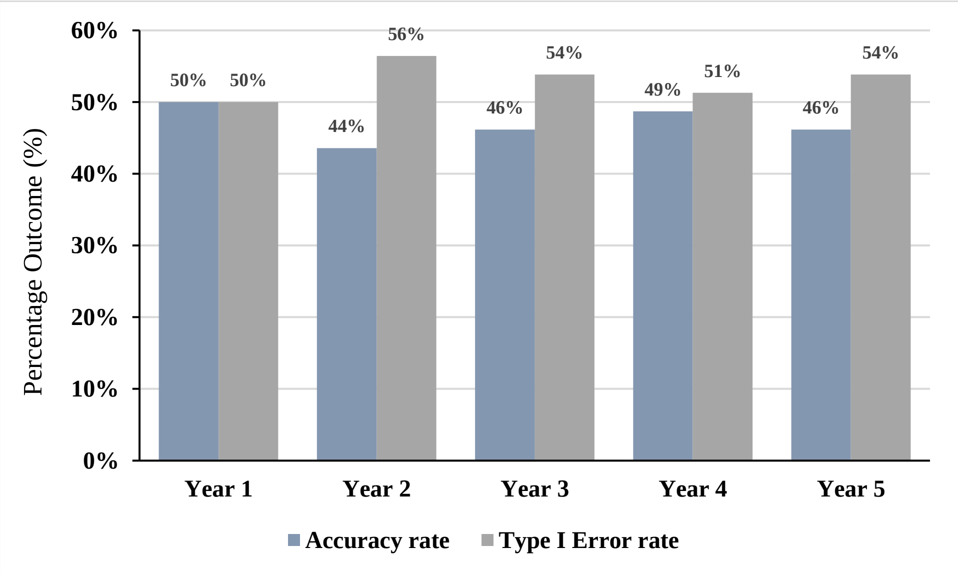


Figure 4.11: Predictive accuracy of the Clarke, Hamman and Smit Z-Score in correctly classifying failed firms

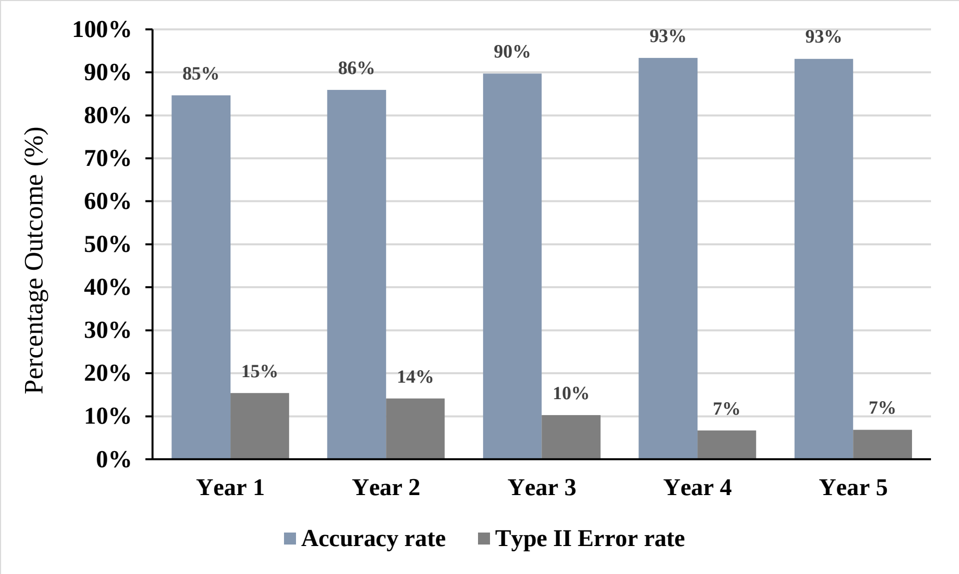


Figure 4.12: Predictive accuracy of the Clarke, Hamman and Smit Z-Score in correctly classifying non-failed firms

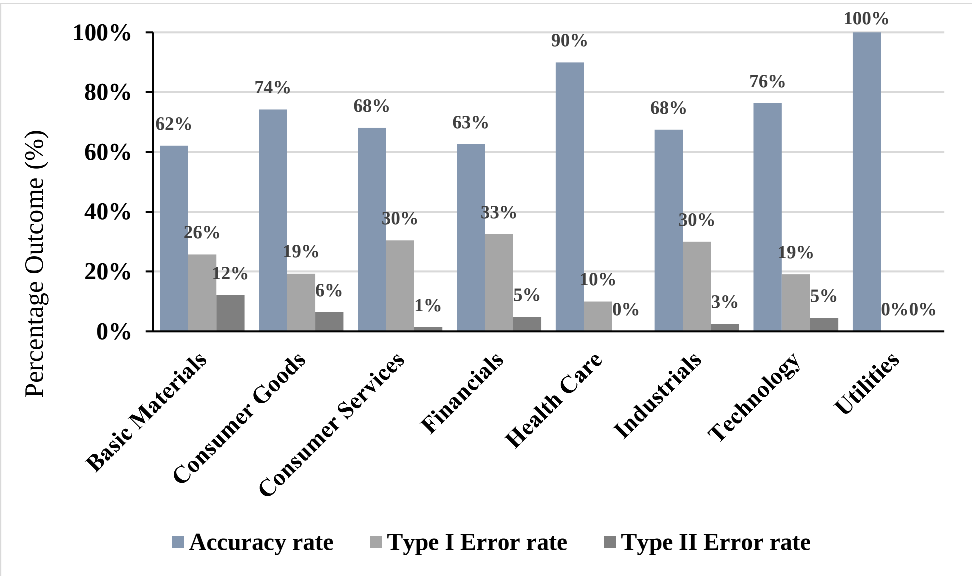


Figure 4.13: Overall predictive accuracy of the Clarke, Hamman and Smit Z-Score by economic sector

4.4.4 Ohlson (1980) – Logit model

Ohlson's logit model achieved an overall prediction accuracy of 63% within the parameters of testing. The results were significantly lower than the prediction accuracy that surfaced in Aziz and Dar's (2006) research in respect of logit models, which covered a review of previous studies in this area. The accuracy and the error rates of the model are reflected in Figures 4.14 to 4.17.

In line with expectations, the model's ability to correctly identify failed companies improved in the progression towards the year of failure. Overall, the average prediction accuracy in the classification of failed firms was 58% in the year before failure, with a reduced accuracy rate of 48% over the five-year period. In respect of non-failed firms, the model performed better with an overall rate of accuracy, excluding the 2020 financial year, of 79%.

When considering the sector performance, the Consumer Goods sector yielded the highest accuracy rate at 72%, with the Financials sector fairing worse at 50%, cumbered with both Type I and Type II errors.

Given the outcomes of testing and within the parameters of testing, the Ohlson O-Score is not the most suitable model for accurately predicting firm failure.

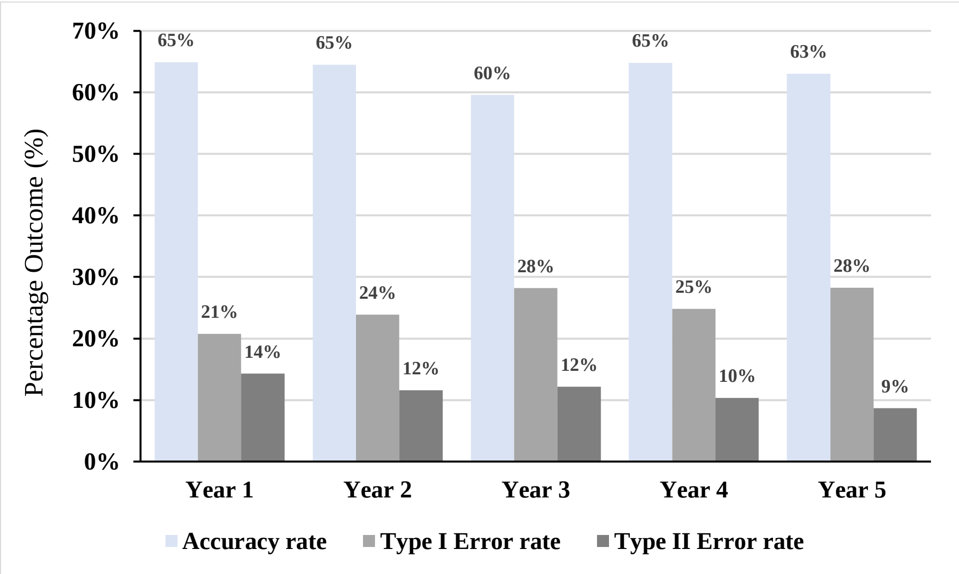


Figure 4.14: Overall predictive accuracy of the Ohlson O-Score

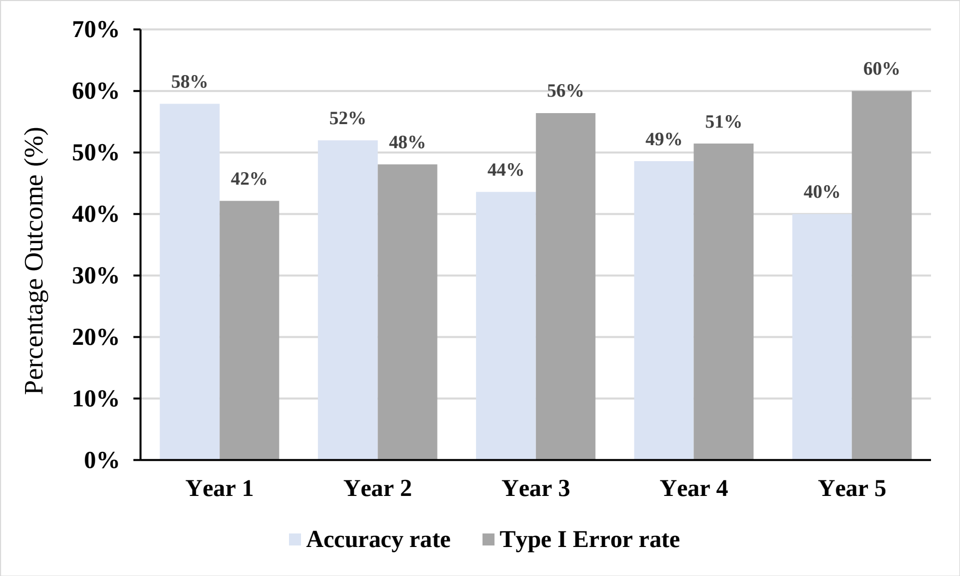


Figure 4.15: Predictive accuracy of the Ohlson O-Score in correctly classifying failed firms

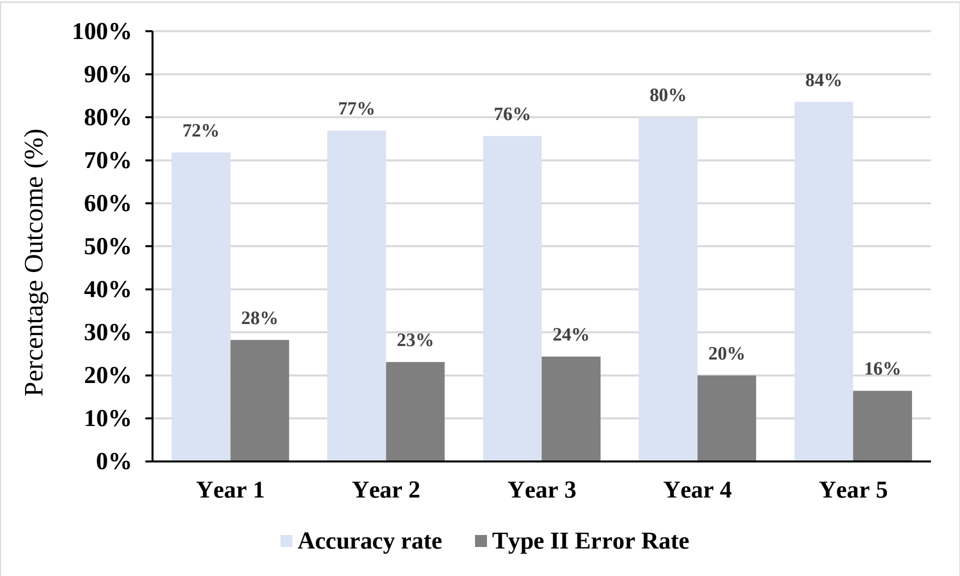


Figure 4.16: Predictive accuracy of the Ohlson O-Score in correctly classifying non-failed firms

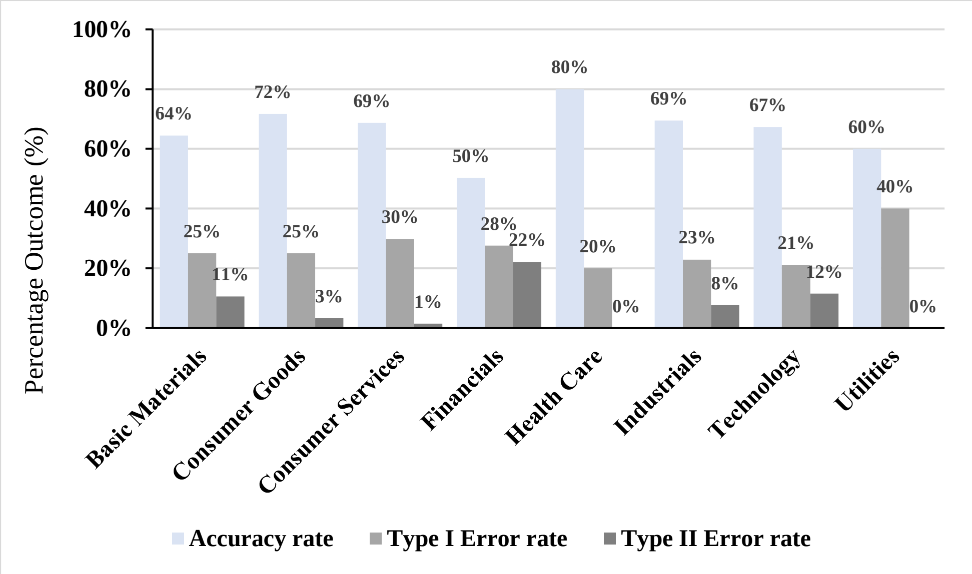


Figure 4.17: Predictive accuracy of the Ohlson O-Score by economic sector

4.4.5 Zmijewski (1984) – Probit model

Similar to Ohlson's logit model outcomes, Zmijewski's probit model, in its application to the dataset, was characterised by a high degree of Type I errors, which dented the overall predictive accuracy of the model. The overall results, which were significantly lower than the prediction accuracy surfaced in Aziz and Dar's (2006) research in respect of probit models, averaged 60% over the five-year review period. The accuracy and the error rates of the model are reflected in Figures 4.18 to 4.21.

While the model performed better in identifying failed firms closer to the year of failure, the accuracy was poor at 44% in the year prior to failure and averaged 31% over the five-year period. In contrast, the model was able to identify non-failed firms with a great degree of accuracy, with a prediction accuracy of 87% over the period.

When considering the sector performance, none of the sectors yielded accuracy rates above 70%, barring the Health Care sector, which had a low prevalence in the data set.

Under the parameters applied in this research, Zmijewski's X-score model is not considered to be suitable for accurately predicting firm failure.

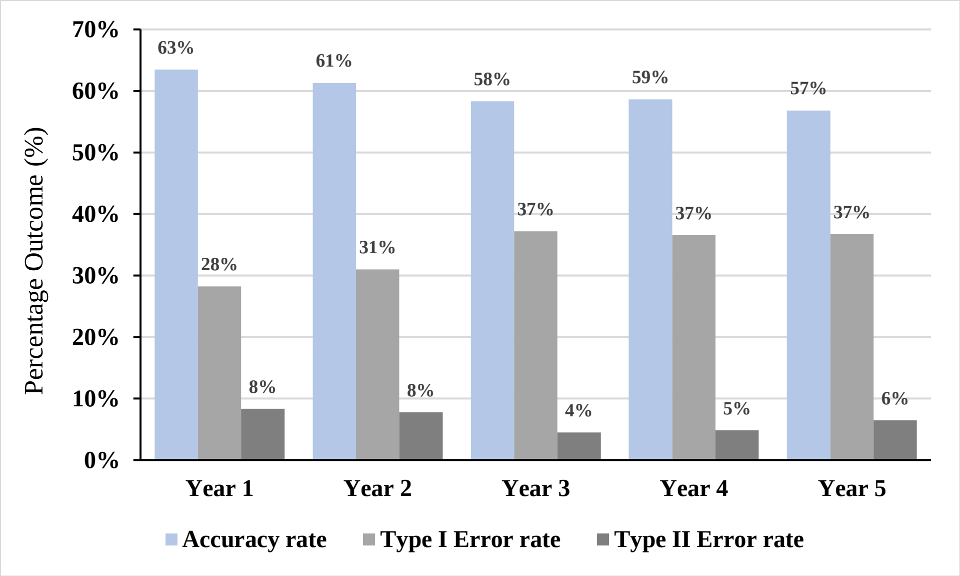


Figure 4.18: Overall predictive accuracy of the Zmijewski X-Score

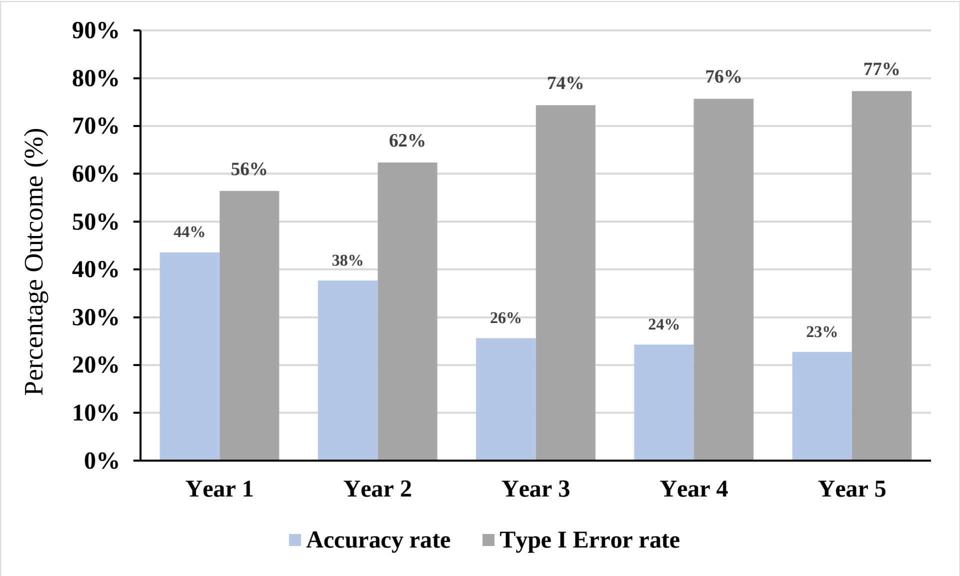


Figure 4.19: Predictive accuracy of the Zmijewski X-Score in correctly classifying failed firms

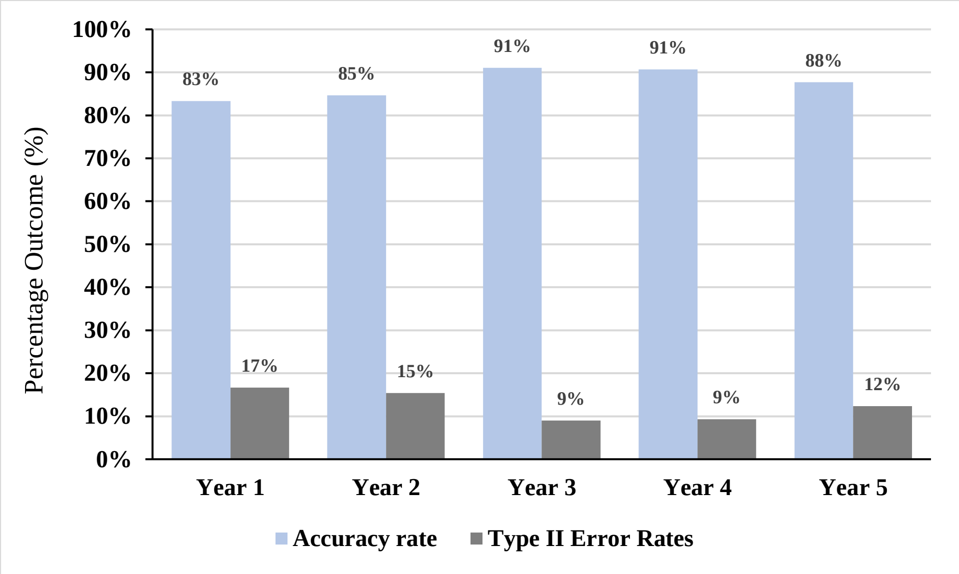


Figure 4.20: Predictive accuracy of the Zmijewski X-Score in correctly classifying non-failed firms

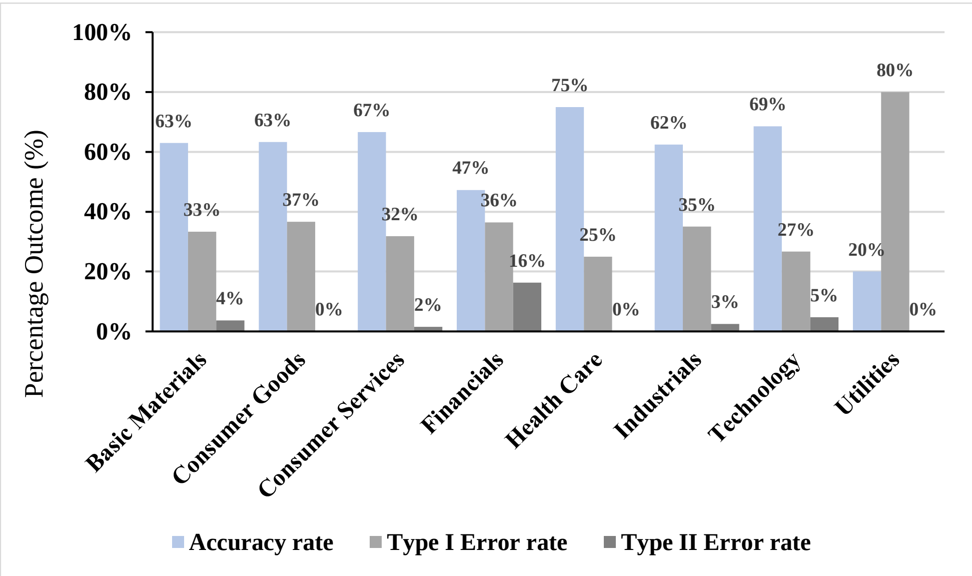


Figure 4.21: Predictive accuracy of the Zmijewski X-Score by economic sector

4.4.6 Steyn-Bruwer and Hamman (2006) – Recursive partitioning

The recursive partitioning model was the best-performing model in the model set, achieving a high prediction accuracy of 83%. The model performed well, despite being lower than the prediction accuracy surfaced in Aziz and Dar's (2006) research in respect of RPA models.

This model, which was cash-focused, affirmed the importance of the traditional and rudimentary marker between distressed and non-distressed firms, which is echoed in both South African company regulations and previous studies. That is, the abundance of cash or the lack thereof is the key differentiating mark between failure and success. In addition, the model's unique approach of considering the cumulative impact of certain variables, instead of basing predictive outcomes on the performance of a single financial year, tended not to fall prey to the error types prevalent in the other models in the model set. Shumway's hazard model (Wu, Gaunt and Gray, 2010:34-35) also applied this less static approach.

In evaluating the number of tree-splits to be comprehended in the model and as noted by inferences made by Balcaen and Ooghe's research (2004:10) (see section 2.3.2.3), a trade-off was undertaken between the number of splits required to yield the lowest possible errors and the complexity of the model. In essence, while more splits would generally yield a higher accuracy, this comes at the cost of complexity. In this regard, a capability potential (Cp) assessment was utilised to assist in the decision-making process, with the results leading to the selection of a 7-node decision tree.

In measuring the importance of the variables applied to the model, the size variable, denoted by LogTA/GDP, was by far the most important in the model. When this variable was removed from the model, the predictive accuracy of the model suffered significantly. This reaffirmed what was echoed by Ohlson (1980:122), who underscores that the size of the firm is the most important predictor of bankruptcy.

The decision tree as well as other pertinent model results are reflected in Figures 4.22 to 4.25.

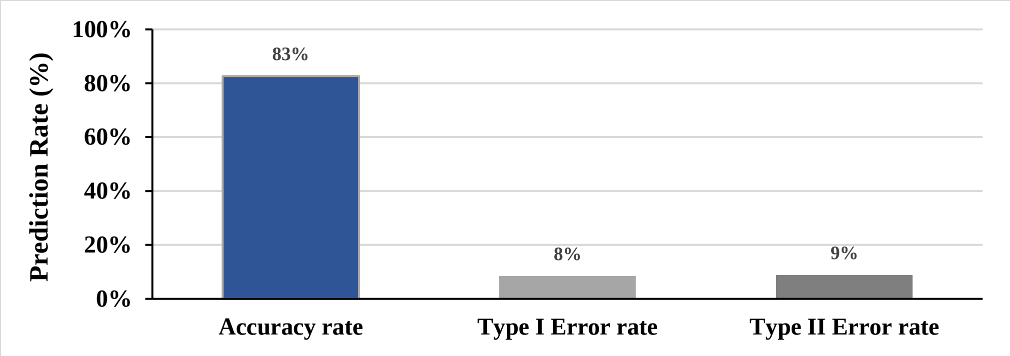


Figure 4.22: Overall predictive accuracy of the Steyn-Bruwer and Hamman RPA model

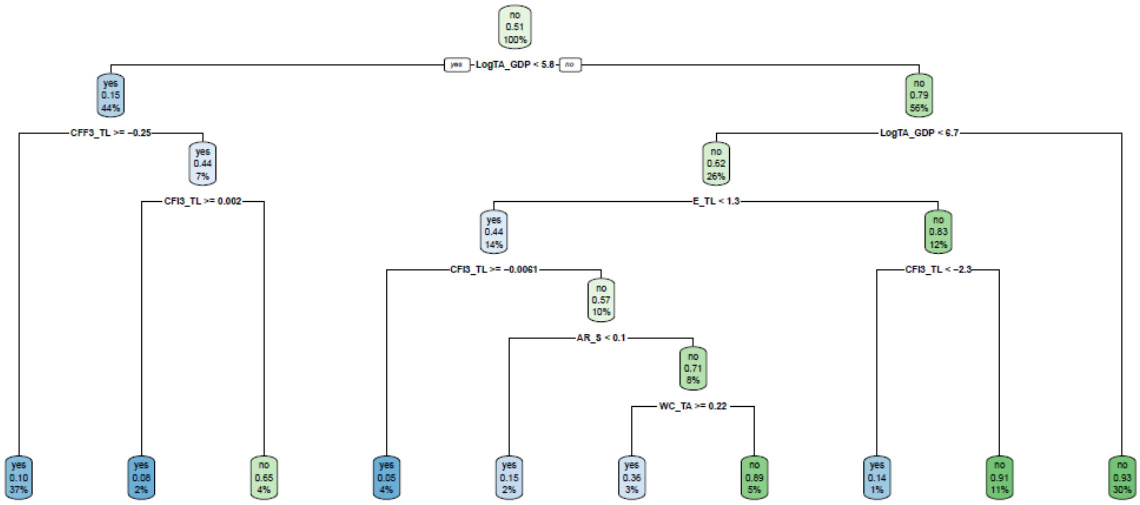


Figure 4.23: Steyn-Bruwer and Hamman RPA model decision tree

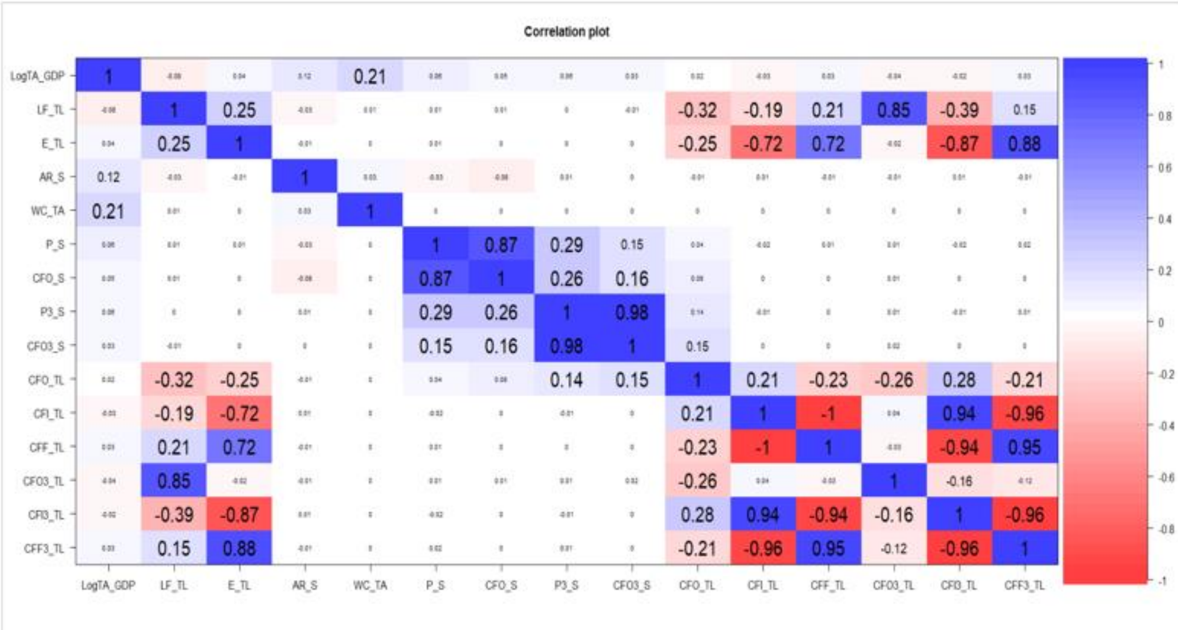


Figure 4.24: Steyn-Bruwer and Hamman RPA model correlation plot[19]

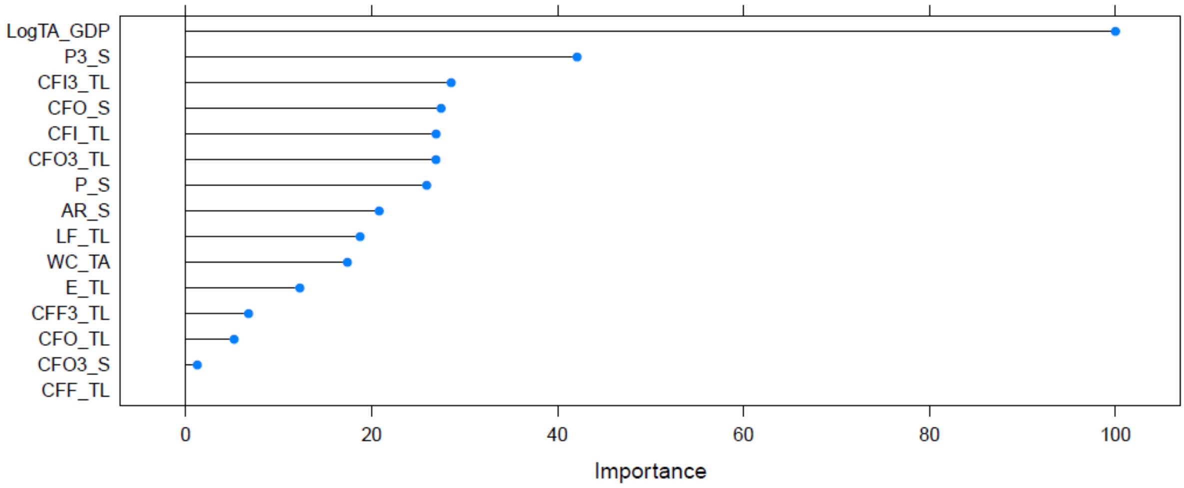


Figure 4.25: Steyn-Bruwer and Hamman RPA model variable importance[20]

[19] The correlation plot identifies features or variables that may be either highly positively correlated or highly negatively correlated.

[20] In measuring the importance of the variables applied, the size of the firm variable, denoted by LogTA/GDP, was by far the most important variable in the model.

4.4.7 Court (1991) – Non-financial and financial variables

Given the methodology applied in the application of this model as denoted in section 3.3.4.7, a reduced sample of firms formed the basis for the testing. An overall prediction accuracy of 73% was achieved within the parameters of testing. Pertinent model results and aspects are reflected in Figures 4.26 to 4.30.

The model followed the trend prevalent in the application of other models, in that it performed poorer than in its original application in 1991 (Court, 1991). While the model outperformed the MDA, logit and probit models, it succumbed to the same issue these models faced, which was a high prevalence of Type I errors. The model misclassified failed firms as healthy at a rate of 63%. Conversely, the Type II error rate was only 8%. The model also benefited from a higher degree of non-failed firms being included in the reduced sample of firms, as more failed firms were excluded from the sample due to missing data.

While the non-financial variables, especially the delay in the publishing of the annual financial statements, are the central variables in driving the most accurate overall predictive outcomes of the model[21], these variables do not serve as a key differentiator between failed and non-failed firms, given the misclassification rate of failed firms by the model. In this regard, what becomes apparent in reviewing the model, is that the model has to some extent suffered from a change in subsequent regulations, that have closed the gap between what was used as non-financial markers of success and failure. For example, while a delay in publishing the annual financial statements would have been viewed at the time the model was developed as a key marker between successful and failed firms, the revised Companies Act issued in May 2011 made it a breach of the Act, for certain companies, if the annual financial statements were not prepared within six months after its year-end. The consequences that would follow from this, especially for JSE-listed firms, would include the possibility of such an event being a reportable irregularity and the suspension of the firm from the exchange. The provisions of the King Report of Corporate Governance[22], the first which was issued in 1994, would also have guided board structures in the period post the model's establishment.

[21] Refer to Figure 4.30, which includes the variable importance of the Court model applied.

[22] The King Report on Corporate Governance is a guideline for the operational and governance structures of South African companies. The first report was issued in 1994, with further editions in 2002 and 2009. A fourth revised code was issued in 2016. JSE-listed companies must apply the King Code of principles.

Non-financial variables can provide meaningful insight into the potential frailty towards failure. An avenue for further study would be the establishment of a model incorporating more relevant non-financial variables, especially those applicable in the South African context.

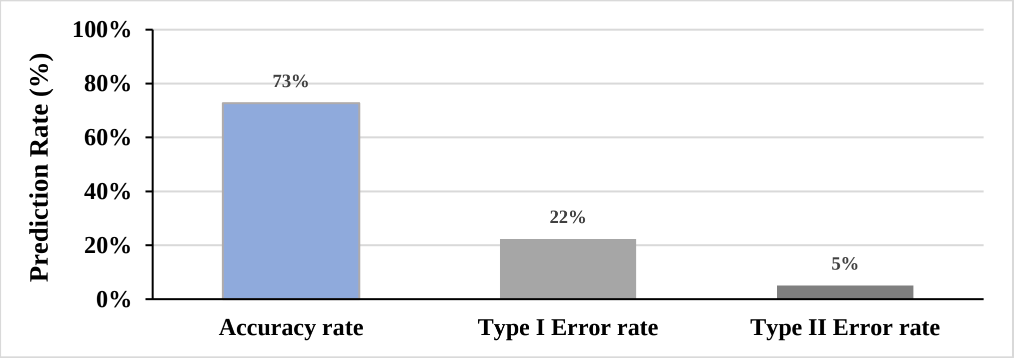


Figure 4.26: Overall predictive accuracy of the Court model

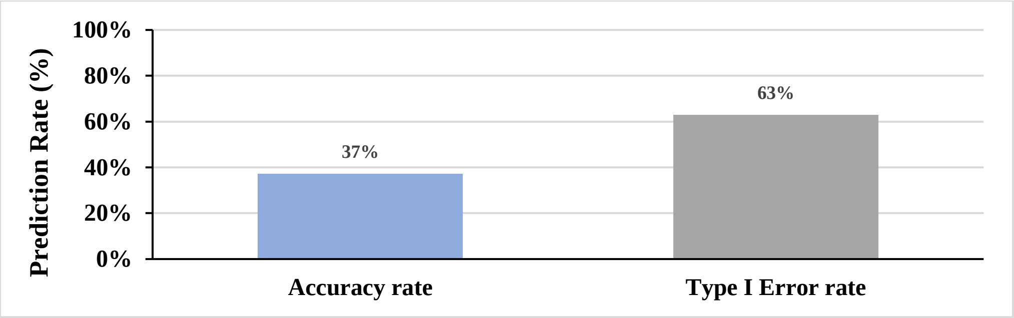


Figure 4.27: Predictive accuracy of the Court model in correctly classifying failed firms

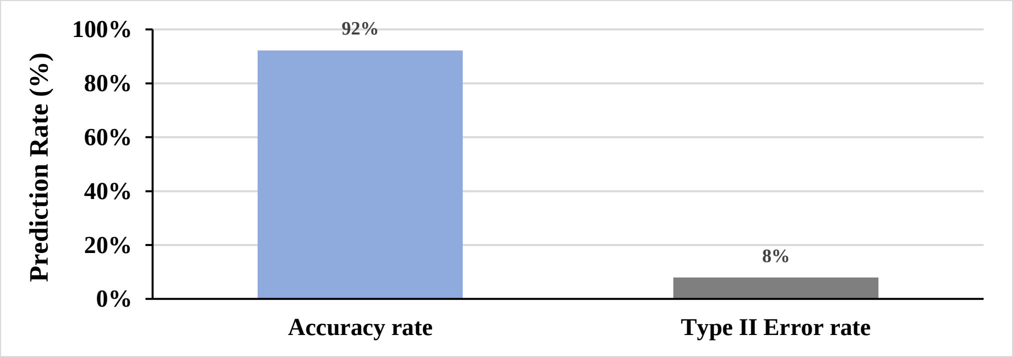


Figure 4.28: Predictive accuracy of the Court model in correctly classifying non-failed firms

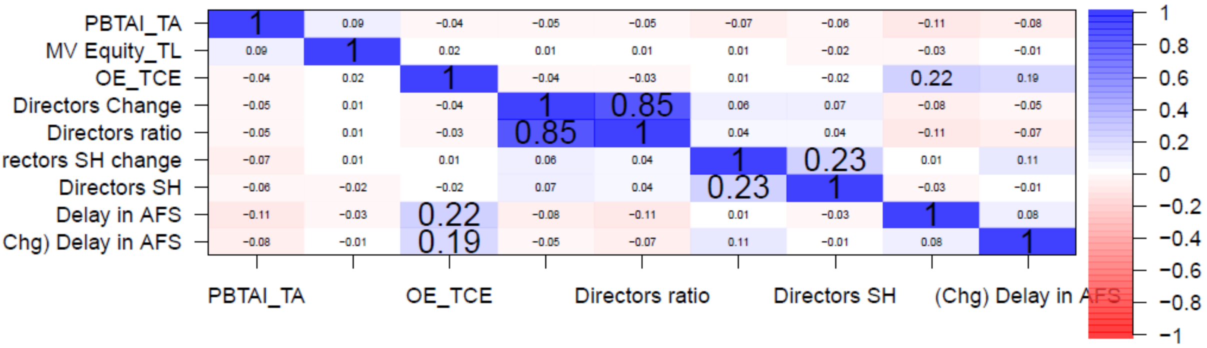


Figure 4.29: Court model correlation plot[23]

	Overall
'Delay in AFS'	3.9210951
'MV Equity_TL'	3.1491850
'Directors SH change'	2.2764733
'Directors Change'	1.8734255
'Directors ratio'	1.7846329
'Change in Delay in AFS'	1.6468946
PBTAI_TA	1.1109380
OE_TCE	0.6054804
'Directors SH'	0.0546708

Figure 4.30: Court model variable importance[24]

[23] The correlation plot identifies features or variables that may be either highly positively correlated or highly negatively correlated

[24] The non-financial variables and in particular the delay in the publishing of the annual financial statements are the most important in the model. These however do not serve as a key differentiator between failed and non-failed firms, given the misclassification rate of failed firms by the model.

4.5 Normalising accounting inputs – a reassessment of model outcomes

The introduction of new international accounting standards in the latter part of the period considered in this research has had a marked impact on accounting ratios. As accounting inputs are key drivers in the predictive outcomes of the models used in the model set and given the predictive accuracies that have surfaced, an attempt was made to normalise the inputs for changes in accounting and assess whether this would result in better predictive outcomes.

The attempt to normalize the accounting information in the reassessment of model outcomes, however, is limited by the following factors:

- A very low prevalence of failed firms (less than 3%) in the sample, which failed post the introduction of new accounting standards; and
- The models reflected a higher tendency towards Type I errors. Given the low prevalence of failed firms in the sample, which failed post the introduction of new accounting standards, little can be done to potentially adjust the overall model outcomes in this area.

The attempt, however, was still pursued to test the potential impacts of these accounting changes, with an initial assessment applied to the models which reflected comparatively higher Type II errors. This focus was undertaken due to the low prevalence of failed firms post the introduction of the new accounting standards.

In normalising the accounting inputs, the following adjustments were considered:

- ROU assets and lease liabilities, introduced as a result of IFRS 16, were removed from the balance sheet in the year being assessed. This adjustment results in a change in the asset base, leverage assessment and in the net asset value of the firm;
- Depreciation on ROU assets and interest in respect of leased liabilities were removed. The sum of these components in the year of assessment was viewed as being equivalent to the lease payment that would have been reflected in the income statement under the previous accounting standard. While there may be timing differences, the assumption applied is valid, as the net result of the change introduced by IFRS 16 results in a depreciation and interest charge which equals the lease payments in the income statement under the previous accounting standard, when considering the full term of the lease. The impact of this change results in a comparatively lower EBITDA as the

depreciation and interest components previously excluded from EBITDA are replaced by an equivalent lease payment; and

- Abnormal expected credit losses were removed, where applicable. This change results in a comparatively higher EBITDA.

A subset of the 156 companies in the sample was selected for the exercise. This subset included all the failed companies which failed post the introduction of the new accounting standards and a random sample of non-failed firms. The Altman Z-score model and Ohlson's O-Score model were primed for an initial assessment in applying the "normalisation" exercise, given their higher comparative rate of Type II errors.

The application of these normalised accounting inputs, however, resulted in no material improvement in addressing Type I or Type II errors. As a result, the test was not extended to other models.

Given the limitations of testing, further research is required in this area to understand the impacts of the changes in the accounting landscape on traditional distress models.

4.6 Summary

Under the testing parameters, the outcomes of testing tended to yield predictive accuracies below the outcomes from previous studies, with the models generally plagued by Type I errors. The exception to this was Steyn-Bruwer and Hamman's RPA model, which demonstrated robustness against the general trend of the model set and yielded a high accuracy rate of 83%.

The attempt to reassess the results of distress prediction models in the model set, by adjusting for the impacts of changes in accounting, resulted in an inconclusive outcome. Further research is required in this area.

In addition, given the low predictive accuracy of the traditional distress models applied to the dataset, further investigation is required to unearth the reasons for the comparatively lower prediction tendency, with the aim of potentially revising these models and yielding higher predictive accuracies.

Chapter 5: Conclusion

This research aimed to assess the reliability of various models in predicting the failure of JSE-listed companies during a twenty-year period, which had unique characteristics. Furthermore, given that accounting data and ratios have traditionally been used as inputs in distress prediction models, the research intended to assess the impact that changes in accounting standards had on model outcomes.

With this context, several models were applied, spanning across some of the main model categories from previous literature, with the model set including models developed by South African researchers. These models included macroeconomic data as inputs and a model was included in the model set which included non-financial variables.

Under the testing parameters, the models tended to yield predictive accuracies below the outcomes in previous studies (this is in reference to the research undertaken by Aziz and Dar (2006) and the original application of these models). The models applied in the testing were also generally plagued by Type I errors.

The exception to this was Steyn-Bruwer and Hamman’s RPA model, which demonstrated robustness against the general trend of the model set and yielded a high accuracy rate of 83%. This model, which was cash-focused, affirmed the importance of a traditional and rudimentary marker between distressed and non-distressed firms, which is echoed in both South African company regulations and previous studies. That is, the abundance of cash or the lack thereof is the key differentiating mark between failure and success. This model also highlighted the importance of considering the cumulative impact of variables, instead of basing predictive outcomes on the performance of a single period, in predicting the failure or success of companies. Furthermore, the model confirmed what had been established in previous research in the area. That is, the size of the firm is a significant predictor of bankruptcy.

The attempt to reassess the results of distress prediction models in the model set by adjusting for the impacts of changes in accounting resulted in an inconclusive outcome. This was largely due to the extent of Type I errors across the MDA, logit and probit models, in conjunction with the low prevalence of failed companies towards the latter part of the period considered in this research when changes in accounting standards were introduced. Further research is required in this area to understand the impact of accounting changes on traditional distress prediction models and potentially to revise these distress models, in order to yield higher predictive accuracies.

Bibliography

Aziz, M.A., Dar, H.A. 2006. Predicting corporate bankruptcy: where we stand? *Corporate Governance*. 6 (1): 18-33.

Aziz, A., Emanuel, D.C. and Lawson, G.H. 1988. Bankruptcy prediction - an investigation of cash flow based models. *Journal of Management Studies*. 25 (5): 419-437.

Altman, E.I. 1968. Financial Ratios, Discriminant analysis and prediction of corporate bankruptcy. *The Journal of Finance*. 23 (4): 589-609.

Altman, E.I., Iwanicz-Drozdowska, M., Laitinen, E.K. and Suvas, A. 2014. Distressed firm and bankruptcy prediction in an international context: A review and empirical analysis of Altman's Z-score model. *Available at SSRN 2536340*.

Balcaen, S. and Ooghe, H. 2004. Alternative methodologies in studies on business failure: do they produce better results than the classical statistical methods. *Vlerick Leuven Gent Management School Working Papers Series*. 16.

Bascom, K., Jubels, R., Sylvie, L. and O'Donovan, B. KPMG. 2018. Leases Transition Options: What is the best options for your business? IFRS 16. Available: https://home.kpmg/content/dam/kpmg/xx/pdf/2018/11/leases-transition-options-2018.pdf (Accessed: 25 February 2022)

Beaver, W.H. 1966. Financial ratios as predictors of failure. *Journal of Accounting Research, Empirical Research in Accounting: Selected Studies 1966*. 4: 71-111.

Beaver, W.H., McNichols, M.F. and Rhie, J.W. 2005. Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy. *Review of Accounting studies*. 10 (1): 93-122.

Bisogno, M. and De Luca, R., 2012. Indirect costs of bankruptcy: evidence from Italian SMEs. *Journal of Accounting and Finance*. 2(1): 20-30.

Business Insider SA. 2020. The biggest South African business scandals over the past decade. *Business Insider South Africa*. 11 January 2020. Available: https://www.businessinsider.co.za/the-top-south-african-business-scandals-the-past-decade-2020-1 (Accessed: 19 May 2021)

Bruno, A.V. and Leidecker, J.K. 2001. Causes of new venture failure: 1960s vs. 1980s. *Business Horizon*. 31 (6): 51-56

Cassim, Z. 2016. Predicting financial distress of JSE-listed companies using Bayesian networks. University of Cape Town. Unpublished dissertation.

Chen, G.M. and Merville, L.J. 1999. An analysis of the underreported magnitude of the total indirect costs of financial distress. *Review of Quantitative Finance and Accounting*. 13(3): 277-293.

Cole, R., Johan, S. and Schweizer, D. 2021. Corporate failures: Declines, collapses, and scandals. *Journal of Corporate Finance*. 67: 101872.

Companies Act 71 of 2008 (South Africa). Available: https://www.justice.gov.za/legislation/acts/2008-071amended.pdf (Accessed: 10 May 2022)

Court, P.W. 1991. An investigation into the significance of certain firm specific non-financial variables in a failure prediction model. *De Ratione*. 5 (2): 3-15.

Deloitte. 2014. IFRS industry insights: Telecommunications sector. Available: https://www.iasplus.com/en/publications/global/ifrs-industry-insights/rev-rec-telecom/at_download/file/Telecommunications%20final.pdf (Accessed: 27 February 2022)

Deloitte. 2016. Leases: A guide to IFRS 16. Available: https://www2.deloitte.com/content/dam/Deloitte/sg/Documents/audit/sea-audit-IFRS-16-guide.pdf (Accessed: 27 February 2022)

Desjardins, J. 2019. The 20 Biggest Bankruptcies in U.S. History. *Visual Capitalist*. 25 June. Available: https://www.visualcapitalist.com/the-20-biggest-bankruptcies-in-u-s-history/ (Accessed: 19 May 2021)

Douglas, M.G. and Oellermann, C.M. 2021. The Year in Bankruptcy: 2020. *Jones Day*. February 2021. Available: https://www.jonesday.com/en/insights/2021/02/the-year-in-bankruptcy-2020 (Accessed: 8 February 2022)

Du Preez, W. 2012. The status of post-commencement finance for business rescue in South Africa. University of Pretoria. Unpublished dissertation.

Elloumi F. and Gueyie J. 2001. Financial distress and corporate governance: an empirical analysis. *Corporate Governance.* 1 (1): 15-23.

Fahlman, S. and Lebiere, C. 1989. The cascade-correlation learning architecture. *Advances in neural information processing systems*. 2. 524-532

Frydman H., Altman E.I. and Kao D.L. 1985. Introducing recursive partitioning for financial classification: The case of financial distress. *Journal of Finance.* 54 (1): 269-291.

Grant, M. 2021. Nonparametric Statistics: Overview, Types, and Example. Available: https://www.investopedia.com/terms/n/nonparametric-statistics.asp#:~:text=What%20Are%20Nonparametric%20Statistics%3F,and%20the%20linear%20regression%20model.
(Accessed: 6 November 2022)

Grice, J.S. and Ingram, R.W. 2001. Tests of the generalizability of Altman's bankruptcy prediction model. *Journal of Business Research*. 54: 53-61.

Hamilton, S. and Micklethwait, A. 2006. *Greed and corporate failure: The lessons from recent disasters*. New York. Palgrave Macmillan.

Hattingh, J.H. 2017. Implication of the global financial crisis for financial regulation in South Africa. University of Pretoria. Unpublished dissertation.

Holt, G.D. 2013. Construction business failure: conceptual synthesis of causal agents. *Construction Innovation*. 13 (1): 50-76.

Institute of Directors Southern Africa. 2016. King IV Report on Corporate Governance for South Africa 2016. Available: https://www.adams.africa/wp-content/uploads/2016/11/King-IV-Report.pdf (Accessed: 25 October 2022)

International Accounting Standards Board. 2018. International Accounting Standard 8 Accounting Policies, Change in Accounting Estimates and Errors. Available: https://www.ifrs.org/content/dam/ifrs/publications/pdf-standards/english/2022/issued/part-a/ias-8-accounting-policies-changes-in-accounting-estimates-and-errors.pdf?bypass=on (Accessed: 10 May 2022)

International Accounting Standards Board. 1997. International Accounting Standard 17 Leases. Available: https://www.iasplus.com/en/standards/ias/ias17 (Accessed: 10 May 2022)

International Accounting Standards Board. 2014. International Financial Reporting Standard 9 Financial Instruments. Available: https://www.ifrs.org/issued-standards/list-of-standards/ifrs-9-financial-instruments.html/content/dam/ifrs/publications/html-standards/english/2022/issued/ifrs9/ (Accessed: 10 May 2022)

International Accounting Standards Board. 2014. International Financial Reporting Standard 15 Revenue from Contracts with Customers. Available: https://www.ifrs.org/issued-standards/list-of-standards/ifrs-15-revenue-from-contracts-with-customers.html/content/dam/ifrs/publications/html-standards/english/2022/issued/ifrs15/ (Accessed: 10 May 2022)

International Accounting Standards Board. 2016. International Financial Reporting Standard 16 Leases. Available: https://www.ifrs.org/issued-standards/list-of-standards/ifrs-16-leases.html/content/dam/ifrs/publications/html-standards/english/2022/issued/ifrs16/ (Accessed: 10 May 2022)

International Accounting Standards Board. 2016. Basis for Conclusions on IFRS 16 Leases. Available: https://library.croneri.co.uk/cch_uk/iast/ifrs16-basis-201601 (Accessed: 01 November 2022)

International Standard on Auditing 570 (Revised) Going Concern. 2016. Available: https://www.ifac.org/system/files/publications/files/ISA-570-(Revised).pdf (Accessed: 25 October 2022)

Johnson, P. 2008. The Formation and Development of Small Business: Issues and Evidence. Taylor & Francis. Oxford.

Kien, T.H. 2017. IFRS 15: Revenue from Contract with Customers. PwC. Available: https://www.pwc.com/vn/en/services/assurance/ifrs/ifrs-15.html (Accessed: 10 May 2022)

Kubícková, D. and Nulicek, V. 2016. Predictors of financial distress and bankruptcy model construction. *International Journal of Management Science and Business Administration*. 2(6): 34-42

Lev, B. 1973. Decomposition measures for financial analysis. *Financial Management*, 2 (1): 56-63

Muller, G.H., Steyn-Bruwer, B.W. and Hamman, W.D. 2009. Predicting financial distress of companies listed on the JSE-A comparison of techniques. *South African Journal of Business Management*. 40 (1): 21-32.

Ohlson, J.A. 1980. Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*. 18 (1): 108-131

Open Secrets. (2020). Deloot – how Deloitte gets away with it. *Daily Maverick*. 12 August 2020. Available: https://www.dailymaverick.co.za/article/2020-08-12-deloot-how-deloitte-gets-away-with-it/ (Accessed: 11 February 2022)

Permanent Subcommittee of Investigations. 2002. The role of the board of directors in Enron's collapse. Available: https://www.govinfo.gov/content/pkg/CPRT-107SPRT80393/pdf/CPRT-107SPRT80393.pdf (Accessed: 19 May 2021)

Platt, H.D. and Platt, M.B. 2002. Predicting corporate financial distress: Reflections on choice-based sample bias. *Journal of economics and finance*. 26 (2): 184-199.

PwC. 2017. IFRS 9, Financial Instruments: Understanding the basics. Available: https://www.pwc.com/gx/en/audit-services/ifrs/publications/ifrs-9/ifrs-9-understanding-the-basics.pdf (Accessed: 27 February 2022)

Refaeilzadeh, P., Tang, L. and Liu, H. 2009. Cross-validation. *Encyclopedia of database systems*. 5: 532-538.

Rose, D. 1992. Bankruptcy risk, firm-specific managerial human capital, and diversification. *Review of Industrial Organisation*. 7: 65–73.

Ross, S. 2020. What Major Laws Were Created for the Financial Sector Following the 2008 Crisis? Available: https://www.investopedia.com/ask/answers/063015/what-are-major-laws-acts-regulating-financial-institutions-were-created-response-2008-financial.asp (Accessed: 17 June 2021)

Scott, J. 1981. The probability of bankruptcy: a comparison of empirical predictions and theoretic models. *Journal of Banking and Finance*. 5: 317-344.

Shamsudin, A. and Kamaluddin, A. 2015. Impending Bankruptcy: Examining cash flow pattern of distress and healthy firms. *Procedia Economics and Finance*. 31:766-774.

Shumway, T. 2001. Forecasting Bankruptcy More Accurately: A Simple Hazard Model. *The Journal of Business*. 74 (1): 101-124

Siphelele, D. 2020. KPMG vows to bury controversial past. *IOL*. 17 June 2020. Available: https://www.iol.co.za/business-report/companies/kpmg-vows-to-bury-controversial-past-49476009 (Accessed: 10 February 2022)

Statistics South Africa. 2021. P0043 - Statistics of Liquidations and insolvencies: 2000-2020. Available: http://www.statssa.gov.za/?page_id=1866&PPN=P0043&SCH=72816&page=1 (Accessed: 17 June 2021)

Steyn-Bruwer, B.W. and Hamman, W. D. 2006. Company failure in South Africa: classification and prediction by means of recursive partitioning. *South African Journal of Business*. Management. 37 (4): 7-18

Suresh, S.P., Al Subhi, A.S.M., Al Siyabi, M.M.M. and Al Afari, A.A.M. 2022. Predicting financial distress of Omani tourism companies during Covid-19 using Zmijewski model. *International Journal of Accounting Research*. 7 (1): 95-101

Sutton, R.I. and Callahan, A.L. 1987. The stigma of bankruptcy: Spoiled organizational image and its management. *Academy of Management Journal*. 30 (3): 405-436

Twin, A. 2021. Overfitting. *Investopedia*. Available: https://www.investopedia.com/terms/o/overfitting.asp (Accessed: 3 March 2022)

Wang, T. Y., Winton, A. and Yu, X. 2010. Corporate fraud and business conditions: Evidence from IPOs. *The Journal of Finance*. 65 (6): 2255-2292

Warner, J.B. 1977. Bankruptcy Costs: Some Evidence. *The Journal of Finance*. 32 (2): 337-347

Welc, J. 2022. Financial statement analysis. In Evaluating Corporate Financial Performance. 131-212. Palgrave Macmillan. Cham.

Y. Wu, C. Gaunt, S. Gray. 2010. A comparison of alternative bankruptcy prediction models. *Journal of Contemporary Accounting & Economics*. 6 (1): 34-45

Zmijweski, M.E. 1984. Methodological Issues Related to the Estimation of Financial Distress Prediction Models. *Studies on Current Econometric Issues in Accounting Research*. 22 (1): 59-82

Appendices

Appendix 1: Abbreviations and Glossary of Terms

ANN	Artificial neural networks
AIES	Artificially intelligent expert system models
BC	Basis of Conclusion
BSDM	Balance sheet decomposition models
Cash	Cash management theory
CBR	Case-based reasoning
CEO	Chief Executive Officer
Covid-19	Coronavirus disease 2019
Cp	Capability potential
Credit	Credit risk theories
Cross-Validation	Cross-validation is a method used in statistics when assessing and comparing learning algorithms. The method involves data being segregated into two parts, with one segment applied to train a model and the second segment utilised to validate the model. The goal of such an assessment is to obtain the correct ratio to derive an accurate setting of the model and to derive accurate performance outside of the sample when exposed to new data.
CUMSUM	Cumulative sums model (time series)
Dodd-Frank Act	Dodd-Frank Wall Street Reform and Consumer Protection Act
ECL	Expected credit loss
EBITDA	Earnings before interest, tax, depreciation and amortization
FSOC	Financial Stability Oversight Council
FVPL	Fair value through profit or loss
FVOCI	Fair value through other comprehensive income
GA	Genetic algorithms

Gamb.	Gambler's ruin theory
GDP	Gross Domestic Product
GNP	Gross National Product
GFA	General failure agents
IAS	International Accounting Standard
IASB	International Accounting Standards Board
IFRS	International Financial Reporting Standards
IRESS	Integrated Real-Time Equity System Software
ISA	International Standard on Auditing
JSE	Johannesburg Stock Exchange
LPM	Linear probability model
MDA	Multiple discriminant analysis
NCA	National Credit Act 34 of 2005
NN	Neural networks
Overfitting	A modelling error in statistics that occurs when a function is too closely aligned to a limited set of data points
Par. Adj.	Partial adjustment model (time series)
PPI	Product Price Index
PwC	PricewaterhouseCoopers
ROU	Right-of-use
RPA	Recursive partitioning algorithm
RS	Rough sets model
SARB	South African Reserve Bank
SCA	Sub-causal agents
SPPI	Solely payments of principal and interest
STATSA	Statistics South Africa

Type I error	A Type I error refers to the incorrect classification of a failed company as a non-failed company
Type II error	A Type II error refers to the incorrect classification of a non-failed company as a failed company
United States	United States of America
USD	United States Dollar
ZAR	South African Rand

Appendix 2: List and details of companies included in the sample

Company Name	Failed or Non-failed
1Time Holdings Ltd	Failed
Afgem Ltd	Failed
Africa Cellular Towers Ltd	Failed
African Eagle Resources Plc	Failed
African Phoenix Investments Ltd	Failed
Ag Industries Ltd	Failed
Alert Steel Holdings Ltd	Failed
Alliance Mining Corporation Ltd	Failed
Aludie Ltd	Failed
Aquila Growth Ltd	Failed
Basil Read Ltd	Failed
Beget Holdings Ltd	Failed
Bioscience Brands Ltd	Failed
Blue Financial Services Ltd	Failed
Bryant Technology Ltd	Failed
CCI Holdings Ltd	Failed
Chemical Specialities Ltd	Failed
Comair Ltd	Failed
Computer Configurations Holdings Limited	Failed

Company Name	Failed or Non-failed
Adapt It Holdings Ltd	Non-failed
African Media Entertainment	Non-failed
African Rainbow Capital Investments	Non-failed
Afrocentric Investment Corp	Non-failed
Allied Electronics Corporation	Non-failed
Anglogold Ashanti	Non-failed
Aspen Pharmacare Holdings Limited	Non-failed
Astral Foods Limited	Non-failed
Aveng Group Limited	Non-failed
Bell Equipment Limited	Non-failed
Brait SE	Non-failed
Brikor Limited	Non-failed
British American Tobacco	Non-failed
City Lodge Hotels Limited	Non-failed
Clientele Limited	Non-failed
Conduit Capital Limited	Non-failed
Coronation Fund Managers	Non-failed
Datatec Limited	Non-failed
Distell Group Holdings	Non-failed

Appendix 2: List and details of companies included in the sample (continued)

Company Name	Failed or Non-failed
Conafex Holdings Societe Anonyme	Failed
Congella Federation Ltd	Failed
Core Holdings Ltd	Failed
Corpcapital Ltd	Failed
Corpcom Limited	Failed
Delrand Resources Ltd	Failed
The Don Group Ltd	Failed
Elementone Ltd	Failed
Fashion Africa Ltd	Failed
First Lifestyle Holdings Limited	Failed
Frontrange Ltd	Failed
Gencor Ltd	Failed
Group Five Holdings Limited	Failed
Idion Technology Holdings Ltd	Failed
Industrial And Commercial Holdings Group Limited	Failed
Intertrading Ltd	Failed
Iprop Holdings Ltd	Failed
Ipsa Group Plc	Failed
JCI Ltd	Failed

Company Name	Failed or Non-failed
EOH Holdings	Non-failed
Etion Limited	Non-failed
Exxaro Resources Limited	Non-failed
Metair Investments Limited	Non-failed
Growthpoint Properties Limited	Non-failed
Hosken Consolidated Investments Limited	Non-failed
Hudaco Industries Limited	Non-failed
Hwange Colliery Company Limited	Non-failed
Imbalie Beauty Limited	Non-failed
Italtile Limited	Non-failed
Jasco Electronics Holdings	Non-failed
Kibo Energy PLC	Non-failed
Kumba Iron Ore	Non-failed
Lewis Group Limited	Non-failed
Mix Telematics Limited	Non-failed
Mr Price Group	Non-failed
Mustek Limited	Non-failed
Naspers Limited	Non-failed
Nedbank Group Limited	Non-failed

Appendix 2: List and details of companies included in the sample (continued)

Company Name	Failed or Non-failed
Jigsaw Holdings Ltd	Failed
Kairos Industrial Holdings Ltd	Failed
Kirchmann-Hurry Properties Ltd	Failed
M Cubed Holdings Ltd	Failed
Mathomo Group	Failed
Mouldmed Medical Supplies Ltd	Failed
Msauli Asbes	Failed
Nei Africa Holdings	Failed
Net 1 Applied Technology Holdings Ltd	Failed
Ocean Diamond Mining Holdings Limited	Failed
Otr Mining Ltd	Failed
Paradigm Capital Holdings Limited	Failed
Pasdec Resources Sa Ltd	Failed
Psv Holdings	Failed
Rare Earth Extraction Co Ltd	Failed
Rba Holdings Ltd	Failed
Ref Finance & Investment Corporation Ltd	Failed
Rembrandt Beherende Beleggings	Failed
Rentsure Holdings Ltd	Failed

Company Name	Failed or Non-failed
Novus Holdings Limited	Non-failed
PPC Limited	Non-failed
Premier Fishing and Brands	Non-failed
PSG Group Limited	Non-failed
Putprop Limited	Non-failed
Quilter Plc	Non-failed
Raubex Group Limited	Non-failed
Rebosis Property Fund	Non-failed
Redefine Properties Limited	Non-failed
Remgro Limited	Non-failed
Reunert Limited	Non-failed
Sanlam Limited	Non-failed
Sebata Holdings Limited	Non-failed
Sephaku Holdings Limited	Non-failed
SilverBridge Holdings Limited	Non-failed
South Ocean Holdings	Non-failed
South32 Limited	Non-failed
Super Group Limited	Non-failed
The Foschini Group	Non-failed

Appendix 2: List and details of companies included in the sample (continued)

Company Name	Failed or Non-failed
Safmarine and Rennies Holdings Limited	Failed
Securedata Holdings	Failed
Siltek Holdings Ltd	Failed
Simmer & Jack Mines Ltd	Failed
Softline Ltd	Failed
Southern Mining Corporation Ltd	Failed
Storeco	Failed
Terrafin Holdings Ltd	Failed
The Laser Group Ltd	Failed
Total Client Services Ltd	Failed
Tridelta Magnet Technology Holdings Limited	Failed
Unitrans Ltd	Failed
Universal Growth Holdings Ltd	Failed
Ventron Corporation	Failed
Vogelstruisbult Metal Holdings Limited	Failed
The Waterberg Coal Company Ltd	Failed
Winecorp Ltd	Failed
Zarara Energy Ltd	Failed
Capestar Growth Inv Ltd	Failed

Company Name	Failed or Non-failed
Transaction Capital Ltd	Non-failed
Transpaco Limited	Non-failed
Zeder Investments Limited	Non-failed
AECI Limited	Non-failed
African Dawn Capital	Non-failed
Bauba Resources Limited	Non-failed
Gemfields Group Limited	Non-failed
Invicta Holdings Limited	Non-failed
Kaap Agri Limited	Non-failed
London Finance & Investment Group Plc	Non-failed
Master Drilling Group Limited	Non-failed
MC Mining Limited	Non-failed
Merafe Resources Limited	Non-failed
Metrofile Holdings Limited	Non-failed
Nvest Financial Holdings Limited	Non-failed
Omnia Holdings Limited	Non-failed
PBT Group Limited	Non-failed
Quantum Foods Holdings	Non-failed
Sygnia Limited	Non-failed

Appendix 2: List and details of companies included in the sample (continued)

Company Name	Failed or Non-failed
Masterfridge Ltd	Failed
M-Web Holdings Limited	Failed

Company Name	Failed or Non-failed
Tharisa Plc	Non-failed
Union Atlantic Minerals Limited	Non-failed

Appendix 3: Data points applied as inputs to the model set

Data Point
Accounts Payable
Accounts Receivable
Amortisation
Cash Balance
Cash Flow from Financing Activities
Cash Flow from Investing Activities
Cash Flow from Operating Activities
Current Assets
Current Liabilities
Depreciation
Director Shareholding
Dividends
Earnings before interest and tax (EBIT)
Financial Statements Signing Date
Financial Year End
Interest
Inventory

Data Point
Listed Investments
Market Value of Equity (Market Cap)
Net Cash Flow for The Year
Net Profit After Tax
Net Profit Before Tax
Number Of Directors
Number Of Outstanding Shares
Retained Earnings
Revenue
Total Assets
Total Borrowings
Total Equity
Total Liabilities
Gross Domestic Product (GDP) %
Inflation %
Production Price Index (PPI)
Gross National Product (GNP) Index

Appendix 4: Failed Companies – statistics of variables included in the dataset[25]

Data Point	Mean	Median	Standard Deviation	Min	Max
Figures expressed in thousands					
Accounts Payable	275,205	32,828	1,041,574	-	18,382,000
Accounts Receivable	324,339	37,048	1,504,185	-	21,230,000
Amortisation	6,517	-	36,567	-177,198	406,641
Cash Balance	165,298	11,993	472,250	-	3,828,000
Cash Flow from Financing Activities	-35,379	166	588,157	-8,862,000	2,072,657
Cash Flow from Investing Activities	-32,474	-3,332	410,402	-1,423,717	4,650,771
Cash Flow from Operating Activities	77,088	-	779,657	-4,559,199	10,297,000
Current Assets	575,011	79,700	2,045,566	-	25,937,000
Current Liabilities	462,851	56,479	1,811,900	-	26,437,000
Depreciation	31,361	1,971	86,222	-	678,137
Director Shareholding	41,275	1,545	172,348	-	2,329,548
Dividends	20,171	-	156,900	-	1,526,000
Earnings before interest and tax (EBIT)	-4,542	353	721,309	-11,783,000	5,048,000
Interest	60,845	2,047	365,938	-	4,564,000
Inventory	80,320	3,620	207,175	-	1,263,414
Listed Investments	247,546	-	1,235,093	-565	13,317,000
Market Value of Equity (Market Cap)	698,372	64,066	2,352,480	-	17,590,000
Net Cash Flow for The Year	8,291	-	150,188	-1,235,835	860,432
Net Profit After Tax	80,295	-	562,299	-4,199,000	5,042,000
Net Profit Before Tax	108,042	404	627,394	-3,990,000	5,181,000
Number Of Outstanding Shares	305,294	100,291	724,026	-	7,117,288

[25] The table excludes the non-financial variables related to the financial year-end, the financial statements signing date and the number of directors.

Appendix 4: Failed Companies – statistics of variables included in the dataset (continued)

Data Point	Mean	Median	Standard Deviation	Min	Max
Figures expressed in thousands					
Retained Earnings	100,719	1,395	727,731	-1,816,615	5,593,000
Revenue	865,815	77,446	1,958,066	-	13,401,174
Total Assets	1,582,139	196,244	6,285,505	-	67,466,000
Total Borrowings	592,285	9,520	3,845,749	-	45,738,000
Total Equity	656,055	77,787	2,251,863	-434,806	17,590,000
Total Liabilities	926,084	80,994	4,605,145	-	57,662,000

Appendix 5: Non-failed Companies – statistics of variables included in the dataset[26]

Data Point	Mean	Median	Standard Deviation	Min	Max
Figures expressed in thousands					
Accounts Payable	6,553,802	752,905	22,678,425	-	210,560,585
Accounts Receivable	19,854,713	877,613	119,341,960	-	1,279,281,566
Amortisation	-	-	-	-	-
Cash Balance	3,947,589	362,174	12,455,019	-	160,809,957
Cash Flow from Financing Activities	690,284	-3,273	17,693,748	-63,210,734	334,568,797
Cash Flow from Investing Activities	-1,990,031	-188,069	18,574,544	-319,508,484	102,749,587
Cash Flow from Operating Activities	1,632,296	101,225	7,291,684	-39,570,199	75,863,469
Current Assets	26,758,906	2,453,055	124,923,308	-	1,318,030,770
Current Liabilities	19,979,689	1,271,135	104,291,112	-	1,003,747,000
Depreciation	685,209	95,184	1,905,836	-	11,859,141
Director Shareholding	48,281	6,601	95,534	-	543,039
Dividends	1,890,077	87,646	9,221,746	-	100,164,752
Earnings before interest and tax (EBIT)	2,834,325	203,166	19,033,943	-24,958,000	210,204,606
Interest	1,362,127	71,474	6,160,979	-	53,513,000
Inventory	2,872,957	241,804	12,334,484	-	119,494,975
Listed Investments	17,796,496	83,531	90,097,472	-	1,101,839,201
Market Value of Equity (Market Cap)	15,315,405	2,313,305	31,845,788	-	199,672,720
Net Cash Flow for The Year	332,549	-	8,967,659	-128,559,733	95,605,658
Net Profit After Tax	4,608,823	175,773	35,835,688	-23,744,838	646,735,807
Net Profit Before Tax	5,132,454	290,470	31,392,113	-22,715,650	507,573,713
Number Of Outstanding Shares	722,341	260,458	1,655,801	-	19,369,644

[26] The table excludes the non-financial variables related to the financial year-end, the financial statements signing date and the number of directors.

Appendix 5: Non-failed Companies – statistics of variables included in the dataset (continued)

Data Point	Mean	Median	Standard Deviation	Min	Max
Figures expressed in thousands					
Retained Earnings	15,983,118	1,183,466	81,289,360	-46,309,064	837,560,561
Revenue	18,637,775	5,007,706	51,478,566	-	543,890,174
Total Assets	89,091,692	6,820,806	320,883,397	-	2,743,124,894
Total Borrowings	26,493,327	691,542	133,053,937	-	1,013,485,000
Total Equity	29,897,296	2,983,301	125,351,921	-4,161,989	1,254,219,099
Total Liabilities	59,194,396	2,580,353	223,233,127	-	1,488,905,795