AN INVESTIGATION INTO UNIFYING EARLY WARNING PREDICTION MODELS

JASON ANDREW GRIEVE

(GRVJAS001)

Research dissertation presented for the approval of the University of Cape Town Senate in fulfilment of part of the requirements for the degree of Master of Commerce (Specialising in Financial Reporting, Analysis and Governance) in approved courses and a minor dissertation. The other part of the requirement for this qualification was the completion of a programme of courses.

I hereby declare that I have read and understood the regulations governing the submission of Master of Commerce dissertations, including those relating to length and plagiarism, as contained in the rules of the University, and that this dissertation conforms to those regulations.

SUPERVISOR: ASSOCIATE PROFESSOR NAVITHA SINGH SEWPERSADH

(JANUARY 2023)

DECLARATION

I know the meaning of plagiarism and declare that all the work in the document, save for that which is properly acknowledged, is my own. This dissertation has been submitted to the Turnitin module and I confirm that my supervisor has seen my report and any concerns revealed by such have been resolved with my supervisor.

Signed by candidate

ACKNOWLEDGEMENTS

This dissertation is a culmination of support, guidance, team-work and overwhelming love from my family, friends, and mentors. I give utmost thanks and appreciation to my wife, Hannah, who was my greatest supporter and companion during this course. My parents, Iain, and Janine, for your continuous encouragement and unwavering kindness. To Sr Martha and Sr Breda who gave me the inspiration I needed when all felt lost. And of course, man's best friends, Cassie and Barkley for your addictive joy and cuddles.

I give tremendous thanks for the fortitude and invaluable advice and guidance of my supervisor, Navitha, who directed and encouraged me throughout this dissertation. I have broadened my horizons beyond any expectations and express appreciation to all my new friends, lecturers, professors, and guest speakers.

Education is a powerful tool and in the words of Nelson Mandela, "A good head and good heart are always a formidable combination. But when you add to that a literate tongue or pen, then you have something very special."

ABSTRACT

Forecasting financial distress has been regarded as a serious and significant problem, and if not signalled in time, has catastrophic ramifications on worldwide economies. Financial distress models are in existence and have been tested with varying results of success. However, there are varying definitions of financial distress which have contributed to the in-cohesiveness of financial distress literature where users have a limited ability to know what condition of financial distress is being forecast. Following a comprehensive literature review, it was found that financial distress models (Altman, 1968; Beaver, 1966; Gupta, 1983; Ohlson, 1980; Taffler, 1983; Zmijewski, 1984) have not been unified into an early warning signal (EWS) framework according to the specific financial distress conditions they have abilities to predict. Findings also found that risk (Beneish, 1999; Schilit, 2003) and earnings management measures (Sloan, 1996) play a significant role in financial distress forecasting but have also yet to be unified into an EWS framework. This study aims to unify financial distress, risk prediction and earnings management measurements into an EWS framework developed by Tavlin et al. (1989) to enable users the ability to identify the type of EWSs predicted and contributing reasons reducing the fragmentation of the extant literature. The investigation period of the study was for six years (2016 to 2021) using paired sampling methodology with a final sample of 72 delisted and 72 listed companies from the Johannesburg Stock Exchange (JSE). The study employed descriptive analysis to interrogate the results. The results indicated that financial distress models (Altman, 1968; Beaver, 1966; Gupta, 1983; Taffler, 1983; Zmijewski, 1984) and risk and earnings management measures (Beneish, 1999; Schilit, 2003; Sloan, 1996) could be unified into an EWS framework.

Key words: bankruptcy prediction; credit risk; probability of default (PD); early warning signals; financial distress, JSE; risk; earnings management

TABLE OF CONTENTS

TABLE OF FIGURES

LIST OF TABLES

CHAPTER 1: INTRODUCTION

1.1 RELEVANCE OF EARLY WARNINGS

The impact of the COVID-19 pandemic, the Russia-Ukraine conflict and unforeseen influences have resulted in an overall downward trend in the world economy seeing companies face significantly challenging environments and highly competitive burden. (Altman, 2021; Altman, 2020). The challenges and continued shocks the world faces impose adverse effects on company sustainability where companies are likely to encounter financial difficulties, excess debt, inadequate liquidity, and more seriously total financial demise. These problems impact significant losses to stakeholders and when the number of companies encountering financial distress aggregates to an alarming level, the greater social distress will develop ultimately affecting and undermining the stability and sustainability of the macroeconomic environment. In today's landscape where economic scandal and company collapse is so prevalent, early warning distress models are in a prime position to offer predictive abilities to give stakeholders sufficient time to address issues prior to collapse (Platt & Platt, 2002).

Despite financial systems and technology, international regulatory guidelines, and the continuous innovations in financial models assessing default risk capably and precisely, steadfastness of commercial institutions is still never guaranteed and financial distress and risk remain vital issues for corporate studies.

The objective of company credit risk modelling is to forecast a company's financial distress, a period of monetary conditions, or bankruptcy which is a formal legislative process commonly known as administration or liquidation (The British Accounting Review, 2022). These models that forecast failure play a major role for stakeholders such as regulators, investors, and lenders. According to Platt & Platt (2002) for several decades the topic of forecasting financial distress has been regarded as a serious and significant problem and of interest to financial academia studies where early warning models are vitally important for corporations reducing asymmetries of information allowing decision makers the ability to rectify impending failure.

1.2 RATIONALE FOR THIS STUDY

Predicting corporate financial distress has been a topic of research interest in accounting and finance since 1960 and continues to be used widely in practice today by auditors, analysts, risk institutions and financial institutions and appears throughout literature. According to Platt & Platt (2002) the copious literature theorising early warning prediction models of company bankruptcy has resulted in minimal research focused on EWSs identifying the onset of financial distress. Platt & Platt (2002) continued that where research ostensibly studies financial distress instead actually examines bankruptcy. Agarwal & Taffler (2008) concluded similar concerns which has contributed to the in-cohesiveness of the financial distress literature where researchers have limited ability to know which early warning model provides appropriate signals of a specific economic distress condition.

Early warning models forecasting distress have undertaken numerous modifications in modern times. Previous studies forecasting distress are principally grounded on reporting data obtained from financial statements (Wilcox, 1973). Some academics as early as the 1960's established scoring models using financial ratios such as Altman (1968), these were developed further by Ohlson (1980) and Zmijewski (1984). These models have been utilised throughout the world, in various industries as well a listed and private securities. For example, the Altman (1968) financial distress model has been tested in an array of countries such as the United States of America, Japan, Ireland, Canada, Netherlands, and France, to mention a few, with the model reporting accuracy between 64% and 90% (Altman, 1984) and has been tested in African countries like South Africa by Ngwenya (2018) with outputs signalling early warnings of financial distress defined as bankruptcy. According to Platt & Platt (2002) the effectiveness of EWS models has become more imperative for financial institutions in assessing the financial strength of a company. Platt & Platt (2002) continued to explain how stakeholders such as investors, creditors and government agencies rely on early warning models to determine the financial strength of companies. This need has been expanded to supply chain perspectives whereby manufacturers rely on early warning models to determine the financial credibility of suppliers and further to banking sectors using these models to indicate financial difficulties of companies. EWS models play an important role in society identifying financial issues allowing sufficient time to remedy the situation (Muller et al., 2009; Platt & Platt, 2002, 2006).

Well known EWS models such as Altman (1968), Beaver (1966), Gupta, (1983), Ohlson (1980), Taffler (1983), and Zmijewski (1984) have been successfully used in commercial industry, academic research and throughout the world predicting companies that will experience various conditions of financial distress. However, according to Hernandez Tinoco & Wilson (2013) the numerous financial distress models developed need to be established further so that users can reliably use EWS models knowing that a certain model can predict a condition of financial distress according to varying stages that exist to assist company turnaround strategies prior to catastrophe.

According to Giannopoulos et al. (2022) an early warning framework can protect a company from failure. This study intends to review the strengths of existing models of financial distress predictors, risk and earnings management measurements and develop a framework that could be used practically in industry categorising EWS models according to the models' output abilities so that there is sufficient time to address financial problems.

1.3 RESEARCH PROBLEM

According to Muller et al. (2009) a decision maker does not have the benefit of hindsight when analysing a company's financial statements and may disregard attempts to assess the future probability of financial distress if all seems well whereas if the company does appear to be in financial trouble the decision maker is expected to be interested in the stage of financial distress whether it be early distress where turnaround might be possible or beyond the point of no return.

Prior empirical research plays a significant role in the field of early warning models forecasting company distress and death assisting those decision makers Muller et al. (2009) referred to above. Research performed by Aziz & Dar (2006) accumulated 46 literature articles reporting 89 empirical studies on predicting corporate bankruptcy. Despite these several internationally recognised EWS models, predominantly, predicting bankruptcy, financial distress may not have to advance to the extreme form and may be prevented early (Pham Vo Ninh et al., 2018) such as different distress stages Muller et al. (2009) referred to. Researchers (Cybinski, 2001; Muller et al., 2009; Platt & Platt, 2002) have implied the need for these numerous existing models to be examined further to incorporate various EWSs to assist users know which models provide appropriate indicators of financial distress according to various stages of peril that exist.

A study in the United States of America by Hing & Lau (1987) used existing EWS models such as Altman (1968), Beaver (1966), and Ohlson (1980), among others, to demonstrate the importance of computing the different stages a company may be financially distressed. Using various financial states, the study successfully demonstrated the importance of the need, however, concluded that more research needs to follow. A study by Naidoo & du Toit (2007) understood the immense value of developing various stages of financial health in the South African context using an existing early warning model and, a newly developed one, to determine their predictive abilities according to the various stages of health. However, recognised that other models need to be incorporated to provide additional predictive clarity on initial early warning distress outputs.

There still remains a gap in research where studies have not unified the numerous financial distress prediction models according to their abilities to predict the various stages of distress a company may exhibit into a framework despite researchers emphasising the need for this. Furthermore, studies have not unified other models into such a framework that may contribute to identifying EWSs which may lead to financial distress and ultimately bankruptcy. Developing a unified framework would assist not only academia but could be used in practice to assist industry ensuring economic sustainability.

1.3.1 Hypothesis

The null hypothesis of this research (H0) is that financial distress, risk prediction, and earnings management measure cannot be unified into an EWS framework. The alternative hypothesis (H1) is that financial distress, risk prediction, and earnings management measure can be unified into an EWS framework.

1.3.2 Research Objective

Financial distress, risk and earnings managements measures have not been unified into an early warnings signal framework, resulting in the fragmentation of existing literature. Such conclusions could provide significant assistance to researchers, companies, credit risk experts, investors, turnaround specialists and business rescue practitioners ensuring companies long term survival.

The gap identified in this study contributes to the literature by expanding the application of Tavlin et al. (1989) framework of financial distress to early warning models. It suggests that there are important benefits in identifying the types of early warnings that the models are predicting in advance to avoid the demise of a business.

The following research objectives are applicable to satisfy the research aim of this study:

1. To determine whether financial distress models[1] predict distress according to Tavlin et al. (1989) condition 1: economic failure (Objective 1).
2. To determine whether financial distress models predict financial distress according to Tavlin et al. (1989) condition 2: technical insolvency (Objective 2).
3. To determine whether financial distress models predict financial distress according to Tavlin et al. (1989) condition 3: bankruptcy (Objective 3).
4. To determine whether a new category entitled “initial warnings” comprising of risk model[2] and earnings management measurement[3] may compliment early warning financial distress (Objective 4).

Refer to Appendix A, where the research objectives applicable to satisfy the research aim of this study have been depicted.

1.3.3 Thesis statement

Financial distress, risk prediction and earnings management measurements should be unified into an EWS framework to enable users the ability to identify the type of EWSs predicted reducing the fragmentation of the extant literature.

[1] Financial distress models examined in this study relate to Altman, 1968; Beaver, 1966; Gupta, 1983; Ohlson, 1980; Taffler, 1983; Zmijewski, 1984.
[2] Risk models examined in this study relates to Beneish, 1999; Schilit, 2003.
[3] Earnings management measure examined in this study relate to Sloan 1996.

1.4 RESEARCH APPROACH

This study used a quantitative approach to statistically calculate the financial distress, risk prediction and earnings management measures as envisaged by their respective model variables. The target population for this research consisted of all South African organisations that delisted from the main board of the JSE between the periods 2016 and 2021. The data collected included secondary quantitative data. Paired sampling methodology was employed to ensure the reasonability of findings.

1.5 MAIN RESEARCH FINDINGS

The results signify that financial distress, risk prediction and earnings management measurements can be unified into an EWS framework to enable users the ability to identify the type of EWSs predicted and the implied reason why distress exists.

A key finding in this study is that only certain financial distress models can provide EWSs of specific distress conditions. Some models produced appropriate warnings of distress conditions where others produced no warnings of distress. Findings also demonstrated that company financial structure played a vital role in determining the ability to recover or fail once a distress condition presented itself.

Further findings indicated that risk and earnings management measures produce appropriate initial warnings where financial distress may follow suit.

Although there have been numerous studies and revisions on financial distress techniques worldwide, there is no known published study to date that focuses on unifying financial distress, risk prediction and earnings management measurements into an EWS framework identifying the type of EWSs predicted and the implied reason why distress exists, based on an exhaustive literature review. Grounded in the data and findings contributing to the literature, this is a unique study based on unifying EWSs. The suggestive results highlight that whilst existing early warning models can be unified into a framework. Future research needs to develop financial distress models that may provide early warnings of a specific economic condition so that turnaround may occur prior to complete catastrophe.

1.6 DISSERTATION STRUCTURE

This dissertation is presented according to five chapters, inclusive of the Introduction (Chapter 1). The following segment (Chapter 2) presents a review of prior literature covering fundamental theories, the various early warning models of financial distress and the various financial distress definitions used by early warning models, risk, and earnings management measures. After this (Chapter 3) the research method utilised in this study will be presented and the methodology of examination discussed, following this (Chapter 4) the findings of this study will be discussed. Lastly (Chapter 5), a conclusion summarising the key findings proposed by the research question highlighting the culmination of this dissertation whereby further research may be conducted.

CHAPTER 2: LITERATURE REVIEW

This literature review commences by considering the theoretical frameworks of EWSs of distress. The review will examine other models that may contribute to identifying early warnings of financial distress. This is followed by a review of empirical literature examining EWS models that may be considered to unify early warning prediction models.

2.1 THEORETICAL FRAMEWORK

The theory of financial distress has undergone numerous developments over the years given its significant importance in the economy. According to prior literature, various definitions of financial distress have been used due to theoretical research not stipulating how to measure the decay of a company's wellbeing (Lukason & Hoffman, 2014; Pretorius, 2008; Sun et al., 2014). According to Gordon (1971) financial distress theory is explained as a company's earning power falling below a certain point whereby it will no longer be able to pay its debt. However, this theoretical explanation has been highlighted as an issue and has been elaborated further in studies such as Cybinski (2001) stating that the nature of "failure" is poorly defined and dichotomist groupings of failed or non-failed is a constraint that needs to be overcome. Further studies such as Gupta (1983) found a problem in the two-fold categorization of healthy and non-health companies and Pham Vo Ninh et al. (2018) emphasised companies go through a process of failure which may or may not ultimately lead to bankruptcy. Tavlin et al.(1989) also identified the challenge of defining failure recognising that there were two extremes of financial distress whereby revenues do not exceed costs and bankruptcy when a company's net worth is negative and that in-between these two extremes existed a range of distress possibilities that might allow time for corrective action to take place but, if not remedied may lead to the liquidation of the company. Ohlson (1980) explained that there was no accord on what establishes failure and that there is a clear difference between financial distress and bankruptcy. The researcher continued to discuss the importance of assessing various levels of financial distress and the contrasting levels as problems worsen. Tavlin et al. (1989) addressed these concerns by summarising three types of financial distress, firstly, economic failure, secondly, technical insolvency and, thirdly, bankruptcy.

The three types of financial distress summarised by Tavlin et al. (1989) provide a structured definition of distress incorporating two extremes and an in-between. Firstly, economic failure is defined as a company's expenses exceeding its income or that its cost of capital is greater than its return on investments or internal rates of return. Secondly, technical insolvency whereby a company is unable to settle its debts as they become due, and lastly bankruptcy whereby the company's fair value of assets does not exceed it liabilities, and the company has no possible means to meet its obligations. These financial distress definitions of Tavlin et al. (1989) are in line with legislation adopted world-wide such as that of South Africa and the Companies Act 2008 whereby technical insolvency and bankruptcy are defined as "companies that are reasonably unlikely to be able to pay all of their debts as they fall due and payable within the immediately ensuing six months, or it appears to be reasonably likely that the company will become insolvent within the immediately ensuing six months" (Parliament of the Republic of South Africa, 2008). The United Kingdom adopted technical insolvency and bankruptcy categories whereby two tests are performed to determine solvency, firstly, the cashflow test determining if a company is unable to pay its debts as they fall due, secondly, the balance sheet test determines if assets exceed liabilities, considering both contingent and prospective liabilities (Parliament of the United Kingdom, 1986). The United States of America identifies two categories of financial distress, firstly, condition of bankruptcy when liabilities exceed assets, the second, technical insolvency, occurs when the company is unable to pay its debts as they mature due to the company's poor financial liquidity. Notably, the first type of distress, economic failure, defined by Tavlin et al. (1989) has not been incorporated into legislation despite the condition being a potential EWS.

2.2 FINANCIAL DISTRESS PREDICTION MODELS

Early warnings signals of financial distress have been a topic of interest among academics for many decades with numerous studies focused on predicting a company's financial distress prior to demise so that mitigating actions may be implemented for turnaround. One of the earliest studies focused on predicting financial distress was that of Beaver (1966) who identified ratio models such as debt-to-asset, sales-to-assets, and cash flow-to-debt as commanding predictors of distress when their results were high.

Since initial studies by Beaver (1966) early financial distress warnings models have been tested with various outcomes of precision and are still powerful predictors in today's economic climate such as the Altman (1968) failure prediction model which was developed to predict failure defined as companies that filed for bankruptcy. Altman's model is as follows (Altman, 1968):

$$Z = 0.012X1 + 0.014X2 + 0.033X3 + 0.006X4 + 0.999X5$$

Where: X1 = Working Capital/Total assets

X2 = Retained Earnings/Total assets

X3 = Earnings before interest and taxes/Total assets

X4 = Market value of equity/ Book value of total debt

X5 = Sales/Total assets

Z = Overall index

The independent variables in the above equation produce results for the dependent variable known as the z-score, which can be interpreted as follows: A score of 2.67 or greater represents a zone where early warnings of financial distress is unlikely, a score between 1.81 and 2.67 is considered uncertain for early warnings of financial distress and a score of 1.81 or lower indicates early warnings of financial distress where a company is predicted for bankruptcy (Altman, 1968; Maccarthy, 2017).

Based on the foundations of early warning distress models, researchers continued developing theoretical frameworks to predict financial distress such as Gupta (1983) who believed that three perspectives represented degrees of early warnings of financial distress which led the researcher to conclude that financial ratio models relating to profitability, most specifically, earnings before depreciation, interest and taxes-to-sales and operating cash flow-to-sales, provided strong early warnings and financial ratio models relating to solvency, most specifically, net worth-to-total debt (including both short and long term) and all outside liabilities-to-tangible assets also provided early warnings of financial distress.

Since the development of Altman (1968) failure prediction model, early warning financial distress models have advanced further, such as the formulation of the o-score. Ohlson (1980) computed the o-score to predict failure defined as bankruptcy or those that notified intentions of filing for bankruptcy. Ohlson's model is as follows (Ohlson, 1980):

$$O = -1.3 - 0.4X1 + 6.0X2 - 1.4X3 + 0.1X4 - 2.4X5 - 1.8X6 + 0.3X7 - 1.7X8 - 0.5X9,$$

Where: X1 = Log(Total Assets / GNP Price Index Level)

X2 = Total Liabilities / Total Assets

X3 = Working Capital / Total Assets

X4 = Current Liabilities / Current Assets

X5 = one if total liabilities exceed total assets, zero otherwise

X6 = Net Income / Total Assets

X7 = Funds provided by operations / Total Liabilities

X8 = one if net income was negative for the last two years, zero otherwise

X9 = Measure of change in Net Income

O = Overall index

The independent variables in the above equation produce results for the dependent variable known as the o-score, which can be interpreted as follows: A score of 0.38 or greater represents a zone where early warnings of financial distress are likely, and a score of 0.38 or lower indicates early warnings of financial distress is unlikely (Ohlson, 1980; Salim & Ismudjoko, 2021).

Following similar methodology as Ohlson (1980) and Altman (1968) further early warning studies were forged such as Zmijewski (1984), who established an early warnings model known as the X-score using financial ratio that measured company liquidity, leverage and performance whereby financial distress was defined as the act of filing for bankruptcy. Zmijewski model is as follows (Zmijewski, 1984):

$X = -4.3 - 4.5X1 + 5.7X2 - 0.004X3$

Where X1 = Net income / Total assets

X2 = Total Debt / Total Assets

X3 = Current Assets / Current Liabilities

X = Overall index

The independent variables in the above equation produce results for the dependent variable known as the X-score, which can be interpreted as follows: A score below zero represents a zone where early warnings of financial distress are likely, and a score above zero indicates early warnings of financial distress is unlikely (Hantono, 2019; Zmijewski, 1984).

A study that also focused on predicting early warnings of company failure was the z-score developed by Taffler (1983). This study focused on forecasting financial distress such as receivership or voluntary liquidation ultimately defined as bankruptcy. Taffler's model is as follows (Taffler, 1983):

$Z = 3.20 + 12.18X1 + 2.50X2 - 10.68X3 + 0.029X4$

Where X1 = Profit before Tax/Current Liabilities

X2 = Current Assets/Total Liabilities

X3 = Current Liabilities/Total Assets

X4 = No credit interval derived by (quick assets – current liabilities)/daily operating expenses with the denominator proxied by (sales –PBT – depreciation)/365

Z = Overall index

The independent variables in the above equation produce results for the dependent variable known as the z-score, which can be interpreted as follows: A score below 0.2 represents a zone where early warnings of financial distress are likely, and a score above 0.3 indicates early warnings of financial distress is unlikely. A score between 0.2 and 0.3 is considered risky.

These various early warning financial distress models, with varying degrees of success, have been developed over many decades with a primary focus on predictive accuracy and have contributed to financial distress theory providing the foundational measures to be considered when examining companies for EWSs of financial distress. However, these models have been theorised based on varying definitions of financial distress, which researchers consider a concern (Hernandez Tinoco & Wilson, 2013).

2.3 FINANCIAL DISTRESS DEFINITION

Beaver (1966) defined a company's financial distress as an inability to settle its financial debts as they fall due and might include events such as bankruptcy, default on bond repayments, significant overdraft, or non-payment dividends on preference shares. In formulating his model, Altman (1968) focused his research on that of bankruptcy. Gupta (1983) mentioned previous studies such as Beaver (1966) where the use of the definition of failure was tantamount to the legal definition of bankruptcy, taking place at a specific moment in time, and proceeded to highlight that bankruptcy is the extreme culmination of failure. In his study, Gupta (1983) believed that failure culminates a few years prior to formal bankruptcy and defined financial distress from three perspectives. Firstly, a company threatens to cease operating or is on the brink of ceasing operations, secondly, due to default on debt covenants it appears lending institutions are unable to recover the funds, thirdly, when no preference or ordinary dividends are paid or the prospect of receiving dividends of any kind in the future seems unlikely, fall in share prices below normal levels, default on debt covenants and if the company's return on equity is unreasonable. Ohlson (1980), like Altman (1968), defined failure in terms of legislation, most specifically companies that filed for bankruptcy or those that notified intentions of filing for bankruptcy. Agarwal & Taffler (2007) assessed Taffler (1983) model acknowledging additional events, other than bankruptcy, may indicate early warnings of financial distress.

Financial distress researchers (Cybinski, 2001; Gupta, 1983; Lukason & Hoffman, 2014; Ohlson, 1980; Pham Vo Ninh et al., 2018; Pretorius, 2008; Sun et al., 2014) have highlighted that defining financial distress is complex and using "bankruptcy" as a sole definition is unsuitable considering there are various levels a company may be in financial distress. Hernandez Tinoco & Wilson (2013) recognised the varying definitions of financial distress used by financial distress researchers in their model creation consequently highlighted the need for early warning models to have abilities to provide signals of financial distress according to varying stages. This implies that a framework such as Tavlin et al. (1989) and the definitions of financial distress according to three categories namely, economic failure, technical insolvency, and bankruptcy is appropriate to be used in a study. Notably, recent literature has not expanded financial distress models to test their early warning ability according to Tavlin et al. (1989) framework.

As demonstrated by research performed on predominant company scandals Enron Corporation (Maccarthy, 2017) and Steinhoff International Holdings (Grove et al., 2019), early warnings of financial distress should not solely be based on one early warnings model result. There is a need to determine if financial distress is warned and most importantly, what the contributing cause might be, such as, manipulation of accounting records or a violation of accounting principles. Agency theory has provided the foundational measurers to be considered when examining companies for potential EWSs of financial manipulation which may lead to distress (Bosse & Phillips, 2016).

2.4 FINANCIAL MANIPULATION

According to Jensen et al. (1976), agency theory is an agreement that occurs with one or more persons (the principals) who engage another person (the agent) to perform actions on behalf of the principal to maximise the principal's utility. In general terms, a transfer of control and authority to make certain decisions to the agent by the principal is made. However, conflicts occur between the agent and principal as the agent is also a utility maximiser. These conflicts occur because the agents have authority to utilize a company's assets to benefit the individual agent whilst the principal's wealth might diminish adversely. The agent may not always act in the principal's best interests, resulting in costs incurred by the principal known as agency costs. In the commercial context, managers are often referred to as the agent and the principal's referred to as the shareholders. A problem between the principal and the agent relates to information where the agent (manager) may not share all the information with the principal (shareholders) or may selectively share information to maximise the agent's utility (salary, bonuses, profit share incentives) at the expense of the principal resulting in information asymmetry and contributing to the agency problem (Kuliks, 2005). As highlighted by Kuliks (2005), the case of the Enron Corporation evidenced agency theory where the executives (agents) acting on behalf of the shareholders (principals) might have interpreted agency theory to act in a self-fulfilling and unscrupulous manner resulting in agency costs and ultimately financial distress for the entity.

To manage agency theory, earnings management and fraud detection models have evolved to monitor and resolve agency costs incurred by the principal. According to prior studies financial distress is an extension of the misuse and mishandling of a company's funds and these studies have successfully used risk models and accrual measurement models complementing early warning financial distress models to detect and signal potential manipulation in financial statements so that further investigation could be performed prior to a company becoming financially distressed (Grove et al., 2019; Maccarthy, 2017).

2.5 FRAUD PREDICTION

Fraud is considered an intentional violation of generally accepted accounting principles harmful to company stakeholders (Dechow & Skinner, 2000; Diri, 2017). A risk model that has varying results of success is that of Beneish (1999) M-score model. This model consisting of 8 independent variables and an intercept was formulated to provide early warnings of manipulation or prerequisites that may provoke a company to engage in manipulative activities. Beneish's model is as follows (Beneish, 1999):

M = -4.84 + 0.920*DSRI + 0.528*GMI + 0.404*AQI + 0.892*SGI + 0.115*DEPI-0.172*SGAI + 4.679*TATA - 0.327*LVGI

Where DSRI = (Accounts receivable (cy) / Sales (cy)) / (Accounts receivable (py) / Sales (py))

GMI = (Sales(cy) – Cost of sales (cy) / Sales (cy)) / (Sales(py) – Cost of sales (py) / Sales (py))

AQI = (Total assets (cy) – PPE (CY) / Total assets (cy)) / (Total assets (py) – PPE (py) / total assets (py))

SGI = Sales (cy) / Sales (py)

DEPI = (Depreciation exp. (cy) / Depreciation exp. (cy) + PPE (cy)) / = (Depreciation exp. (py) / Depreciation exp. (py) + PPE (py))

SGAI = (Sales, distribution, and administration cost (cy) / Sales (cy)) / (Sales, distribution, and administration cost (py) / Sales (py))

TATAI = Change in Working Capital – Depreciation / total assets

LEVGI = Total Liabilities / Total assets

M = overall score

According to Beneish (1999), Talab et al. (2017), and Maccarthy (2017), the 8 independent variables in the M-score model are DSRI which measures days sales in receivables index where a score of 1.465 or above indicates that the company has changed its credit terms and greater credit has been granted or is an indication of manipulation. The GMI measures gross margin index where a score of 1.193 or above indicates manipulation. The AQI measures asset quality index where a score of 1.254 or above indicates manipulation of certain intangible assets have been capitalized and some delayed to the future. The SGI measures the sales growth index where a score of 1.067 or above indicates sales manipulation. The SGAI measures sales, general and administrative expenses index where a score of 1.041 or above indicates an inconsistent increase in sales hence possible manipulation. The DEPI measures depreciation expense alongside the value of property plant and equipment where a score of 1.077 or above indicates manipulation in the revaluation of assets or extension of useful life. The LVGI measurers the leverage index where a score of 1.111 or above indicates manipulation and lastly the TATAI measures total accruals to total assets index where a score of 0.031 indicates the degree to which goodwill and amortisation have been manipulated. An overall M-score of -1.49 or greater indicates manipulation.

Further risk identification research was performed by Schilit (2003) who developed a ratio to screen for “red flags” such as fraudulent reporting and earnings management focusing on the quality of revenues and earnings. According to Koornhof (2000), “red flags” are initial warnings of conditions or threats that may lead to fraud and manipulation. Schilit (2003) believed that revenue manipulation was a repetitive method utilised by companies to hide poor results where manipulation occurred whereby credit limits increased significantly, and/or deferred revenues were recorded in the current period to inflate reported revenue (Grove et al., 2019). The researcher also believed that companies unnaturally inflated earnings such as premature revenue recognition or recording fictitious revenue whereby earnings may not be appropriately converted into operational money. To identify these initial warnings Schilit (2003) developed the Schilit Quality of Revenues ratio where cash collected from customers-to-revenue and the Schilit Quality of Earnings ratio where operating cashflow-to-net income. These ratio indicate early warnings of manipulation if the resultant is less than 1.0.

A significant concern was highlighted by risk researchers (Dechow & Skinner, 2000) whereby earnings management may mislead stakeholders but does not generally violate generally accepted accounting principles (GAAP). Whilst earnings management may not violate GAAP the company can be severely adversely affected if a significant portion of a company's earnings are predominantly accruals rather than operating cash flows resulting in company stock prices adversely affected in the future questioning its sustainability since income is not being generated by operating cashflow (Grove et al., 2019). To analyse accrual mechanisms of earnings, Sloan (1996) devised the Sloan accrual as follows:

Accrual measure = Net Income – cashflow from operating activities-cashflow from investing / average total assets

The model produces measures for accruals included in income whereby if the resultant is greater than 0.10 initial warnings are present indicating significant accruals and company sustainability issues.

According to various forensic studies (Grove et al., 2019; Grove & Basilico, 2011; Grove & Clouse, 2017) risk and earnings management models have successfully been used together with predictive financial distress models but have not been unified into an early warnings framework despite researchers (Amoa-Gyarteng, 2014; Maccarthy, 2017) implying the significant importance of doing so.

2.6 EMPIRICAL RESEARCH

To successfully predict early warnings of financial distress, several studies based on theoretical frameworks have emerged with successful results such as the study by Beaver (1966) using 79 failed and non-failed companies over a 10-year period between 1954 and 1964 where it was determined certain financial ratio predicted a 78% success rate (Arhin et al., 2020). This model by Beaver (1966) was extended by Gupta (1983) who tested Beaver (1966) ratios and other financial ratio over a 13-year period between 1962-1974 using a sample of 20 companies also concluding certain financial ratio produced successful predictive abilities of financial distress. According to researchers (Garcia, 2022; Jones et al., 2017) financial ratios continue to be extensively used to study early warnings of financial distress in an array of industries such as US corporate bankruptcies to emerging markets (Beaver et al., 2010; Islami & Rio, 2018; Jones et al., 2017; Manodamrongsat et al., 2020) and are considered statistical distress models (Arhin et al., 2020). Research performed by Hlahla (2010) using listed securities in South Africa successfully used financial ratio as a means to predict financial distress finding some ratio formulated by Beaver (1966) as appropriate means to predict financial distress. These studies resulted in further early warning distress studies employing financial ratio as a lever such as that by Altman (1968) and the z-score model.

The Altman (1968) model was studied using 66 failed and non-failed companies in the manufacturing industry between 1946 and 1965 correctly predicting bankruptcy 95% one year prior. The Altman (1968) z-score model has successfully been used throughout the world such as in larger established countries, developing countries and smaller economies incorporating a variety of industries (Altman, 1984) with continued high levels of predictive abilities of distress (Altman, 2018). More recently, the z-score provided early warning abilities of financial distress in the infamous Enron Corporation scandal (Maccarthy, 2017) and was presented before the US House of Representatives Finance Committee’s deliberation determining whether to provide financial support to financially distressed companies General Motors, Inc (GM) and Chrysler Corporation (Altman, 2018). The model has also been successfully tested in the South African economy such as studies by Ngwenya (2018) who assessed the economic outlook of listed gold and platinum mining companies. Based on the foundations of Altman (1968) the o-score was developed by Ohlson (1980).

The Ohlson (1980) o-score used 105 failed companies and 2058 non-failed companies between 1970 and 1976 successfully predicting bankruptcy 96% one year prior. Studies have subsequently been performed by Salim & Ismudjoko (2021) concluding the o-score is as predictive as Altman (1968) with a 90% accuracy rate. Further studies (Low et al., 2001) have been performed in Malaysia using the model concluding that the related ratio were important determinants in predicting bankruptcy and according to Grice & Dugan (2001) using the o-score to predict distressed companies concluded that the model is suitable to be used not solely for bankruptcy but can be used to identify financially distressed companies. Studies based on the South African economy by Oz & Simga-Mugan (2018) concur with researchers on the appropriateness of the Ohlson (1980) o-score. Further studies by Ofori & Gvozdanovic (2017) using Zmijewski (1984) and Altman (1968) models exploring listed entities on the Ghana Stock Exchange and Johannesburg Stock Exchange, found that the o-score might be better suited to emerging markets.

The x- score developed by Zmijewski (1984) is a commonly used model by accounting researchers according to Grice & Dugan (2003). The development of the model used 40 failed and 800 non failed companies between 1972 and 1978. Studies (Grice & Dugan, 2001; Salim & Ismudjoko, 2021; Suresh, 2022) have since used the x-score model in various financial markets and countries reporting an 80% upward financial distress predictive accuracy. According to studies by Husein & Pambekti (2014) who used the x-score on the List of Islamic Securities concluded the model was appropriate to be used as an early warning distress model. In their study incorporating South African markets, Oz & Simga-Mugan (2018) agreed that the x-score model generated consistent results however, encouraged users of the model in developing economies to be cautious of the outputs inferring a re-estimation of the model might produce superior predictive results.

Based on Altman (1968) a z-score model was constructed by Taffler (1983) using a sample of all failed listed industrial companies and 46 non failed industrial companies between 1968 and 1976 in the United Kingdom (Agarwal & Taffler, 2007). Like Altman (1968), the model predicted 98% accuracy of distress one year prior. Subsequent studies (Agarwal & Taffler, 2007) have assessed the model's durability and confirmed the models continued predictive abilities. Further studies by Berrangé & Willows (2016) used the z-score on the Alternate Exchange (AltX) of the JSE also finding strong predictive financial distress accuracies. Findings of significant predictive powers were also determined in studies (Arhin et al., 2020) in Ghana where the z-score produced early warnings of financial distress of 88% accuracy abilities.

According to Arhin et al. (2020), early warning financial distress models should be applied to the m-score model derived by Beneish (1999) to predict distress and detect manipulation. This conclusion was also documented in findings by Maccarthy (2017) where the researcher successfully identified early warnings of financial distress and manipulation in the Enron Corporation scandal by integrating the two models in an analysis of the company. Studies by Grove et al. (2019) in analysing the corporate scandal of Steinhoff International Holdings' also utilised Altman (1968) and Beneish (1999) to determine the early warnings of catastrophe. Maccarthy (2017) further concluded that Altman (1968) and Beneish (1999) should be incorporated as an important tool in audits. Researchers (Grove et al., 2019; H. M. Schilit & Perler, 2010) have also successfully used risk models Schilit Quality of Revenues ratio and the Schilit Quality of Earnings ratio (Schilit ,2003) to determine successfully financial statement manipulation in company scandals such as Steinhoff International Holdings'. These models have further been tested effectively in other financial statement manipulations such as Valeant Pharmaceuticals together with Beneish (1999) m-score with emphasis on using financial distress models together (Grove & Clouse, 2017). The conclusion by Maccarthy (2017) as well as other researchers discussed above has postulated Amoa-Gyarteng (2014) who concluded that using early warning distress models together with risk models assist investors avoid fraudulent companies.

According to Grove et al. (2019) the Sloan accrual measure (Sloan, 1996) using analysis of accrual components successfully determines the quality of a company's earnings based on the number of accruals included in income and appropriately identified the shorting of shares between Barclays Global Investors and JetBlue demonstrating its output abilities. According to Dechow et al. (2012) using a case study performed on one of the largest homebuilders in the United States, KB Home, successfully used the Sloan accrual measure to identify the measure of accruals and the significant impact it had on the share price over multiple years depending on the magnitude of accruals present. Further studies (Richardson et al., 2005) have validated the importance of using accrual measures such as Sloan (1996) concluding that there are substantial losses related to financial statements that report less reliable accrual information. Grove & Basilico (2011) successfully used the Sloan accrual measure together with risk models and financial distress models correctly predicting financial distress and financial manipulation in companies like Global Crossing, Lehman Brothers, and WorldCom. The model has also successfully been used in South Africa when analysing Steinhoff International Holdings' (Grove et al., 2019).

2.7 EARLY WARNING SIGNAL FRAMEWORK

The main objective of early warning financial distress models is to provide the user, with relative accuracy, a measure of the financial stability of a company and whether failure is predicted. According to Platt & Platt (2002), despite numerous early warning distress models, there has been limited research sought to predict financial distress according to appropriate early warning categories and implied that existing models may provide alternative distress prediction abilities, such as those developed by Tavlin et al. (1989), other than solely the extreme form of failure known as bankruptcy.

The framework developed by Tavlin et al. (1989) whereby categories of financial distress are created has been referred to in various early warning distress studies such as Manodamrongsat et al. (2020) who utilised Tavlin et al. (1989) economic failure definition successfully to identify financial distress in its earliest form. This framework allows researchers to consider the various stages of distress reducing definition ambiguity issues and gives EWSs to users of financial statements and introduces categories of problem companies signalling early warnings of failure before complete catastrophe (Manodamrongsat et al., 2020).

To address desires raised by researchers referenced above to appropriately categorize financial distress models according to their predictive abilities, the author proposes using Tavlin et al. (1989) framework and applying early warning financial distress models to the framework to determine the type/s of financial distress a model has abilities to predict. Furthermore, in addressing the need raised by researchers to incorporate risk and earnings management measures with early warning financial distress models, the author proposes developing an additional category in Tavlin et al. (1989) framework entitled “initial warnings” to include risk and earnings management measures unifying early warning prediction models. This framework is depicted in Appendix A.

CHAPTER 3: METHODOLOGY

The following chapter addresses the methodology applied to the research objective and hypothesis in order of validity and reliability, research design, scope of limitations, population sampled, and method of analysis.

3.1 RESEARCH METHODOLOGY OVERVIEW

3.1.1 Research design

Balcaen & Ooghe (2004) stated that most financial distress researchers use paired sampling methodology where researchers pair samples of companies that failed with non-failed. This type of methodology was performed by researchers in their studies such as Altman (1968), Beaver (1966) and Zmijewski (1984). For this reason, a paired sampling methodology was performed in this study, whereby an equivalent number of delisted firms was paired to non-delisted companies.

However, Balcaen & Ooghe (2004) highlighted shortcomings to prior researchers who matched samples according to industry, size class and age where this type of research design might exclude industries, sizes and company age or mislead indications of model's predictive accuracy resulting in ineffective forecasting. This study avoids this limitation by not differentiating between companies' asset size or industry but rather focusing on the economic conditions that may present themselves and whether these conditions can be forewarned. Furthermore, companies listed on the JSE top 100 index were used in the pairing as it is unlikely these companies will be suffering from financial distress whilst in this index. Using JSE top 100 index attempts to ensure that there is complete data representing various populations of healthy companies, reducing over or under representation of industries.

The period for this study was determined to be 2016 to 2021 and was deemed suitable due to the commencement of King IV Report in 2016 (King IV Report on Corporate Governance for South Africa, 2016) and the latest completed calendar year at the date of this research being 2021.

A complete list of delisted companies was sourced and obtained from the JSE in April 2022. This listing was analysed according to Tavlin et al. (1989) framework. The main source of company financial data was obtained from company's annual financial statements as aggregated by the JSE and IRESS Research Domain. For Companies that did not meet any of the financial distress criteria according to the Tavlin et al. (1989) framework was excluded from the population. The reason for their delisting was beyond the scope and excluded for the purposes of this study. The banking sector is heavily regulated indicating that failure is more predictable where authorities have abilities to regulate to avoid collapse. Therefore, banks were excluded from the population.

Data was limited to Statement of Comprehensive Income, Statement of Financial Position and Statement of Cashflow of companies. Where a company was suspended between 2016 and 2021, and financial data is not available for the full period the maximum number of years financial data was available between this period was extracted.

In addressing the research question, a quantitative approach was used to statistically calculate the financial distress, risk prediction, and earnings management measures as envisaged by their respective model variables. A statistical package was used to calculate the various models and analyse the data in this study. The results of this study were compiled using Excel.

This study employed descriptive analysis to interrogate the results of the models in a meaningful way.

3.1.2 Scope of Limitations

A limitation of this study related to economic failure as defined by Tavlin et al. (1989) where the internal rate of return was not available for all companies in the sample therefore for the purposes of condition 1, economic failure was defined where a company's expenses exceeding its income or that its cost of capital is greater than its return on external investments.

Private and smaller companies contribute significantly to the economy and are at more risk of financial distress than larger companies. However, obtaining financial data for these companies is a challenge. Therefore, only companies listed on the JSE were analysed. A further limitation in this study is the exclusion of the banking sector from the sample. The banking sector is heavily regulated therefore failure should be more predictable. Excluding the banking sector reduced the sample of companies analysed.

3.1.3 Population and data collection

The South African economic market is deemed appropriate for this study as condition two and three of Tavlin et al. (1989) have been adopted by South African legislation (Parliament of the Republic of South Africa, 2008).

The JSE is the largest stock exchange in South Africa comprising of the main board, the alternative exchange Altx, Yield X, South African Futures Exchange, and the Bond Exchange of South Africa (JSE Limited, 2023). Local and international investors gain insight into South African capital markets by way of the JSE due to its worldwide recognition and reputation. The collection and validity of data is mitigated by the quality and safeguards the JSE have in place ensuring the highest level of information authenticity (JSE Limited, 2023). Therefore, for the purposes of this study data was collected from the JSE for companies listed and delisted on the main board of the JSE between 2016 and 2021.

The IRESS is a provider of fundamental research data for JSE Companies and has built a strong reputation catering to the precise needs of researchers (University of Cape Town, 2022) and thus the data collected for the population is determined suitable to be relied upon.

3.1.4 Method of analysis

The financial data retrieved in excel format from the JSE and IRESS comprised of 133 delisted companies between 2016 and 2021. The delisted companies that did not meet Tavlin et al. (1989) framework are excluded together with the banking sector resulted in a population of 72 companies that delisted due to possible reasons of financial distress. The largest ranked 72 companies based on market capitalisation listed on the JSE top 100 index were paired with the 72 delisted companies. This population can be reviewed in Appendix C.

A quantitative approach was used to statistically calculate the financial distress, risk identification, and earnings management measures as envisaged by their respective model variables. The results will be categorised into a Tavlin et al. (1989) theoretical framework with an additional category for risk entitled ‘initial warnings’ as follows:

Research Objective 1 economic failure: firstly, the point at which a company meets economic condition where a company’s expenses exceeding its income or that its cost of capital is greater than its return on external investments[4] will be determined, secondly, financial data for the preceding years prior to economic failure will be obtained for that company, thirdly, the financial distress model[1] will be calculated. Where a model predicts risk of failure a year prior to the event as articulated by the model's methodology of classification, this will determine whether the model can predict economic failure as defined.

Study	Exhibiting EWSs of economic failure	Not exhibiting EWSs of economic failure
Altman (1968)	< 1.81	>1.81
Beaver (1966)	debt-to-asset = high sales-to-assets = high cash flow-to-debt = high	debt-to-asset = low sales-to-assets = low cash flow-to-debt = low
Gupta (1983)	earnings before depreciation, interest, and taxes-to-sales = high operating cash flow-to-sales = high net worth[5]-to-total debt (including both short and long term) = high All outside liabilities-to-tangible assets = high	earnings before depreciation, interest, and taxes-to-sales = low operating cash flow-to-sales = low net worth -to-total debt (including both short and long term) = low All outside liabilities-to-tangible assets = low

[4] Cost of Capital and Return on external investment obtained from IRESS at company specific year end date.
[5] Net worth (assets less liabilities) is calculated as envisaged by Gupta (1983).

Ohlson (1980)	> 0.38	< 0.38
Taffler (1983)	< 0.2	> 0.2
Zmijewski (1984)	< 0	> 0

Research Objective 2 technical insolvency: firstly, the point at which a company meets economic condition defined by Tavlin et al. (1989) "technical insolvency" whereby a company is unable to settle its debts as they become due will be determined, secondly, financial data for the preceding years prior to technical insolvency will be obtained for that company, thirdly, the financial distress model[1] will be calculated. Where a model predicts risk of failure a year prior to the event as articulated by the model's methodology of classification, this will determine whether the model can predict technical insolvency as defined.

Study	**Exhibiting EWSs of technical insolvency**	**Not exhibiting EWSs of technical insolvency**
Altman (1968)	< 1.81	>1.81
Beaver (1966)	debt-to-asset = high sales-to-assets = high cash flow-to-debt = high	debt-to-asset = low sales-to-assets = low cash flow-to-debt = low
Gupta (1983)	earnings before depreciation, interest, and taxes-to-sales = high	earnings before depreciation, interest, and taxes-to-sales = low

	operating cash flow-to-sales = high net worth-to-total debt (including both short and long term) = high All outside liabilities-to-tangible assets = high	operating cash flow-to-sales = low net worth-to-total debt (including both short and long term) = low All outside liabilities-to-tangible assets = low
Ohlson (1980)	> 0.38	< 0.38
Taffler (1983)	< 0.2	> 0.2
Zmijewski (1984)	< 0	> 0

Research Objective 3 bankruptcy: firstly, the point at which a company meets economic condition defined by Tavlin et al. (1989) "bankruptcy" whereby the company's fair value of assets does not exceed it liabilities and the company has no possible means to meet its obligations will be determined, secondly, financial data for the preceding years prior to bankruptcy will be obtained for that company, thirdly, the financial distress model[1] will be calculated. Where a model predicts risk of failure a year prior to the event as articulated by the model's methodology of classification, this will determine whether the model can predict bankruptcy as defined.

Study	**Exhibiting EWSs of bankruptcy**	**Not exhibiting EWSs of bankruptcy**
Altman (1968)	< 1.81	>1.81
Beaver (1966)	debt-to-asset = high	debt-to-asset = low

	sales-to-assets = high cash flow-to-debt = high	sales-to-assets = low cash flow-to-debt = low
Gupta (1983)	earnings before depreciation, interest, and taxes-to-sales = high operating cash flow-to-sales = high net worth-to-total debt (including both short and long term) = high All outside liabilities-to-tangible assets = high	earnings before depreciation, interest, and taxes-to-sales = low operating cash flow-to-sales = low net worth-to-total debt (including both short and long term) = low All outside liabilities-to-tangible assets = low
Ohlson (1980)	> 0.38	< 0.38
Taffler (1983)	< 0.2	> 0.2
Zmijewski (1984)	< 0	> 0

Research Objective 4 initial warnings: Apply the risk model[2] and real earnings management measure[3], where results are predicted indicating material misstatement and/or real earnings measures, the company will be determined to be exhibiting signs of early warnings which may lead to financial distress.

Study	Exhibiting EWSs of manipulation	Not exhibiting EWSs of manipulation
Beneish (1999)	> -1.49	< -1.49
Schilit (2003) Quality of Revenues	<1	>1
Schilit (2003) Quality of Earnings	<1	>1
(Sloan, 1996)	>0.10	<0.10

To determine the appropriate effectiveness and accuracy of economic predictions a model produces, "Guilford's rule of thumb" (Guildford, 1956) will be applied to identify parameters of the results degree of strength. Refer to Appendix D. Where research findings report a corresponding association being that as "high relationship" and "very high relationship" the financial distress model is deemed to predict the economic condition as defined. Where research findings report a corresponding association being that as "moderate relationship," "high relationship" and "very high relationship" the risk and earnings management model is deemed to provide initial early warnings which may lead to financial distress.

3.1.5 Validity and reliability

The research employed empirically sound models that have been tested extensively by the extant literature, such as Altman (1968), Beaver (1966), Gupta (1983), Ohlson (1980), Taffler (1983), Zmijewski (1984), Beneish (1999), Schilit (2003) and Sloan (1996). These prominent models were used to predict specific economic conditions in South African corporations. An exhaustive literature review was conducted to incorporate relevant aspects of their models and methodologies into this study, ensuring the content validity of the research.

A comprehensive dataset of South African corporations was used to assess the parameter validity of the prediction models within the context of predicting a specific economic condition. JSE delisted and listed company samples based on financial indicators were matched consistent to prior research set forth by financial distress researchers.

The selection of the research sample adhered closely to methodologies outlined by financial distress researchers such as Altman (1968), Beaver (1966),Zmijewski (1984) and Balcaen & Ooghe (2004). A combination of stratified random sampling and purposive sampling was employed. Delisted companies were included to ensure that the sample represented a spectrum of financial conditions, including those that had experienced financial distress. Additionally, the inclusion of the JSE top 100 index based on top market capitalisation listed companies allowed the research to capture the financial stability and diversity present in the South African corporate environment. The research adhered to the criteria set forth in the models for classifying distressed and non-distress companies within these samples, minimizing selection bias, and maintaining internal validity.

The works of Altman (1968), Beaver (1966), Gupta (1983), Ohlson (1980), Taffler (1983), Zmijewski (1984), Beneish (1999), Schilit (2003) and Sloan (1996) have had significant impact on financial distress, risk, and earnings management prediction literature worldwide. The application of the models in the South African context to predict specific economic conditions, it is asserted that their findings and principles are generalizable to the South African corporate landscape in relation to the specific economic condition. The international recognition and validation of these models further support this research context.

The reliability of the financial distress, risk and earnings managements models have been established through extensive empirical research. This study meticulously followed their methodologies and calculated reliability coefficients to assess the internal consistency of the applications. The results indicated high internal consistency, aligning with the robustness of these models as documented in prior studies.

The models were subjected to a sensitivity analysis under various economic conditions to evaluate the robustness of the model's prediction abilities and assumptions specific to the South African financial market. By subjecting these models to scenarios involving industry specific shocks such as during the period of COVID-19, we confirmed their ability to provide reliable predictions across diverse financial circumstances.

CHAPTER 4: RESULTS AND DISCUSSION

The following chapter presents the results and discussion of this study in relation to the research objectives. Overall, the results indicate financial distress, risk prediction, and earnings management measures can be unified into an EWS framework.

4.1 TAVLIN ET AL (1989)

A total sample of 133 delisted (unhealthy) companies were assessed from the JSE between 2016 and 2021. Findings per Figure 1 demonstrated of the 133 unhealthy companies, on average, 22 companies delisted per year between 2016 and 2021 where 2017 recorded the highest during the period. 72 (54%) companies exhibited at least one financial distress criteria according to Tavlin et al. (1989) framework. On average 12 companies delisted per year between 2016 and 2021 where 2019 recorded the highest peak during the period under those financial distress criteria defined by Tavlin et al. (1989) framework.

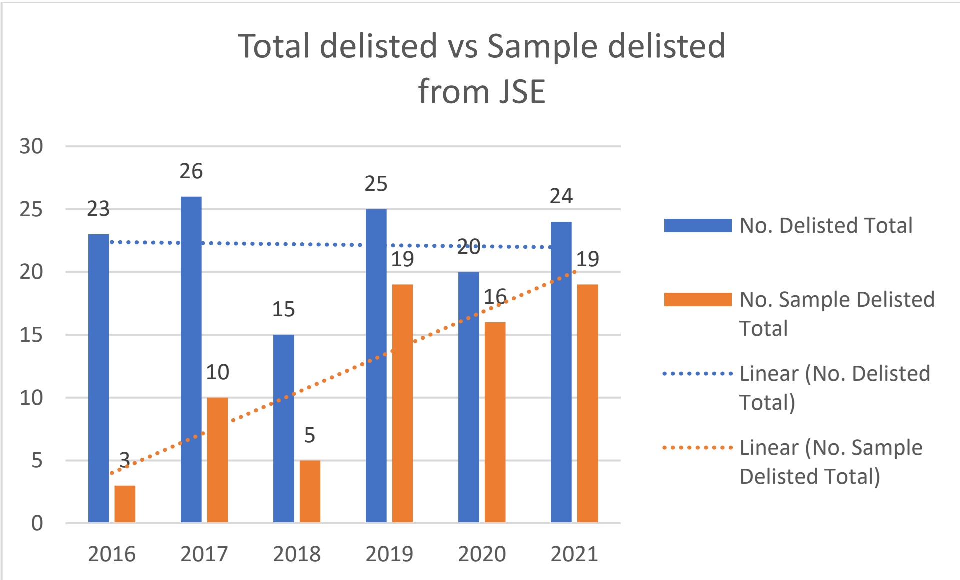


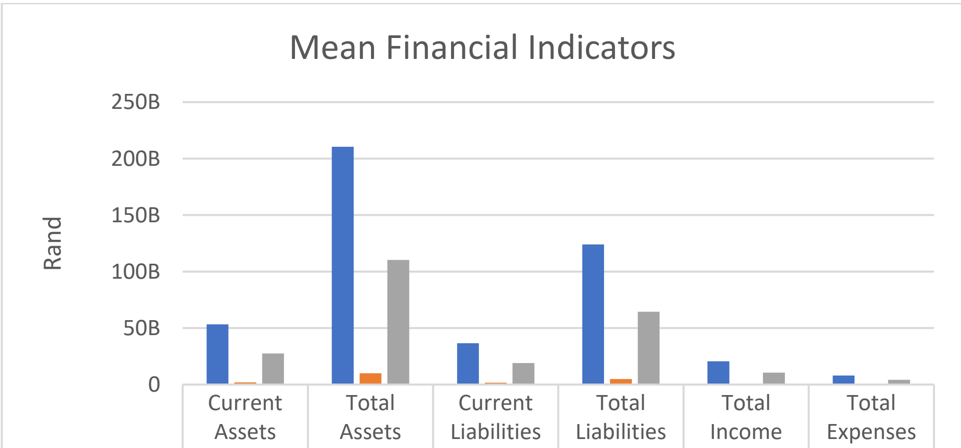
Figure 1: Total companies unhealthy from JSE

Source: Compiled by author

As per the methodology followed, unhealthy companies were paired to JSE top 100 index hereafter referred to as “healthy” companies. The mean of Tavlin et al. (1989) financial indicators over a six-year period were calculated as shown in figure 2.

Analysis from figure 2 exhibits that the mean of total current assets of unhealthy companies were significantly lower than the mean of total current assets for healthy companies, where the mean for unhealthy companies is R1.8 billion and that of healthy companies is R52 billion. The mean for total assets of unhealthy companies was also lower than the mean of total assets for healthy companies, where the mean for unhealthy companies is R10 billion and that of healthy companies is R210 billion. This analysis implies that unhealthy companies made significantly less investment resulting in an inability to produce sustainable profits.

The mean total current liabilities of unhealthy companies were also lower than the mean of total current liabilities for healthy companies, where the mean for unhealthy companies is R1.6 billion and that of healthy companies is R36 billion. The mean for total liabilities of unhealthy companies were lower than the mean total liabilities for healthy companies, where the mean for unhealthy companies is R4.8 billion and that of healthy companies is R124 billion. This implies that companies with a smaller balance sheet are more vulnerable to financial distress in the wake of adverse factors that may affect the company's performance.



	Current Assets	Total Assets	Current Liabilities	Total Liabilities	Total Income	Total Expenses
Healthy	53,265,12	210,417,8	36,498,34	124,029,8	20,558,80	8,049,980
Unhealthy	1,848,306	10,028,93	1,682,029	4,884,044	465,333,9	238,253,5
Combined	27,556,71	110,223,3	19,090,18	64,456,93	10,512,06	4,144,117

Figure 2: Mean Financial Indicators of unhealthy and healthy companies

Source: Compiled by author

The mean for unhealthy companies' total income was lower than that for healthy companies, where the mean for unhealthy companies is R465 million and that of healthy companies is R20 billion. The mean for total expenses of unhealthy companies were lower than the mean of total expenses for healthy companies, where the mean for unhealthy companies is R238 million and that of healthy companies is R8 billion. This implies that companies with a smaller income statement are more vulnerable to financial distress in the wake of adverse factors that may affect the company's performance.

Table 1: Tavlin et al (1989) indicators of unhealthy and healthy companies

Tavlin et al (1989)	Listed on JSE	No. delisted	Condition 1[6]	Condition 1.1.[7]	Condition 2[8]	Condition 3[9]	Condition 1 & 1.1[10]	Condition 1 & 2[11]	Condition 1 & 2 & 3[12]
Unhealthy									
No. Companies	**72**	**72**	**48**	**53**	**35**	**5**	**31**	**14**	**3**
% of Companies			**67%**	**74%**	**49%**	**7%**	**43%**	**19%**	**4%**
Mean reported in years			**1.79**	**2.4**	**2.1**	**1.4**	**1.7**	**1.4**	**1.0**
Total times reported			**20%**	**30%**	**17%**	**2%**	**12%**	**4%**	**1%**
2016	**72**	**3**	**33%**	**57%**	**39%**	**4%**	**21%**	**10%**	**3%**
2017	**69**	**10**	**29%**	**43%**	**22%**	**4%**	**15%**	**4%**	**0%**
2018	**62**	**5**	**25%**	**39%**	**24%**	**1%**	**14%**	**4%**	**1%**
2019	**67**	**19**	**18%**	**28%**	**15%**	**0%**	**11%**	**4%**	**0%**
2020	**53**	**16**	**11%**	**13%**	**3%**	**0%**	**8%**	**3%**	**0%**
2021	**56**	**19**	**3%**	**1%**	**1%**	**0%**	**1%**	**1%**	**0%**
Healthy									
No. Companies	**72**		**35**	**49**	**33**	**0**	**21**	**9**	**0**
% of Companies			**49%**	**67%**	**46%**	**0%**	**29%**	**13%**	**0%**
Mean reported			**2.17**	**3.60**	**3.54**	**0.00**	**1.95**	**1.88**	**0.00**
Total times reported	**72**		**106%**	**242%**	**163%**	**0%**	**57%**	**24%**	**0%**
Total Conditions			**83**	**102**	**68**	**5**	**52**	**23**	**3**
% of unhealthy			**58%**	**52%**	**51%**	**100%**	**60%**	**61%**	**100%**

Source: Compiled by author

[6] Condition 1: expenses greater than income
[7] Condition 1.1: Cost of capital greater than return on external investment.
[8] Condition 2: Technical insolvency
[9] Condition 3: Bankruptcy
[10] Condition 1&1.1: expenses greater than income & Cost of capital greater than return on external investment.
[11] Condition 1 & 2: Income greater than expenses & cost of capital greater than return on investment & technical insolvency.
[12] Condition 1 & 2 & 3: Income greater than expenses & cost of capital greater than return on investment & technical insolvency & bankruptcy.

Tavlin et al. (1989) determined that a condition of financial distress was that of economic failure defined as a company's expenses exceeding its income or that its cost of capital is greater than its return on external investments. As per table 1 and figure 3, between 2016 and 2021, 48 of the 72 (67%) unhealthy companies exhibited expenses exceeding their income. Of those 48 companies, the mean for this condition was exhibited 1.79 times. This implies that companies reporting expenses exceeding income 1.79 or more consecutive periods have a greater early warning likelihood of being financially distressed where recovery is small. As per table 1 and figure 4, 53 of the 72 (74%) unhealthy companies exhibited its cost of capital greater than its return on investments. Of those 53 companies, the mean for those companies exhibited this condition 2.4 times. This implies that companies reporting cost of capital greater than its return on external investments for a period of 2.4 consecutive years or more have a greater early warning likelihood of being financially distressed where recovery is small.

Where an unhealthy company exhibited expenses exceeding income or cost of capital greater than return on external investments, it was noted that there was no recovery from this condition. When comparisons were made to the paired healthy companies per table 1 and figure 3, 35 of the 72 (49%) companies exhibited expenses exceeding its income. Of those 35 companies, the mean of this condition was exhibited 2.17 times. 48 of the 72 (67%) companies per table 1 and figure 4 exhibited cost of capital exceeding return on investment. Of those 48 companies, the mean for this condition was exhibited 3.6 times. This implies that economic failure is an early warning of financial distress. However as per figure 2 and discussion above, as an EWS of company demise reliance is placed upon the monetary size of the company and reserves available to recover from the condition.

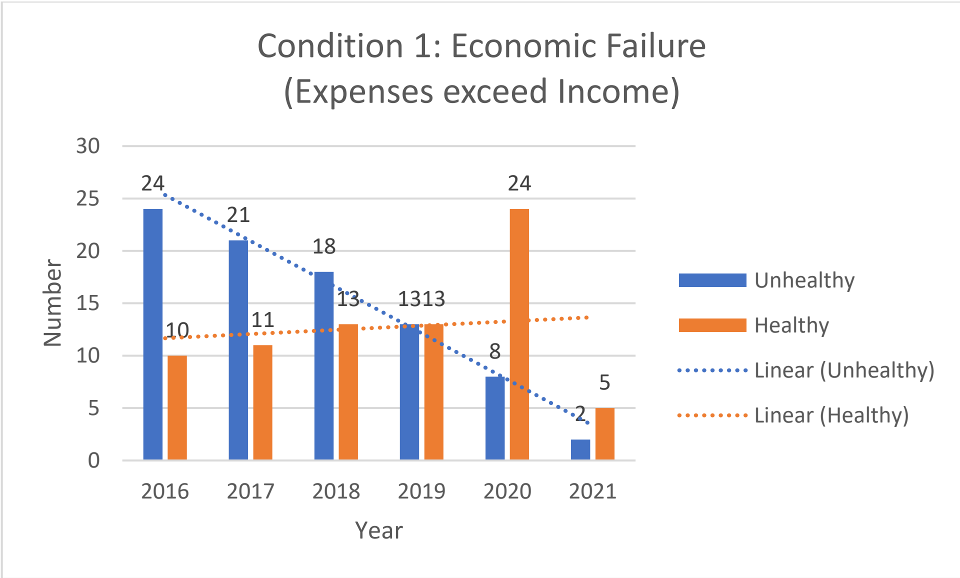


Figure 3: Condition 1 Economic Failure (Expenses exceed Income)

Source: Compiled by author

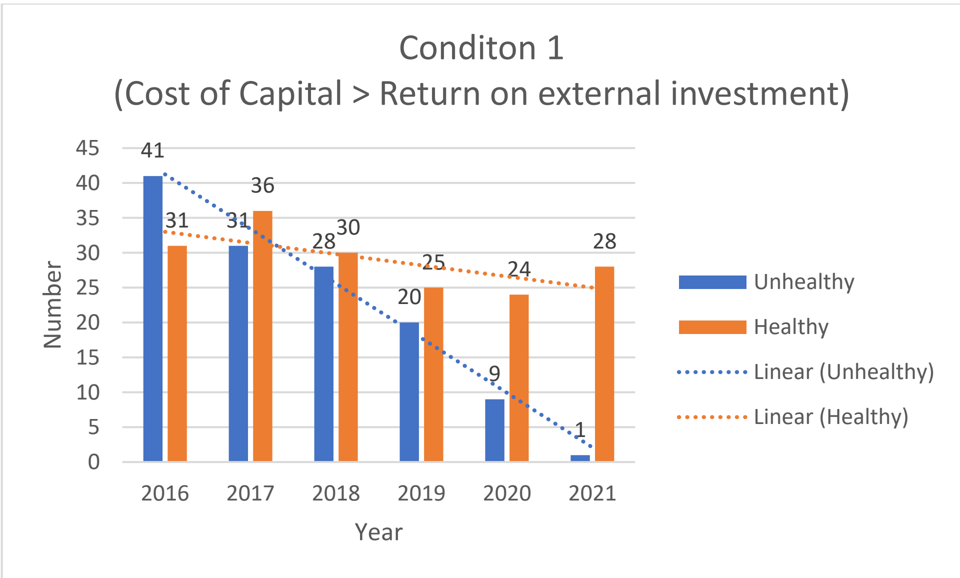


Figure 4: Condition 1 Economic Failure (Cost of Capital > Return on external investment)

Source: Compiled by author

Economic failure consists of two conditions namely expenses exceeding income or cost of capital greater than return on investment. Analysis was performed beyond the scope of Tavlin et al. (1989) condition per table 1 and figure 5 to determine if economic failure could highlight EWSs whereby economic failure was demonstrated where expenses exceeded income and cost of capital was greater than return on investment. 31 of the 72 (43%) unhealthy companies exhibited this condition in comparison to 21 of 72 (29%) healthy companies. This implies that this extended financial distress condition is a useful early warning indicator and could be incorporated into this EWS framework.

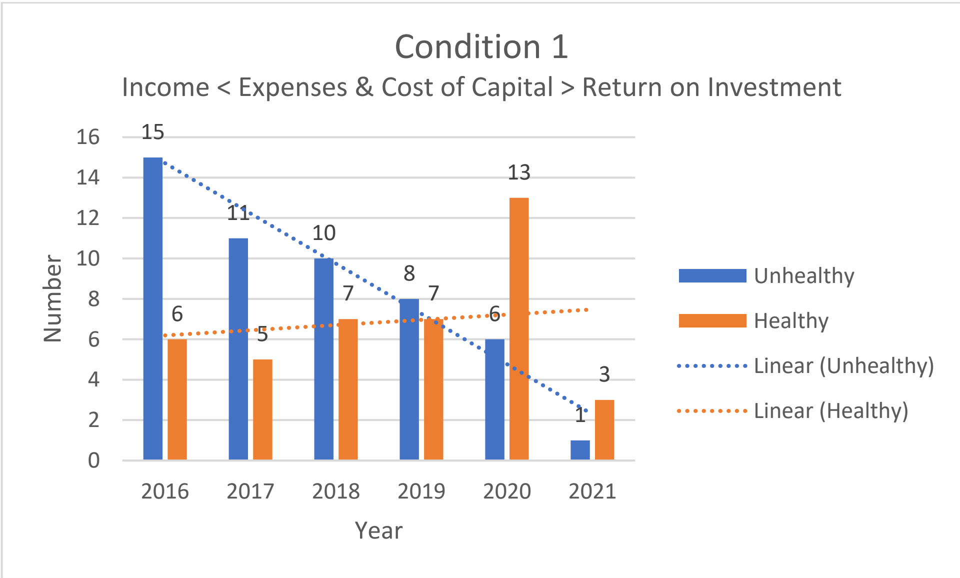


Figure 5: Condition 1 Economic Failure (Income < Expenses and Cost of Capital > Return on Investment)

Source: Compiled by author

Technical insolvency is defined by Tavlin et al. (1989) where a company is unable to settle its debts as they become due. As per table 1 and figure 6, between 2016 and 2021, 35 of the 72 (49%) unhealthy companies exhibited an inability to settle its debts as they become due. Of those 35 companies, the mean for this condition was exhibited 2.1 times.

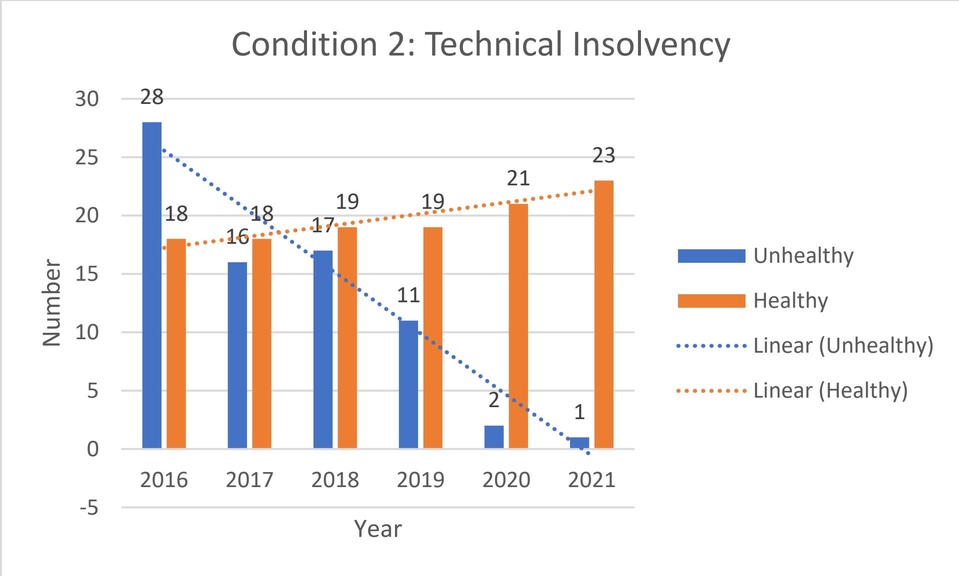


Figure 6: Condition 2 Technical Insolvency

Source: Compiled by author

When comparisons were made to the paired healthy companies per table 1 and figure 6, 33 of the 72 (46%) companies exhibited technical insolvency. Of those 33 companies, the mean for this condition was exhibited 3.54 times. This implies that this financial distress condition is a useful early warning indicator, however, might be dependent upon the company's financial structure.

As per table 1 and figure 7, analysis was performed to determine the impact of companies exhibiting condition 1 where expenses exceed income and cost of capital is greater than return on external investment and condition 2 technical insolvency. Findings demonstrated that between 2016 and 2021, 14 of the 72 (19%) unhealthy companies exhibited both condition 1 and condition 2 in comparison to the healthy companies where 9 of the 72 (13%) companies exhibited both condition 1 and condition 2. Whilst findings were low, the results to imply that this amalgamation of conditions may report EWSs.

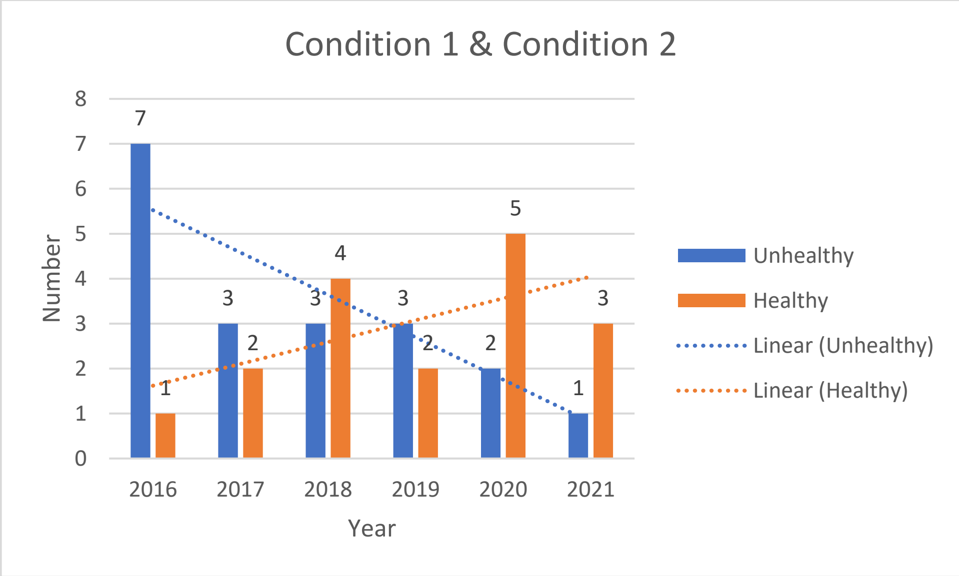


Figure 7: Condition 1 & Condition 2 (Income < Expenses & Cost of Capital > Return on Investment & Technical Insolvency)

Source: Compiled by author

Bankruptcy is defined as the company's fair value of assets not exceeding its liabilities, and the company has no possible means to meet its obligations (Tavlin et al., 1989). As per table 1 and figure 8, between 2016 and 2021, 5 of the 72 (7%) unhealthy companies exhibited the fair value of assets not exceeding it liabilities. Of those 5 companies, the mean for this condition was exhibited 1.4 times. Findings demonstrated that, 0 of the 74 (0%) paired healthy companies exhibited bankruptcy. Where an unhealthy company exhibited bankruptcy, it was noted that there was no recovery from this, and that delisting followed 1.4 years after the condition first presented itself implying that this is an early warning of financial distress.

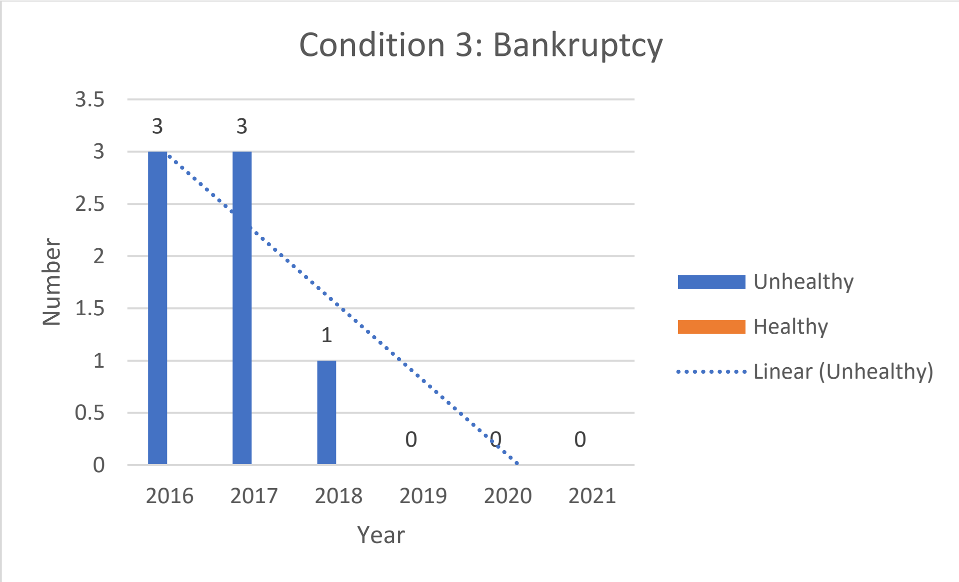


Figure 8: Bankruptcy

Source: Compiled by author

As per table 1 and figure 9, analysis was performed to determine the impact of companies exhibiting condition 1 where expenses exceed income and cost of capital is greater than return on external investment and condition 2 technical insolvency and condition 3 bankruptcy, between 2016 and 2021, 3 of the 72 (4%) unhealthy companies exhibited both condition 1 and condition 2 and condition 3. In comparison to the healthy companies 0 of the 72 (0%) companies exhibited both condition 1 and condition 2 and condition 3. This implies that companies reporting all three conditions are unlikely to recover and is an appropriate EWS.

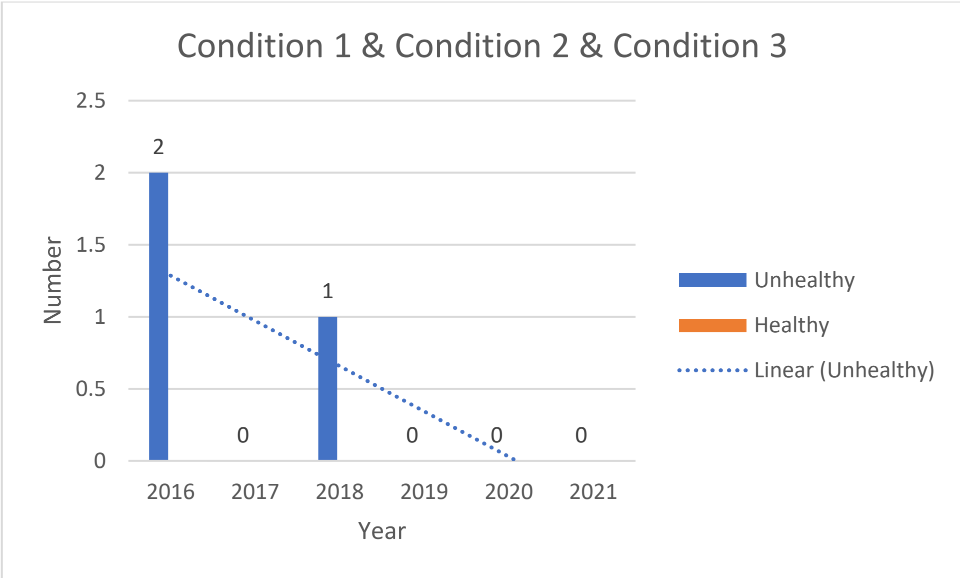


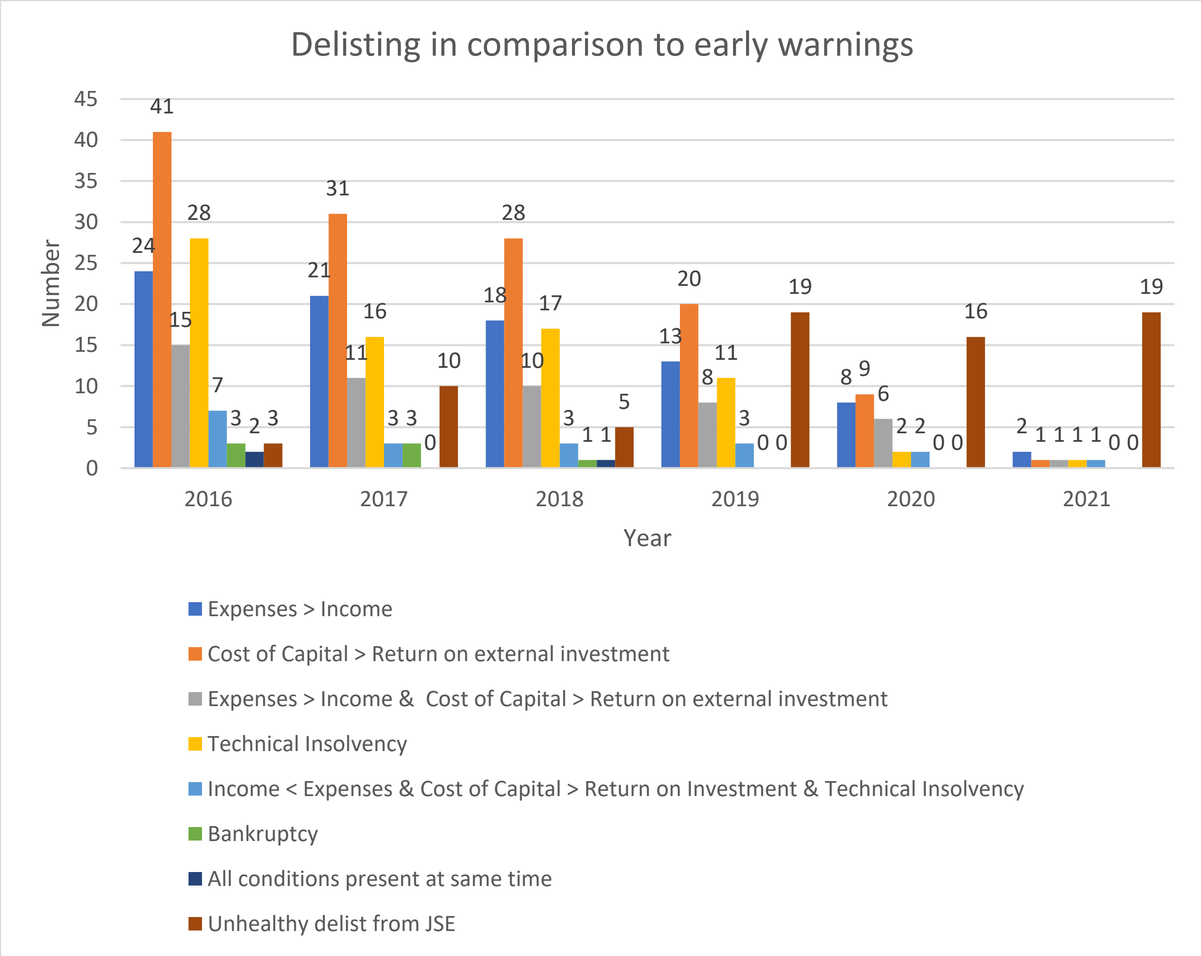
Figure 9: Condition 1 & Condition 2 & Condition 3 (Income < Expenses & Cost of Capital > Return on Investment & Technical Insolvency & Bankruptcy)

Source: Compiled by author

As per table 1, figure 10 and analysis above there is a correlation between unhealthy companies reporting early warnings of financial distress per Tavlin et al. (1989) framework as a standalone means. Analysis demonstrates that a company might exhibit early warnings of financial distress and have an ability to recover from this. However, the ability to recover is dependent upon the size of the company's balance sheet and access to funding as shown in figure 2. Findings also showed that whilst a company may appear to have recovered from initial early warnings of financial distress, a company may have utilised all its resources to recover from the condition and still determined to delist as there were no retained resources remaining to continue operations. According to Husna & Satria (2019) who corroborates findings whereby company size plays an integral part in value where greater assets available indicate the prospects of profit generation. These findings are conclusive to those noted under Figure 2 where companies with a smaller balance sheet are more vulnerable to financial distress in the wake of adverse factors that may affect performance. Findings have implied that a company is more susceptible to financial distress when early warnings of distress are exhibited where a company's financial statements report the following amounts or less where current assets are R1.8b, current liabilities are R1.6b, total assets are R10b, total liabilities are R4.8b, total income are R465m and total expenses are R238m. Findings per table 1, incorporating company size considerations established that economic failure defined as where cost of capital is greater than return on investment provides the most appropriate early warnings of financial distress followed by expenses exceeding income and technical insolvency. The condition of bankruptcy is low, per table 1, implying that the condition as an early warning is too late to recover from.

Findings have also demonstrated per figures 1-6 that the year 2020 and 2021 implied high levels of financial distress for healthy companies where the expectation was that minimal financial distress would have been exhibited based on their standing in the top 100 of the JSE index. In 2020, the world saw unforeseen challenges with the detection of the Coronavirus disease (COVID-19) (WHO, 2022). This event continued into 2021 and continues at the time of this research. COVID-19 provides some explanatory reasoning for healthy companies exhibiting significantly higher than usual indications of financial distress due to world economies from all sectors suffering from the global pandemic and country lockdowns (Ozili & Arun, 2023).

The above discoveries have revealed that Tavlin et al. (1989) framework is applicable and valuable in today's economic society and can be incorporated into an early warning framework. These findings have further highlighted that this framework needs to be analysed further to determine whether distress models could be used to predict these economic conditions giving companies much needed EWSs to recover from predicted economic turmoil.



10Figure 10: Unhealthy companies in comparison to early warnings

Source: Compiled by author

4.2 ALTMAN (1968)

According to Altman (1968), the z-score model was developed to provide early warnings of financial distress being that of bankruptcy. Results per table 2 over a six-year period analysed 72 unhealthy and 72 healthy companies where early warnings of bankruptcy were noted 48 times. Of those 48 warnings related to 20 (42%) companies that delisted from the JSE. The z-score provides early warnings of bankruptcy for a score of 1.81 or less. Over a six-year period, unhealthy companies reported a mean z score of 93.15. This further implies that for most companies that delisted from the JSE, the z-score did not report early warnings of delisting, indicating the z-score did not produce appropriate early warnings of financial distress.

Table 2: Altman (1989)

Model prediction n=20/72 (42%)

Altman (1968)	Listed on JSE (Count)	Likely	Uncertain	Unlikely	No. delisted	Total Percentage Unhealthy	Minimum	Maximum	Mean	Std. Deviation
Unhealthy	72	28	21	170	72	7%	-0.09	4437.28	93.15	516.70
2016	72	8	3	56	3	11%	-0.01	4055.31	85.20	493.10
2017	69	6	3	48	10	9%	0.00	3013.31	65.79	394.45
2018	62	9	3	37	5	15%	-0.01	1477.13	41.53	207.91
2019	67	4	7	21	19	6%	-0.09	303.54	23.99	54.98
2020	53	-	5	7	16	0%	1.99	3528.15	308.47	971.54
2021	56	1	-	1	19	2%	0.08	4437.28	2218.68	2218.60
Healthy	n=72	20	5	378			-0.01	20420.09	151.50	1299.15

Source: Compiled by author

Z-score is derived using the variables and parameter estimates of Altman (1968).

With reference to table 1, 83 companies reported, at least once, their expenses exceeding income over a six-year period. Where the z-score was below 1.81 the model could predict early warnings, per table 11, of expenses exceeding income for 7 (8%) companies one year prior to the reported event. Findings demonstrated 102 companies reported, at least once, their cost of capital greater than return on investment over a six-year period. Where the z-score was below 1.81 the model was able to predict early warnings, per table 11, of cost of capital greater than return on investment for 9 (8%) companies one year prior to the reported event.

With reference to table 1, 68 companies reported, at least once, technical insolvency over a six-year period. Where the z-score was below 1.81 the model could predict early warnings, per table 11, of an inability to settle its debts as they become due for 7 (10%) companies one year prior to the reported event.

Referencing table 1, 5 companies reported, at least once, bankruptcy over a six-year period. Where the z-score was below 1.81 the model could predict early warnings, per table 11, of liabilities exceeding the fair value of assets for all (100%) companies.

In satisfying the first research objective, Altman (1968) demonstrated a negligible relationship and did not appear to be able to provide early warnings of financial distress according to Tavlin et al. (1989) condition 1. In satisfying the second research objective, Altman (1968) demonstrated a negligible relationship and did not appear to be able to provide early warnings of financial distress according to Tavlin et al. (1989) condition 2. In satisfying the third research objective, Altman (1968) demonstrated a very high relationship to provide early warnings of financial distress according to Tavlin et al. (1989) condition 3 which is consistent with findings by researchers (Altman, 1968, 1984, 2018; Maccarthy, 2017).

4.3 OHLSON (1980)

According to Ohlson (1980), the o-score model was developed to provide early warnings of financial distress being that of bankruptcy. Results per table 3 over a six-year period analysed 72 unhealthy and 72 healthy companies where early warnings of bankruptcy were noted 12 times. Of those 12 warnings related to 9 (13%) companies that delisted from the JSE. The o-score provides early warnings of bankruptcy for a score of 0.38 or less. Over a six-year period, unhealthy companies reported a mean z score of -2.96. This implies that for most companies that delisted from the JSE, the 0-score did report early warnings of delisting indicating the 0-score did produce appropriate early warnings of financial distress.

Table 3: Ohlson (1980)

Model prediction n=9/72 (13%)

	Count								
Ohlson (1980)	**Listed on JSE**	**Likely**	**Unlikely**	**No. delisted**	**Total Percentage Unhealthy**	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
Unhealthy	**72**	**9**	**138**	**72**	**2%**	**-22.43**	**16.72**	**-2.96**	**3.44**
2016	**72**	**-**	**-**	**3**	**0%**	**0.00**	**0.00**	**0.00**	**0.00**
2017	**69**	**4**	**49**	**10**	**6%**	**-6.41**	**5.98**	**-2.56**	**2.22**
2018	**62**	**2**	**46**	**5**	**3%**	**-11.82**	**16.72**	**-2.72**	**3.63**
2019	**67**	**1**	**31**	**19**	**1%**	**-22.43**	**0.58**	**-3.57**	**3.93**
2020	**53**	**1**	**11**	**16**	**2%**	**-19.52**	**0.58**	**-4.26**	**4.92**
2021	**56**	**1**	**1**	**19**	**2%**	**-4.57**	**0.89**	**-1.84**	**2.73**
Healthy	**72**	**3**	**330**			**-54.84**	**95.76**	**-3.81**	**6.33**

Source: Compiled by author

O-score is derived using the variables and parameter estimates of Ohlson (1980).

With reference to table 1, 83 companies reported, at least once, their expenses exceeding income over a six-year period. Where the o-score was below 0.38 the model was able to predict early warnings, per table 11, of expenses exceeding income for 4 (5%) companies one year prior to the reported event. Findings demonstrated 102 companies reported, at least once, their cost of capital greater than return on investment over a six-year period. Where the o-score was below 0.38 the model was able to predict early warnings, per table 11, of cost of capital greater than return on investment for 2 (2%) companies one year prior to the reported event.

With reference to table 1, 68 companies reported, at least once, technical insolvency over a six-year period. Where the 0-score was below 0.38 the model was able to predict early warnings, per table 11, of an inability to settle its debts as they become due for 3 (4%) companies one year prior to the reported event.

Referencing table 1, 5 companies reported, at least once, bankruptcy over a six-year period. Where the 0-score was below 0.38 the model was able to predict early warnings, per table 11, of liabilities exceeding the fair value of assets for 1 (20%) company.

In satisfying the first research objective, Ohlson (1980) demonstrated a negligible relationship and does not appear to have abilities to provide early warnings of financial distress according to Tavlin et al. (1989) condition 1. In satisfying the second research objective, Ohlson (1980) demonstrated a negligible relationship and does not appear to have abilities to provide early warnings of financial distress according to Tavlin et al. (1989) condition 2. In satisfying the third research objective, Ohlson (1980) demonstrated a low relationship to provide early warnings of financial distress according to Tavlin et al. (1989) condition 3 consistent to results documented by researchers (Grice & Dugan, 2003; Low et al., 2001; Salim & Ismudjoko, 2021).

4.4 ZMIJEWSKI (1984)

According to Zmijewski (1984), the x-score model was developed to provide early warnings of financial distress being that of bankruptcy. Results per table 4 over a six-year period analysed 72 unhealthy and 72 healthy companies where early warnings of bankruptcy were noted 544 times. Of those 544 warnings related to 63 (88%) companies that delisted from the JSE. The x-score provides early warnings of bankruptcy for a score of 0 or less. Over a six-year period, unhealthy companies reported a mean z score of -1.33. This implies that for most companies that delisted from the JSE, the x-score did report early warnings of delisting indicating the x-score did produce appropriate early warnings of financial distress.

Table 4: Zmijewski (1984)

Model prediction n=63/72 (88%)

	Count								
Zmijewski (1984)	**Listed on JSE**	**Likely**	**Unlikely**	**No. delisted**	**Total Percentage Unhealthy**	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
Unhealthy	**72**	**182**	**37**	**72**	**45%**	**-7.66**	**16.31**	**-1.33**	**2.71**
2016	**72**	**57**	**10**	**3**	**79%**	**-7.66**	**7.59**	**-1.52**	**2.20**
2017	**69**	**48**	**9**	**10**	**70%**	**-4.82**	**14.36**	**-1.04**	**3.43**
2018	**62**	**38**	**11**	**5**	**61%**	**-4.77**	**16.31**	**-1.14**	**3.01**
2019	**67**	**27**	**5**	**19**	**40%**	**-4.93**	**3.96**	**-1.54**	**1.85**
2020	**53**	**10**	**2**	**16**	**19%**	**-5.75**	**0.81**	**-1.51**	**1.67**
2021	**56**	**2**		**19**	**4%**	**-5.91**	**-1.32**	**-3.62**	**2.29**
Healthy	**72**	**362**	**43**			**-6.11**	**1.21**	**-1.67**	**1.33**

Source: Compiled by author

X-score is derived using the variables and parameter estimates of Zmijewski (1984)

With reference to table 1, 83 companies reported, at least once, their expenses exceeding income over a six-year period. Where the x-score was below 0 the model was able to predict early warnings, per table 11, of expenses exceeding income for 58 (70%) companies one year prior to the reported event. Findings demonstrated 102 companies reported, at least once, their cost of capital greater than return on investment over a six-year period. Where the x-score was below 0 the model was able to predict early warnings, per table 11, of cost of capital greater than return on investment for 76 (75%) companies one year prior to the reported event.

With reference to table 1, 68 companies reported, at least once, technical insolvency over a six-year period. Where the x-score was below 0 the model was able to predict early warnings, per table 11, of an inability to settle its debts as they become due for 51 (75%) companies one year prior to the reported event.

Referencing table 1, 5 companies reported, at least once, bankruptcy over a six-year period. Where the x-score was below 0 the model was able to predict early warnings of, per table 11, liabilities exceeding the fair value of assets for 0 (0%) companies.

In satisfying the first research objective, Zmijewski (1984) demonstrated a high relationship and appears to be able to provide early warnings of financial distress according to Tavlin et al. (1989) condition 1. In satisfying the second research objective, Zmijewski (1984) demonstrated a high relationship and appears to be able to provide early warnings of financial distress according to Tavlin et al. (1989) condition 2. In satisfying the third research objective, Zmijewski (1984) demonstrated a low relationship to provide early warnings of financial distress according to Tavlin et al. (1989) condition 3 which was unexpected in comparison to the successful results according to researchers (Grice & Dugan, 2003; Husein & Pambekti, 2014; Salim & Ismudjoko, 2021; Suresh, 2022). However, this is consistent with the Oz & Simga-Mugan (2018) findings where a re-estimation of the model for developing economies was encouraged to improve accuracy.

4.5 TAFFLER (1983)

According to Taffler (1983), the z-score model was established to provide early warnings of financial distress being that of bankruptcy. Results per table 5 over a six-year period analysed 72 unhealthy and 72 healthy companies where early warnings of bankruptcy were noted 135 times. 38 (53%) of those 135 warnings related to companies that delisted from the JSE. The z-score provides early warnings of bankruptcy for a score of 0.2 or less. Over a six-year period, unhealthy companies reported a mean z score of 7.59. This implies that for most companies that delisted from the JSE, the x-score did not report early warnings of delisting indicating the z-score did not produce appropriate early warnings of financial distress.

Table 5: Taffler (1983)

Model prediction n=38/72 (53%)

	Count								
Taffler (1983)	Listed on JSE	Likely	Unlikely	No. delisted	Total Percentage Unhealthy	Minimum	Maximum	Mean	Std. Deviation
Unhealthy	72	72	147	72	18%	-1778.84	1136.76	7.59	164.68
2016	72	20	47	3	28%	-1778.84	419.13	-14.49	223.55
2017	69	16	41	10	23%	-549.86	272.60	6.00	88.65
2018	62	16	33	5	26%	-48.18	338.55	10.39	50.35
2019	67	11	21	19	16%	-89.76	206.73	9.31	41.14
2020	53	8	4	16	15%	-337.20	737.20	29.60	232.74
2021	56	1	1	19	2%	-6.63	1136.76	565.07	571.69
Healthy	72	63	342			-4857.32	4573.34	21.55	422.50

Source: Compiled by author

Z-score is derived using the variables and parameter estimates of Taffler (1983)

With reference to table 1, 83 companies reported, at least once, their expenses exceeding income over a six-year period. Where the z-score was below 0.2 the model was able to predict early warnings, per table 11, of expenses exceeding income for 27 (33%) companies one year prior to the reported event. Findings demonstrated that 102 companies reported, at least once, their cost of capital greater than return on investment over a six-year period. Where the z-score was below 0.2 the model was able to predict early warnings, per table 11, of cost of capital greater than return on investment for 28 (27%) companies one year prior to the reported event.

With reference to table 1, 68 companies reported, at least once, technical insolvency over a six-year period. Where the z-score was below 0.2 the model was able to predict early warnings, per table 11, of an inability to settle its debts as they become due for 20 (29%) companies one year prior to the reported event.

Referencing table 1, 5 companies reported, at least once, bankruptcy over a six-year period. Where the z-score was below 0.2 the model was able to predict early warnings, per table 11, of liabilities exceeding the fair value of assets for all (100%) companies.

In satisfying the first research objective, Taffler (1983) demonstrated a low relationship and does not appear to have abilities to provide early warnings of financial distress according to Tavlin et al. (1989) condition 1. In satisfying the second research objective, Taffler (1983) demonstrated a low relationship and does not appear to have abilities to provide early warnings of financial distress for according to Tavlin et al. (1989) condition 2. In satisfying the third research objective, Taffler (1983) demonstrated a very high relationship to provide early warnings of financial distress according to Tavlin et al. (1989) condition 3 consistent with other researcher's findings (Agarwal & Taffler, 2008; Arhin et al., 2020; Berrangé & Willows, 2016).

4.6 FINANCIAL RATIO

Beaver (1966) defined a company's failure as an inability to settle its financial debts as they fall due and might include events such as bankruptcy, default on bond repayments, significant overdraft, or the non-payment dividends on preference shares. The researcher identified ratio debt-to-asset, sales-to-assets, and cash flow-to-debt as commanding predictors of distress when their results were high. Similar studies were performed by Gupta (1983) who believed that failure culminates a few years prior to formal bankruptcy concluding that financial ratio relating to profitability, most specifically, earnings before depreciation, interest and taxes-to-sales and operating cash flow-to-sales provided strong early warnings and financial ratio relating to solvency, most specifically, net worth-to-total debt (including both short and long term) and all outside liabilities-to-tangible assets. Both these researchers identified early warning instruments however did not quantify their results and merely highlighted early warnings of financial distress defined as that of "high" results. Several subsequent researchers such as Islami & Rio (2018) and Beaver et al. (2010) have attempted to identify benchmarks in various countries and industries for various financial ratio with varying results. However, it appears a further gap exists in research and further research is required to quantify financial ratio benchmarks to provide early warnings of distress.

To quantify a ratio indicative of distress to answer the research objectives, this author utilised early warning financial distress models (Altman, 1968; Beaver, 1966; Gupta, 1983; Ohlson, 1980; Taffler, 1983; Zmijewski, 1984) together with the sample population to determine a benchmark. The financial ratio for each year was calculated for the sample population. Thereafter the distress models were filtered according to their extreme distress criteria. The mean of the ratios was extracted. Per table 6, the mean of the respective total ratios was obtained to be used as a distress range quantifying a value to be utilised to answer the research questions.

Based on the methodology employed to obtain appropriate benchmarks for Beaver (1966) per table 6 were 0.56 for debt to assets, 0.85 for sales to assets, 1.64 for cashflow to debt and for Gupta (1983) per table 6, -3.91 for EBITDA to sales, 3.81 for operating cash flow to sales, 70.95 net worth to total debt and 0.64 for all outside liabilities to tangible assets.

Table 6: Financial Ratio Benchmarks

		Altman (1968)	Ohlson (1980)	Taffler (1983)	Zmijewski (1984)	
		Model Cut-off				
		<1.81	>0.38	<0.2	<0	
		Financial Ratio				
Researcher	**Description**	**Mean**	**Mean**	**Mean**	**Mean**	**Range**
Beaver (1966)	Debt to Assets	0.50	0.80	0.50	0.44	**0.56**
Beaver (1966)	Sales to Assets	0.83	0.92	0.83	0.80	**0.85**
Beaver (1966)	Cashflow to Debt	0.68	4.42	0.68	0.80	**1.64**
Gupta (1983)	EBITDA to Sales	-4.94	-0.17	-4.94	-5.60	**-3.91**
Gupta (1983)	Operating Cashflow to Sales	4.87	-0.04	4.87	5.55	**3.81**
Gupta (1983)	Net worth to total debt	30.05	189.30	30.05	34.43	**70.95**
Gupta (1983)	All outside liabilities-to-tangible assets	0.58	0.86	0.58	0.52	**0.64**

Source: Compiled by author

With reference to table 1, 83 companies reported, at least once, their expenses exceeding income over a six-year period. Where debt to assets was above 0.56, sales to assets was above 0.85 and cashflow to debt was above 1.64 the ratio were able to predict early warnings of expenses exceeding income, per table 11, for 22 (27%), 24 (29%) and 1 (1%) company respectively one year prior to the reported event. Referencing table 1, 102 companies reported, at least once, their cost of capital greater than return on investment over a six-year period. Where debt to assets was above 0.56, sales to assets was above 0.85 and cashflow to debt was above 1.64 the ratio were able to predict early warnings, per table 11, cost of capital greater than return on investment for 30 (29%), 33 (32%), 0 (0%) companies respectively one year prior to the reported event.

With reference to table 1, 68 companies reported, at least once, technical insolvency over a six-year period. Where debt to assets was above 0.56, sales to assets was above 0.85 and cashflow to debt was above 1.64 the ratio was able to predict early warnings, per table 11, of an inability to settle its debts as they become due for 30 (44%),14 (21%), 0 (0%) companies respectively one year prior to the reported event.

Referencing table 1 and discussion above, 5 companies reported, at least once, bankruptcy over a six-year period. Where debt to assets was above 0.56, sales to assets was above 0.85 and cashflow to debt was above 1.64 the ratio was able to predict early warnings, per table 11, of liabilities exceeding the fair value of assets for all (100%), 0 (0%), 0 (0%) respectively one year prior to the reported event.

In relation to Gupta (1983) where EBITDA to sales was greater than -3.91, operating cashflow to sales was above 3.81, net worth to total debt was above 70.95 and all outside liabilities-to-tangible assets was above 0.64 the ratio was able to predict early warnings, per table 11, of expenses exceeding income for 1 (1%), 0 (0%), 66 (80%) and 68 (82%) companies respectively one year prior to the reported event. Findings for the same ratio and benchmarks were able to predict early warnings, per table 11, of cost of capital greater than return on investment for 1 (1%), 1 (1%), 76 (75%) and 86 (84%) companies respectively one year prior to the reported event. Using the same ratio findings predicted early warnings, per table 11, of an inability to settle its debts as they become due for 0 (0%), 0 (0%), 55 (81%) and 52 (76%) companies respectively one year prior to the reported event. Lastly, the ratio was able to predict early warnings, per table 11, of liabilities exceeding the fair value of assets for 0 (0%), 0 (0%), 2 (40%) and for all (100%) companies respectively one year prior to the reported event.

In satisfying the first research objective, Beaver (1966) demonstrated a low relationship for debt to assets and sales to assets to provide early warnings of financial distress according to Tavlin et al. (1989) condition 1 and a negligible relationship in respect of cashflow to debt. Gupta (1983) demonstrated high relationships in comparison to Beaver (1966) for net worth to total debt and all outside liabilities-to-tangible assets and does appear to have abilities to provide early warnings of financial distress according to Tavlin et al. (1989) condition 1 but a negligible relationship for EBITDA to sales or operating cashflow to sales. In satisfying the second research objective, Beaver (1966) demonstrated a moderate relationship for debt to assets and a low relationship for sales to assets and does not appear to have abilities to provide early warnings of financial distress according to Tavlin et al. (1989) condition 2 and a negligible relationship for cashflow to debt. Gupta (1983) demonstrated high relationships in comparison to Beaver (1966) net worth to total debt and all outside liabilities-to-tangible assets and does appear to have abilities to provide early warnings of financial distress according to Tavlin et al. (1989) condition 2 but a negligible relationship for EBITDA to sales or operating cashflow to sales. In satisfying the third research objective, Beaver (1966) demonstrated a very high relationship to provide early warnings of financial distress for debt to assets according to Tavlin et al. (1989) condition 3 but a negligible relationship for sales to assets and cashflow to debt. Gupta (1983) demonstrated similarly moderate and very high relationships in comparison to Beaver's (1966) abilities to provide early warnings of financial distress for net worth to total debt and all outside liabilities to tangible assets according to Tavlin et al. (1989) condition 3 but negligible relationship results for EBITDA to sales and operating cashflow to sales. These findings concur with the extant literature where financial ratios can be used as methodology for providing early warnings of company distress (Arhin et al., 2020; Beaver et al., 2010; Garcia, 2022; Jones et al., 2017).

4.7 INITIAL WARNINGS

In satisfying the fourth research objective, the M-score derived by Beneish (1999), Schilit (2003) quality of revenue and quality of earnings ratio and Sloan (1996) earnings management measure was applied to the sample of 72 unhealthy companies to determine if there were early warnings of manipulation or earnings management which may lead to financial distress.

With reference to Table 7, Schilit (2003) quality of revenue reported initial warnings, at least once, over a six-year period for 72% (high relationship) of unhealthy companies where the mean for this was -1.90 which suggests that the benchmark for the ratio of 1.0 or less is appropriate. According to the researchers (Grove et al., 2019; Schilit, 2003) these findings indicate signs that companies have been inflating sales without corresponding cash inflow.

Schilit (2003) quality of revenue reported initial warnings with reference to Table 7, at least once, over a six-year period for 89% (high relationship) where the mean for this was -0.05 which suggests that the benchmark for the ratio of 1.0 or less is appropriate. According to the researchers (Grove et al., 2019; Schilit, 2003) these findings indicate signs that companies have been exaggeratedly inflating earnings which is not being converted into cash inflows.

With reference to Table 7,Sloan (1996) earnings management measure reported initial warnings, at least once, over a six-year period for 60% (moderate relationship) of unhealthy companies where the mean for this was 203.63 which suggests that the benchmark for the ratio of 0.10 or more should be revised to indicate manipulation that may lead to financial distress. According to the researchers (Grove et al., 2019; Schilit, 2003) these findings indicate signs that companies' income consists of large accruals that have not been converted into cash inflow questioning the future sustainability of the company's earning potential.

Table 7: Initial warnings derived from Schilit (2003) and Sloan (1996)

Researcher	Model	Total Sample Unhealthy	Unhealthy Initial Warnings	% of Unhealthy	Min	Max	Mean	Std. Deviation
Schilit (2003)	Quality of Revenue	72	52	72%	-520.33	3.11	-1.90	37.16
Schilit (2003)	Quality of Earnings	72	64	89%	-127.78	22.26	-0.05	9.78
Sloan (1996)	Accrual Measurement	72	43	60%	-2486.67	55907.45	286.52	3967.84

Source: Compiled by author

Derived using the variables and parameter estimates of Schilit (2003) and Sloan (1996)

Findings imply that Schilit (2003) quality of revenue, quality of earnings ratio and Sloan (1996) earnings management measure per Table 7 is suitable not only for warnings of manipulation but early warning conditions that may lead to financial distress. These findings are in line with other research performed using these measurements by researchers (Grove et al., 2019; Grove & Basilico, 2011; Grove & Clouse, 2017). However, with reference to Table 8, when comparisons are made to the paired sample of healthy companies, where the mean for quality of revenue is 0.99, which is just below the researchers initial warning benchmark of 1.0, implies that the mean identified in Table 7 of -1.90 is a more appropriate benchmark warning of manipulation leading to financial distress. These findings are similar for quality of earnings ratio and earnings management measures.

Table 8: Initial warnings derived from Schilit (2003) and Sloan (1996)

Researcher	Model	Total Sample Healthy	Healthy Initial Warnings	% of healthy	Min	Max	Mean	Std. Deviation
Schilit (2003)	Quality of Revenue	72	70	97%	0.29	2.27	0.99	0.09
Schilit (2003)	Quality of Earnings	72	68	94%	-81.81	130.13	1.98	10.89
Sloan (1996)	Accrual Measurement	72	60	83%	-3417.00	58419.83	162.59	2963.84

Source: Compiled by author

Derived using the variables and parameter estimates of Schilit (2003) and Sloan (1996)

The M-score model identifies features and approximations for detecting manipulation where the variables capture preconditions that may prompt companies to engage in manipulative activities or manipulation that is currently in effect (Beneish, 1999).

With reference to table 9, the M-score detected manipulated earnings for 10 (14%) unhealthy companies. The six-year M-score was above the mean score of -1.49 for 2018 implying this period reported the highest level of manipulated reports of certain unhealthy companies. Table 10 revealed the independent variables of the M-score where implications further imply manipulation. The scores in 2017 and 2019 for DSRI imply that revenue is overstated, in 2017 and 2020 for GMI implications are that gross profit is being manipulated, in 2017, 2018 and 2020 for SGI implications are that sales have grown uncharacteristically indicating manipulation, in 2017,2018, 2019 and 2020 for DEPI implications are that asset revaluations or useful lives of assets were manipulated, in 2017,2018, 2019 and 2020 for SGAI manipulative implications are due to inconsistent increases in sales and in 2017 and 2018 implications for TATA are that amortization of intangible assets have been manipulated.

The M-score implied 14% of unhealthy companies reported strong levels of manipulated reports, however table 9 implied that 32/72 (44%) companies have also been exhibiting strong indications of manipulation based on the variable measures. Therefore overall, 42 (58% moderate relationship) unhealthy companies appeared to be manipulated during the sampling period which may have led or was an attempt to hide financial distress.

Table 9: Initial warnings derived from Beneish (1999)

Model Prediction Initial Warning n=10/72 (14%)

Model Prediction based on variables measures Initial Warning n=32/72 (44%)

Beneish (1999)	Listed on JSE	Initial Warnings	Likely	No. Initial Warnings	No. delisted	Total Percentage Unhealthy	Minimum	Maximum	Mean	Std. Deviation
Unhealthy	**72**	**10**	**45**	**70**	**72**	**14%**	**-22.28**	**75.58**	**-0.49**	**10.25**
2016	**72**				**3**	**0%**				
2017	**69**	**2**	**20**	**23**	**10**	**3%**	**-17.10**	**47.39**	**-0.62**	**8.17**
2018	**62**	**4**	**14**	**25**	**5**	**6%**	**-22.28**	**37.00**	**-1.91**	**7.17**
2019	**67**	**2**	**8**	**17**	**19**	**3%**	**-4.90**	**35.71**	**-0.38**	**7.87**
2020	**53**	**2**	**3**	**5**	**16**	**4%**	**-4.78**	**75.58**	**6.18**	**24.56**
2021	**56**				**19**	**0%**				
Healthy	**72**	**30**	**107**	**227**	**0**		**-13.98**	**25.80**	**-1.90**	**2.31**

Source: Compiled by author

Derived using the variables and parameter estimates of Beneish, (1999)

Table 10: Initial warning inputs derived from Beneish (1999)

Beneish (1999)	Mean of DSRI	Mean of GMI	Mean of AQI	Mean of SGI	Mean of DEPI	Mean of SGAI	Mean of LEVGI	Mean of TATA
Index	**1.465**	**1.193**	**1.254**	**1.067**	**1.077**	**1.041**	**1.111**	**0.031**
Unhealthy	**0.75**	**-0.25**	**0.93**	**0.84**	**0.95**	**0.91**	**0.48**	**-0.02**
2016	**N/A**	**N/A**	**N/A**	**N/A**	**N/A**	**N/A**	**N/A**	**N/A**
2017	1.984*	1.291*	1.051	6.994*	1.096*	1.042*	0.524	0.134*
2018	1.198	0.115	1.042	1.847*	2.247*	1.694*	0.524	0.058*
2019	2.567*	1.153	1.061	0.938	1.368*	1.219*	0.464	0.091
2020	1.118	14.004*	0.976	1.319*	1.449*	1.120*	0.518	0.048
2021	1.035	0.949	0.877	0.816	0.986	0.880	0.453	0.118
Healthy	**1.21**	**0.85**	**1.02**	**1.16**	**1.13**	**1.06**	**0.55**	**0.01**

Source: Compiled by author

Derived using the variables and parameter estimates of Beneish, (1999)

*Highlights possibility that earnings were affected when compared to Beneish (1999) (Maccarthy, 2017).

In comparison to the healthy sample, the mean M-score of -1.90 implies that healthy companies exhibit manipulation per table 9. Manipulation is prominent for SGI,DEPI and SGAI. However, in most cases, the independent m-score is not as extensive as that reported by unhealthy companies. The results of healthy companies imply that the JSE Top 100 companies may manipulate their reports to report favourable earnings when there may not be corresponding cashflow generation.

According to studies by Maccarthy (2017), the M-score appropriately provides early warnings of financial distress when used in conjunction with an early warning financial distress model. This conclusion follows suite corroborating findings satisfying the fourth research objective where risk model (Beneish, 1999; Schilit, 2003) and earnings management measurement (Sloan, 1996) provided suitable measurements as envisaged by their respective model outputs to imply these models are suitable warnings that may lead to financial distress.

4.8 DISCUSSION SUMMARY

Several research objectives were examined to test the hypothesis of this research study. Table 11 and Appendix E demonstrates the high-level results reached for each research objective and includes cross-references to the relevant results discussion sections. Based on the results of those depicted in Table 11, it appears as if the hypothesis of this study has been brought into fruition and has been supported by this research where financial distress, risk prediction, and earnings management measures can be unified into an EWS framework.

Table 11: Summary of Findings

Summary of Findings		Research Question 1		Research Question 2	Research Question 3		
		Economic Failure		Technical Insolvency	Bankruptcy	High level result / conclusion	Cross Reference
		Expenses exceed Income	Cost of Capital > Return on Investment				
Researcher	Model	n=83	n=102	n=68	n=5		
		%	%	%	%		
Altman (1968)	Z-Score	8	8	10	100	The z-score demonstrates negligible relationships to provide early warnings of economic failure or technical insolvency. However, demonstrates a very high relationship to provide early warnings of bankruptcy.	Paragraph 4.2 Table 1 Table 2
Ohlson (1980)	O-Score	5	2	4	20	The o-score demonstrates negligible relationships to provide early warnings of economic failure or technical insolvency and demonstrates low relationships to provide early warnings on bankruptcy.	Paragraph 4.3 Table 1 Table 3
Zmikewski (1984)	X-Score	70	75	75	0	The x-score demonstrates high relationships to provide early warnings of economic failure and technical insolvency. However, a negligible relationship to provide early warnings on bankruptcy.	Paragraph 4.4 Table 1 Table 4
Taffler (1983)	Z-Score	33	27	29	100	The z-score demonstrates low relationships of early warnings of economic failure and technical insolvency. However, has a very high relationship to provide early warnings on bankruptcy.	Paragraph 4.5 Table 1 Table 5

Beaver (1966)	**Debt to Assets**	**27**	**29**	**44**	**100**	**Debt to assets demonstrates low relationships of early warnings of economic failure. The ratio demonstrates moderate relationship of early warning indicators of technical insolvency and very high relationship to provide early warnings of bankruptcy.**	**Paragraph 4.6 Table 1 Table 6**
Beaver (1966)	**Sales to Assets**	**29**	**32**	**21**	**0**	**Sales to assets demonstrates low abilities of early warnings of economic failure and technical insolvency. However, the ratio has a negligible relationship to provide early warning abilities of bankruptcy.**	**Paragraph 4.6 Table 1 Table 6**
Beaver (1966)	**Cashflow to Debt**	**1**	**0**	**0**	**0**	**Cashflow to debt ratio provides negligible relationships to provide early warnings of economic failure, technical insolvency, or bankruptcy.**	**Paragraph 4.6 Table 1 Table 6**
Gupta (1983)	**EBITDA to Sales**	**1**	**1**	**0**	**0**	**EBITDA to sales ratio demonstrates a negligible relationship to provide early warnings of economic failure, technical insolvency, or bankruptcy.**	**Paragraph 4.6 Table 1 Table 6**
Gupta (1983)	**Operatin g Cashflow to Sales**	**0**	**0**	**0**	**0**	**Operating Cashflow to Sales ratio demonstrates a negligible relationship to provide early warnings of economic failure, technical insolvency, or bankruptcy.**	**Paragraph 4.6 Table 1 Table 6**
Gupta (1983)	**Net worth to total debt**	**80**	**75**	**81**	**40**	**Net worth to total debt ratio demonstrates a high relationship to provide early warnings of economic failure and technical insolvency. However, moderate relationship of early warning abilities of bankruptcy.**	**Paragraph 4.6 Table 1 Table 6**
Gupta (1983)	**All outside liabilities-to-tangible assets**	**82**	**84**	**76**	**100**	**All outside liabilities-to-tangible assets ratio provides high relationships of early warnings of economic failure technical**	**Paragraph 4.6 Table 1 Table 6**

						insolvency and a very high relationship of bankruptcy.	
		Research Question 4				High level result / conclusion	Cross Reference
Researcher	Model	n=72					
		%					
Schilit (2003)	Quality of Revenue	72				This ratio provides a high relationship for initial warnings of manipulated revenue without corresponding cash inflow which may ultimately lead to financial distress	Paragraph 4.7 Table 7 Table 8
Schilit (2003)	Quality of Earnings	89				This ratio provides a high relationship for initial warnings of manipulated earnings without corresponding cash inflow which may ultimately lead to financial distress	Paragraph 4.7 Table 7 Table 8
Sloan (1996)	Accrual Measure ment	60				This ratio provides a moderate relationship for initial warnings of earnings management without corresponding cash inflow which may ultimately lead to financial distress	Paragraph 4.7 Table 7 Table 8
Beneish (1999)	M-Score	58				This model provides a moderate relationship for initial warnings of preconditions that may prompt companies to engage in manipulative activities or manipulation that is currently in effect	Paragraph 4.7 Table 9 Table 10

Source: Compiled by author

CHAPTER 5: CONCLUSION

The topic of financial distress continues to be a well-intentioned research area due to its continued economic prowess. EWS models have existed for decades with the primary purpose of warning users as to the future economic outlook of a company and primarily if the company is ostensibly on a direction toward that of complete demise. Researchers have continuously mentioned that company demise, known as bankruptcy, is only one of several distress attributes and that distress consists of other elements that if detected in time may prevent complete catastrophe and result in a turnaround. Despite the existence of numerous early warning models, the practical application of these models has been focused on providing EWSs of bankruptcy and few other warnings such as economic failure or technical insolvency where turnaround may be possible. The objectives of this study were to:

1. Contribute to literature by determining which financial distress models had abilities to provide EWSs of economic failure, technical insolvency and/or bankruptcy.

2. Contribute to literature by determining if risk and earnings management measures could complement financial distress models.

To achieve the objectives a total of 133 companies that delisted from the JSE using income statements, balance sheets and cashflow statements were examined for the period between 2016 and 2021. The results revealed that 72 (54%) companies reported, at least once during the period, a financial distress condition of economic failure and/or technical insolvency and/or bankruptcy defined by Tavlin et al. (1989).

The financial distress models were calculated according to their relevant variables and parameter estimates. Where a model was able to provide early warnings of financial distress a year prior to the identified condition as defined by the parameter “high relationship” and “very high relationship”, the model was deemed to provide early warnings of that distress condition. Where a risk or earnings management model demonstrated results defined by the parameter as “moderate relationship,” “high relationship” and “very high relationship”, the model was deemed suitable to be used together with an appropriate financial distress model to identify if manipulation and/or earnings management might lead to financial distress.

Appropriate conclusions, as directed by the outcomes of this research, relating to the research objectives have been reached and are as follows:

5.1. RESEARCH OBJECTIVE 1

Results have implied that the X-score, developed by Zmijewski (1984) provides early warnings of economic failure where the model has 70% (high relationship) ability to predict expenses exceeding income a year prior to the condition. The X-model demonstrates further abilities to provide early warnings of economic failure where the model has 75% (high relationship) ability to predict cost of capital greater than return on investment a year prior to the condition. Ratio highlighted by Gupta (1983), net worth-to-total debt and all outside liabilities-to-tangible assets provided better results when compared to Zmijewski (1984) early warning abilities where, net worth-to-total debt provided 80% (high relationship) ability to predict expenses exceeding income a year prior to the condition and has 75% (high relationship) ability to predict cost of capital greater than return on investment a year prior to the condition. The ratio, all outside liabilities-to-tangible assets, provided the best EWS abilities where 82% (high relationship) ability to predict expenses exceeding income a year prior to the condition and 84% (high relationship) ability to predict cost of capital greater than return on investment a year prior to the condition were noted. These findings have been summarised accordingly in Appendix B in the EWS framework.

Results of models, Altman (1968), Ohlson (1980), Taffler (1983), Beaver (1966) and Gupta (1983) EBITDA-to-sales and operating cashflow-to-sales did not meet parameters set to indicate sufficient predictive abilities of economic failure to conclude that these models can signal early warnings of economic failure.

5.2. RESEARCH OBJECTIVE 2

Results have implied that the X-score, developed by Zmijewski (1984) provides early warnings of technical insolvency where the model has 75% (high relationship) ability to predict when a company is unable to settle its debts as they become due a year prior to the condition. Ratio highlighted by Gupta (1983), net worth-to-total debt and all outside liabilities-to-tangible assets provided better results when compared to Zmijewski (1984) early warning abilities where, all outside liabilities-to-tangible assets provided EWS abilities where 76% (high relationship) ability to predict when a company is unable to settle its debts as they become due a year prior to the condition were noted. Net worth-to-total debt provided the best EWS abilities where 81% (high relationship) can predict when a company cannot settle its debts as they become due a year prior to the condition. These findings have been summarised accordingly in Appendix B in the EWS framework.

Results of models, Altman (1968), Ohlson (1980), Taffler (1983), Beaver (1966) and Gupta (1983) EBITDA-to-sales and operating cashflow-to-sales did not meet parameters set to indicate sufficient predictive abilities of economic failure to conclude that these models can signal early warnings of technical insolvency.

5.3. RESEARCH OBJECTIVE 3

Results have implied that the z-score as developed by Altman (1968), the z-score as developed by Taffler (1983), debt-to-assets as developed by Beaver (1966) and ratio all outside liabilities-to-tangible assets as highlighted by Gupta (1983) provides early warnings of bankruptcy 100% (very high relationship) a year prior to the condition whereby the company's fair value of assets does not exceed its liabilities and the company has no possible means to meet its obligations. These findings have been summarised accordingly in Appendix B in the EWS framework.

Results of models Ohlson (1980), Zmijewski (1984), Beaver (1966) sales-to-assets and cashflow-to-debt and Gupta (1983) EBITDA-to-sales, net worth-to-debt, operating cashflow-to-sales did not meet parameters set to indicate sufficient predictive abilities of economic failure to conclude that these models can signal early warnings of bankruptcy.

5.4. RESEARCH OBJECTIVE 4

Results have implied that Schilit (2003),Sloan (1996) and Beneish (1999) provide appropriate early warnings of manipulation and earnings management whereby a company may experience financial distress in preceding years.

The most powerful EWS detecting manipulation in unhealthy companies (89%) (high relationship) was that of quality of earnings developed by Schilit (2003) where financial distress followed suite. This EWS model was followed by Schilit (2003) quality of revenue and the Sloan (1996) accrual measure detecting 60% (moderate relationship) of unhealthy companies and lastly Beneish (1999) M-score detecting 58% (moderate relationship) of unhealthy companies where financial distress followed.

These early warning models provided appropriate indicators, as determined by parameters set, where financial distress may be on the horizon and are deemed appropriate to be unified in an early warnings framework which has been summarised accordingly in Appendix B.

5.5. RESEARCH CONTRIBUTION

The findings in this study have contributed to research and existing literature on EWSs in South Africa, as follows:

1. Tavlin et al. (1989) framework of financial distress can be used as an EWS indicator.
2. Highlighted financial structures of unhealthy company means implying that if a company reports those means or below and exhibits financial distress conditions according to Tavlin et al. (1989), a company may not recover.
3. Identified extensions to Tavlin et al. (1989) framework to determine whether conditions could be amalgamated to provide better warnings of distress.
4. Identified Tavlin et al. (1989) framework of financial distress can be used to overcome the constraints of dichotomist classifications of financial distress.
5. Identified that healthy and unhealthy companies frequently engage in earnings management and implied manipulation.
6. Identified benchmarks for certain financial ratio to indicate financial distress.
7. Identified EWS financial distress models that can provide warnings of economic failure, technical insolvency, and bankruptcy.
8. Identified risk and earnings management measurers that can be used as initial warnings where financial distress may precede.

9. Concluded that the alternative hypothesis (H1) whereby financial distress, risk prediction, and earnings management measure can be unified into an EWS framework.

APPENDIX A

The below hierarchy triangle depicts the research objectives applicable to satisfy the research aim of this study.

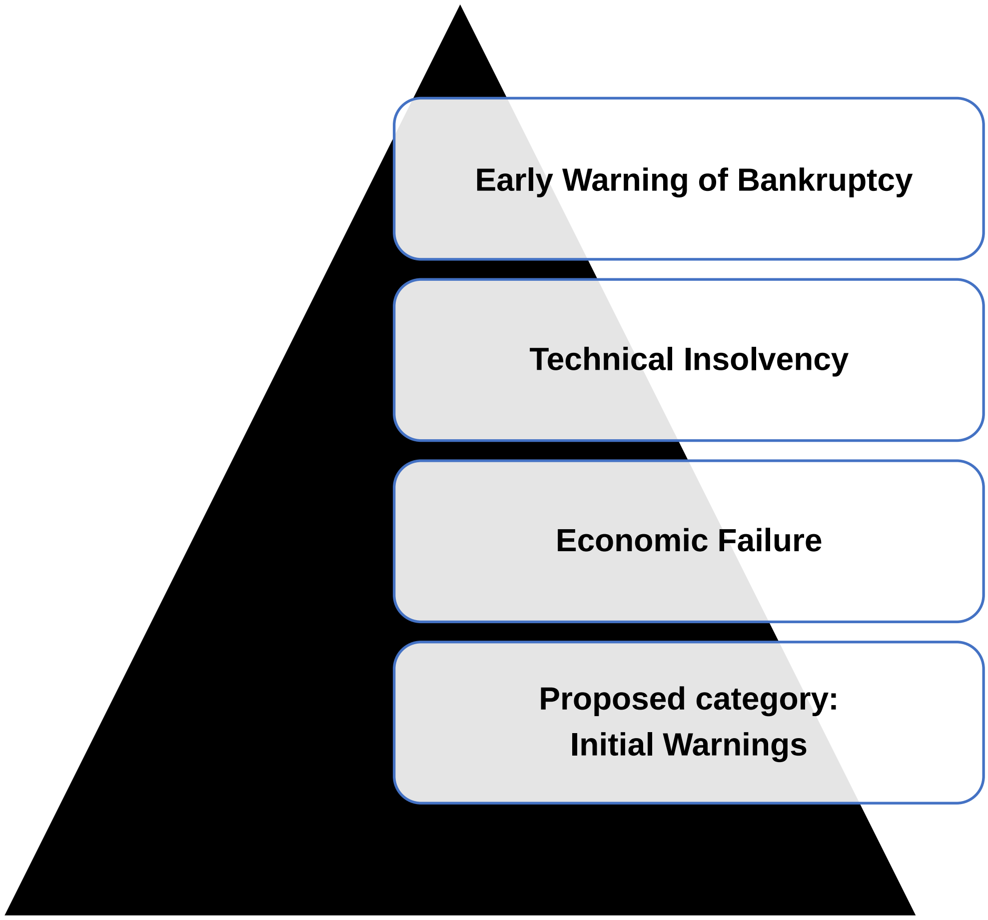


Figure 11 : Research Objective

Source: Compiled by author

APPENDIX B

The below depicts the EWS framework based on the results of this study.

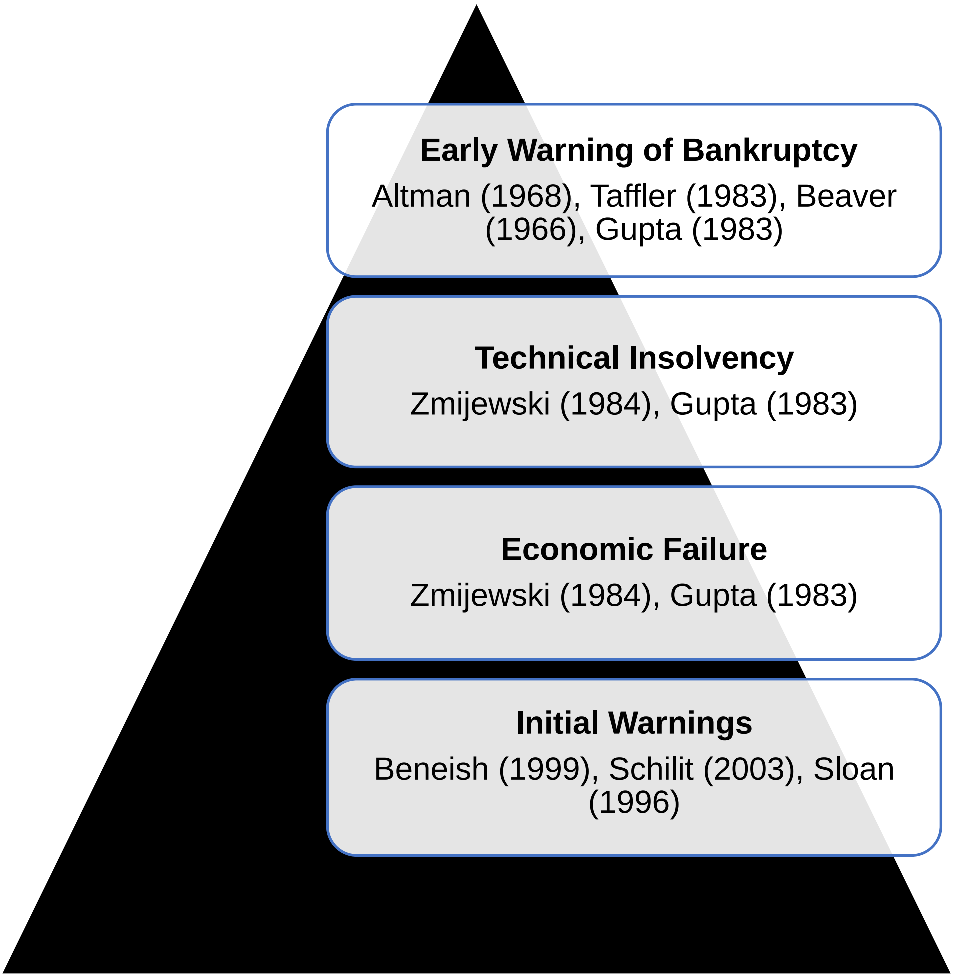


Figure 12: EWS Framework

Source: Compiled by author

APPENDIX C

Table 12: Population

DELISTED COMPANIES	LISTED COMPANIES
Accentuate Limited	Advtech Ltd
Adrenna Property Grp Ltd	Aeci Limited
Aep Energy Africa Ltd	African Rainbow Min Ltd
African Oxygen Limited	Alphamin Resources Corp
African Phoenix Inv Ltd	Anglo American Plc
Anchor Group Limited	Anglogold Ashanti Ltd
Andulela Inv Hldgs Ltd	Aspen Pharmacare Hldgs L
Arrowhead Properties Ltd	Avi Ltd
Ascension Prop Ltd A	Barloworld Ltd
Assore Ltd	Bhp Group Plc
Astrapak Limited	Bid Corporation Ltd
Atlantic Leaf Prop Ltd	Bidvest Ltd
Atlatsa Resources Corp	Capital&Counties Prop Pl
Avior Cap Market Hldg Ld	Clicks Group Ltd
Capevin Holdings Ltd	Compagnie Fin Richemont
Cargo Carriers Ltd	Dis-Chem Pharmacies Ltd
Cartrack Holdings Ltd	Discovery Ltd
Central Rand Gold Ltd	Distell Group Hldgs Ltd
Comair Limited	Exxaro Resources Ltd
Cons Infrastructure Grp	Fortress Reit Ltd A
Distell Group Ltd	Glencore Plc
Distr And Warehousing	Growthpoint Prop Ltd
Efficient Group Ltd	Harmony Gm Co Ltd
Elb Group Ltd	Impala Platinum Hlgs Ltd
Esor Limited	Italtile Ltd
Extract Group Limited	Kap Industrial Hldgs Ltd
Freedom Prop Fund Ltd	Karooooo Ltd
Global Asset Mngment Ltd	Kumba Iron Ore Ltd
Gold Brands Inv Ltd	Life Healthc Grp Hldgs L
Gooderson Leisure Corp	Massmart Holdings Ltd
Grit Real Estate Inc Grp	Mediclinic Int Plc
Group Five Ltd	Mondi Plc
Hospitality Prop Fund B	Mr Price Group Ltd
Howden Africa Hldgs Ltd	Multichoice Group Ltd
Ingenuity Property Inv	Naspers Ltd -N-
Interwaste Hldgs Ltd	Netcare Limited
Intu Properties Plc	Pepkor Holdings Ltd
Ipsa Group Plc	Pick N Pay Stores Ltd
Kaydav Group Ltd	Prosus N.V.
Keaton Energy Hldgs Ltd	Psg Group Ltd

Lonmin Plc	Redefine Properties Ltd
Mainland Real Estate Ltd	Reinet Investments S.C.A
Master Plastics Limited	Remgro Ltd
Mazor Group Ltd	Resilient Reit Limited
M-Fitec Int Ltd	Royal Bafokeng Platinum
Money Web Holdings Ltd	Sanlam Limited
Montauk Holdings Ltd	Santam Limited
New Europe Prop Inv Plc	Sappi Ltd
Niveus Investments Ltd	Sasol Limited
Oakbay Res And Energy Lt	Shoprite Holdings Ltd
Orion Real Estate Ltd	Sibanye Stillwater Ltd
Peregrine Holdings Limit	Sirius Real Estate Ltd
Phumelela Game Leisure	South32 Limited
Pick N Pay Holdings Ltd	Telkom Sa Soc Ltd
Rdi Reit P.L.C	The Foschini Group Limit
Rockwell Diamonds Inc	The Spar Group Ltd
Rolfes Technology Hldgs	Tiger Brands Ltd
Sabmiller Plc	Transaction Capital Ltd
Sacoven Plc	Truworths Int Ltd
Sasol Inzalo Pub Ld (Rf)	Tsogo Sun Gaming Ltd
Sovereign Food Inv Ltd	Vivo Energy Plc
Stellar Cap Partners Ltd	Vodacom Group Ltd
Stratcorp Ltd	Vukile Property Fund Ltd
Tawana Resources Nl	Woolworths Holdings Ltd
Tiso Blackstar Group Se	Textainer Group Hldgs Lt
Torre Industries Limited	Anheuser-Busch Inbev Sa
Tower Property Fund Ltd	Anglo American Plat Ltd
Trans Hex Group Ltd	Northam Platinum Hldgs L
Unicorn Capital Pnr Ltd	Nepi Rockcastle S.A.
Value Group Ltd	Quilter Plc
Wilderness Holdings Ltd	Psg Konsult Limited
Zarclear Holdings Ltd	Omnia Holdings Ltd

Source: Compiled by author

APPENDIX D

Table 13: Strength of the relationship

RANGE	STRENGTH OF RELATIONSHIP
<0.2	Negligible Relationship
0.2 to 0.4	Low Relationship
0.4 to 0.7	Moderate Relationship
0.7 to 0.9	High Relationship
>0.9	Very High Relationship

Source: Guildford (1956)

APPENDIX E

Economic Condition	Altman (1968) predicted success rate	Corresponding Association	Research Findings	Corresponding Finding Association
Economic Failure				
-- Expenses exceed Income	N/A	Negligible Relationship	8%	Negligible Relationship
-- Cost of Capital > Return on External Investment	N/A	Negligible Relationship	8%	Negligible Relationship
Technical Insolvency	N/A	Negligible Relationship	10%	Negligible Relationship
Bankruptcy	95%	Very High Relationship	100%	Very High Relationship
Economic Condition	**Ohlson (1980) predicted success rate**	**Corresponding Association**	**Research Findings**	**Corresponding Association**
Economic Failure				
-- Expenses exceed Income	N/A	Negligible Relationship	5%	Negligible Relationship
-- Cost of Capital > Return on External Investment	N/A	Negligible Relationship	2%	Negligible Relationship
Technical Insolvency	N/A	Negligible Relationship	4%	Negligible Relationship
Bankruptcy	96%	Very High Relationship	20%	Low Relationship
Economic Condition	**Zmikewski (1984) predicted success rate**	**Corresponding Association**	**Research Findings**	**Corresponding Association**
Economic Failure				
-- Expenses exceed Income	N/A	Negligible Relationship	70%	High Relationship
-- Cost of Capital > Return on External Investment	N/A	Negligible Relationship	75%	High Relationship
Technical Insolvency	N/A	Negligible Relationship	75%	High Relationship
Bankruptcy	80%	High Relationship	0%	Negligible Relationship
Economic Condition	**Taffler (1983) predicted success rate**	**Corresponding Association**	**Research Findings**	**Corresponding Association**
Economic Failure				
-- Expenses exceed Income	N/A	Negligible Relationship	33%	Low Relationship
-- Cost of Capital > Return on External Investment	N/A	Negligible Relationship	27%	Low Relationship
Technical Insolvency	N/A	Negligible Relationship	29%	Low Relationship
Bankruptcy	98%	Very High Relationship	100%	Very High Relationship
Economic Condition	**Beaver (1966) predicted success rate (Debt to Assets)**	**Corresponding Association**	**Research Findings**	**Corresponding Association**
Economic Failure				
-- Expenses exceed Income	N/A	Negligible Relationship	27%	Low Relationship
-- Cost of Capital > Return on External Investment	N/A	Negligible Relationship	29%	Low Relationship
Technical Insolvency	N/A	Negligible Relationship	44%	Moderate Relationship
Bankruptcy	N/A	Negligible Relationship	100%	Very High Relationship

Economic Condition	Beaver (1966) predicted success rate (Sales to Assets)	Corresponding Association	Research Findings	Corresponding Association
Economic Failure				
-- Expenses exceed Income	N/A	Negligible Relationship	29%	Low Relationship
-- Cost of Capital > Return on External Investment	N/A	Negligible Relationship	32%	Low Relationship
Technical Insolvency	N/A	Negligible Relationship	21%	Low Relationship
Bankruptcy	N/A	Negligible Relationship	0%	Negligible Relationship
Economic Condition	**Beaver (1966) predicted success rate (Cashflow to Debt)**	**Corresponding Association**	**Research Findings**	**Corresponding Association**
Economic Failure				
-- Expenses exceed Income	N/A	Negligible Relationship	1%	Negligible Relationship
-- Cost of Capital > Return on External Investment	N/A	Negligible Relationship	0%	Negligible Relationship
Technical Insolvency	N/A	Negligible Relationship	0%	Negligible Relationship
Bankruptcy	N/A	Negligible Relationship	0%	Negligible Relationship
Economic Condition	**Gupta (1983) predicted success rate (EBITDA to Sales)**	**Corresponding Association**	**Research Findings**	**Corresponding Association**
Economic Failure				
-- Expenses exceed Income	N/A	Negligible Relationship	1%	Negligible Relationship
-- Cost of Capital > Return on External Investment	N/A	Negligible Relationship	1%	Negligible Relationship
Technical Insolvency	N/A	Negligible Relationship	0%	Negligible Relationship
Bankruptcy	N/A	Negligible Relationship	0%	Negligible Relationship
Economic Condition	**Gupta (1983) predicted success rate (Operating Cashflow to Sales)**	**Corresponding Association**	**Research Findings**	**Corresponding Association**
Economic Failure				
-- Expenses exceed Income	N/A	Negligible Relationship	0%	Negligible Relationship
-- Cost of Capital > Return on External Investment	N/A	Negligible Relationship	0%	Negligible Relationship
Technical Insolvency	N/A	Negligible Relationship	0%	Negligible Relationship
Bankruptcy	N/A	Negligible Relationship	0%	Negligible Relationship
Economic Condition	**Gupta (1983) predicted success rate (Net worth to Total Debt)**	**Corresponding Association**	**Research Findings**	**Corresponding Association**
Economic Failure				
-- Expenses exceed Income	N/A	Negligible Relationship	80%	High Relationship
-- Cost of Capital > Return on External Investment	N/A	Negligible Relationship	75%	High Relationship
Technical Insolvency	N/A	Negligible Relationship	81%	High Relationship
Bankruptcy	N/A	Negligible Relationship	40%	Moderate Relationship

Economic Condition	Gupta (1983) predicted success rate (All outside liabilities-to-tangible assets)	Corresponding Association	Research Findings	Corresponding Association
Economic Failure				
-- Expenses exceed Income	N/A	Negligible Relationship	82%	High Relationship
-- Cost of Capital > Return on External Investment	N/A	Negligible Relationship	84%	High Relationship
Technical Insolvency	N/A	Negligible Relationship	76%	High Relationship
Bankruptcy	N/A	Negligible Relationship	100%	Very High Relationship
Initial Warnings	**Schilit (2003) predicted success rate (Quality of Revenue)**	**Corresponding Association**	**Research Findings**	**Corresponding Association**
Initial Warnings of Financial Distress	N/A	Negligible Relationship	72%	High Relationship
Initial Warnings	**Schilit (2003) predicted success rate (Quality of Earnings)**	**Corresponding Association**	**Research Findings**	**Corresponding Association**
Initial Warnings of Financial Distress	N/A	Negligible Relationship	89%	High Relationship
Initial Warnings	**Sloan (1996) predicted success rate (Accrual Measurement)**	**Corresponding Association**	**Research Findings**	**Corresponding Association**
Initial Warnings of Financial Distress	N/A	Negligible Relationship	60%	Moderate Relationship
Initial Warnings	**Beneish (1999) predicted success rate (M-Score)**	**Corresponding Association**	**Research Findings**	**Corresponding Association**
Initial Warnings of Financial Distress	N/A	Negligible Relationship	58%	Moderate Relationship

Source: Compiled by author

REFERENCES

Agarwal, V., & Taffler, R. (2008). Comparing the performance of market-based and accounting-based bankruptcy prediction models. Journal of Banking & Finance, 32(8), 1541–1551.

Agarwal, V., & Taffler, R. J. (2007). Twenty-five years of the Taffler z-score model: Does it really have predictive ability? Accounting and Business Research, 37(4), 285–300. https://doi.org/10.1080/00014788.2007.9663313

Altman, E. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. The Journal of Finance, 23(4).

Altman, E. (2018). A fifty-year retrospective on credit risk models, the Altman z-score family of models and their applications to financial markets and managerial strategies. Journal of Credit Risk, 14(4), 1–34. https://doi.org/10.21314/JCR.2018.243

Altman, E. (2021). COVID-19 and the Credit Cycle: 2020 Revisited and 2021 Outlook. Journal of Credit Risk, 17(4).

Altman, E. I. (1984). The Success of Business Failure Prediction Models (An International Survey). In Journal of Banking and Finance (Vol. 8).

Altman, E. I. (2020). Covid-19 and the credit cycle. Journal of Credit Risk, 16(2).

Amoa-Gyarteng, K. (2014). Analyzing a Listed Firm in Ghana for Early Warning Signs of Bankruptcy and Financial Statement Fraud: An Empirical Investigation of AngloGold Ashanti. European Journal of Business and Management ISSN, 6(5). www.iiste.org

Arhin, I. ;, Nan, T., Hezkeal, K. ;, & Danso, E. (2020). Assessing predictive power and earnings manipulations : applied study on listed consumer goods and service companies in Ghana using 3 Z-Score models. http://hdl.handle.net/11159/7108

Aziz, M. A., & Dar, H. A. (2006). Predicting corporate bankruptcy: where we stand? Corporate Governance: The International Journal of Business in Society.

Balcaen, S., & Ooghe, H. (2004). Ernst & Young Chair of Growth Management, Vlerick Leuven Gent Management School.

Beaver, W. H. (1966). Financial Ratios As Predictors of Failure. In Empirical Research in Accounting: Selected Studies (Vol. 4).

Beaver, W. H., Correia, M., & McNichols, M. F. (2010). Financial statement analysis and the prediction of financial distress. Foundations and Trends in Accounting, 5(2), 99–173. https://doi.org/10.1561/1400000018

Beneish, M. D. (1999). The Detection of Earnings Manipulation.

Berrangé, N., & Willows, G. (2016). Predicting Financial Distress in South Africa. Academic Fora. www.academicfora.com

Bosse, D. A., & Phillips, R. A. (2016). Agency theory and bounded self-interest. Academy of Management Review, 41(2), 276–297. https://doi.org/10.5465/amr.2013.0420

Parliament of the Republic of South Africa, (2008).

Cybinski, P. (2001). Description, Explanation, Prediction-the Evolution of Bankruptcy Studies? Managerial Finance, 27(4), 29–44.

Dechow, P., Ge, W., Larson, C. R., & Sloan, R. G. (2011). Predicting Material Accounting Misstatements. Contemporary Accounting Research, 28(1), 17–82. https://doi.org/10.1111/j.1911-3846.2010.01041.x

Dechow, P., Khimich, N. V., & Sloan, R. G. (2012). The accrual anomaly. The handbook of equity market anomalies: Translating market inefficiencies into effective investment strategies.

Dechow, P., & Skinner, D. (2000). Earnings Management: Reconciling the Views of Accounting Academics, Practitioners, and Regulators. Accounting Horizons, 14.

Diri, M. el. (2017). Introduction to Earnings Management. Springer Books.

Garcia, J. (2022). Bankruptcy prediction using synthetic sampling. Machine Learning with Applications, 9, 100343. https://doi.org/10.1016/j.mlwa.2022.100343

Giannopoulos, G., Sardar, S. A., Salti, R., & Sykianakis, N. (2022). Analyzing Insolvency Prediction Models in the Period Before and After the Financial Crisis: A Case Study on the Example of US Firms. In International Journal of Finance, Insurance and Risk Management: Vol. XIII (Issue 3).

Gordon, M. J. (1971). Towards a Theory of Financial Distress. In Source: The Journal of Finance (Vol. 26, Issue 2).

Grice, J. S., & Dugan, M. T. (2001). The Limitations of Bankruptcy Prediction Models: Some Cautions for the Researcher Introduction and motivation. In Review of Quantitative Finance and Accounting (Vol. 17). Kluwer Academic Publishers.

Grice, J. S., & Dugan, M. T. (2003). Re-estimations of the Zmijewski and Ohlson bankruptcy prediction models. In Advances in Accounting (Vol. 20, pp. 77–93). JAI Press. https://doi.org/10.1016/S0882-6110(03)20004-3

Grove, H., & Basilico, E. (2011). Major financial reporting frauds of the 21st century: corporate governance and risk lessons learned. Journal of Forensic and Investigative Accounting, 3(2).

Grove, H., & Clouse, M. (2017). Forensic Accounting Procedures Applied to Valeant: Where Were the Gatekeepers? Journal of Forensic & Investigative Accounting, 9(2).

Grove, H., Clouse, M., & Malan, D. (2019). Applying due diligence guidelines and procedures to Steinhoff International Holdings: Could South Africa's largest accounting scandal have been avoided? Oil, Gas & Energy Quarterly, 70(1), 101–122.

Gupta, L. C. (1983). Financial ratios for monitoring corporate sickness : towards a more systematic approach. Delhi : Oxford University Press.

Guilford, J. P. (1956). The structure of intellect. Psychological bulletin, 53(4), 267.

Hantono. (2019). Predicting financial distress using Altman Score, Grover Score, Springate Score Zmijewski Score (Case Study on Consumer Goods Company). Accountability, 8(1), 1. https://doi.org/10.32400/ja.23354.8.1.2019.1-16

Hernandez Tinoco, M., & Wilson, N. (2013). Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables. International Review of Financial Analysis, 30, 394–419. https://doi.org/10.1016/j.irfa.2013.02.013

Hing, A., & Lau, L. (1987). A Five-State Financial Distress Prediction Model. Source: Journal of Accounting Research, 25(1), 127–138.

Hlahla, B. (2010). Assessing corporate financial distress in South Africa. University of the Witwatersrand.

Husein, F., & Pambekti, G. (2014). Precision of the models of Altman, Springate, Zmijewski, and Grover for predicting the financial distress. Journal of Economics, 17(3), 405–416. https://doi.org/10.14414/jebav.14.1703010

Husna, A., & Satria, I. (2019). Effects of Return on Asset, Debt to Asset Ratio, Current Ratio, Firm Size, and Dividend Payout Ratio on Firm Value. International Journal of Economics and Financial Issues, 9(5), 50–54. https://doi.org/10.32479/ijefi.8595

Parliament of the United Kingdom, (1986).

Islami, I. N., & Rio, W. (2018). Financial Ratio Analysis to Predict Financial Distress on Property and Real Estate Company listed in Indonesia Stock Exchange. In JAAF (Journal of Applied Accounting and Finance (Vol. 2, Issue 2).

Jensen, M. C., Meckling, W. H., Benston, G., Canes, M., Henderson, D., Leffler, K., Long, J., Smith, C., Thompson, R., Watts, R., & Zimmerman, J. (1976). Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure. In Journal of Financial Economics (Issue 4). Harvard University Press. http://hupress.harvard.edu/catalog/JENTHF.html

Jones, S., Johnstone, D., & Wilson, R. (2017). Predicting Corporate Bankruptcy: An Evaluation of Alternative Statistical Frameworks. Journal of Business Finance and Accounting, 44(1–2), 3–34. https://doi.org/10.1111/jbfa.12218

JSE Limited. (2023). https://www.jse.co.za/

Koornhof, C. (2000). Red flagging as an indicator of financial statement fraud: The perspective of investors and lenders. Meditari: Research Journal of the School of Accounting Sciences, 8, 69–93.

Kuliks, B. W. (2005). Agency theory, reasoning and culture at Enron: In search of a solution. Journal of Business Ethics, 59(4), 347–360. https://doi.org/10.1007/s10551-004-7308-2

Low, S.-W., Nor, F. M., & Yatim, P. (2001). Predicting corporate financial distress using the logit model: The case of Malaysia. Asian Academy of Management Journal, 6(1), 49–61.

Lukason, O., & Hoffman, R. C. (2014). Firm Bankruptcy Probability and Causes: An Integrated Study. International Journal of Business and Management, 9(11). https://doi.org/10.5539/ijbm.v9n11p80

Maccarthy, J. (2017). Using Altman Z-score and Beneish M-score Models to Detect Financial Fraud and Corporate Failure: A Case Study of Enron Corporation. International Journal of Finance and Accounting, 6(6), 159–166. https://doi.org/10.5923/j.ijfa.20170606.01

Manodamrongsat, P., Tongkong, S., & Boonyanet, W. (2020). Early Warning Signs of Problem Firms. International Journal of Innovation, Creativity and Change. Www.Ijicc.Net, 14(3). www.ijicc.net

Muller, G. H., Steyn-Bruwer, B. W., & Hamman, W. D. (2009). Predicting financial distress of companies listed on the JSE-A comparison of techniques. In J.Bus.Manage (Issue 1).

Naidoo, S. R., & du Toit, G. S. (2007). A predictive model of the states of financial health in South African businesses. Southern African Business Review, 11(3), 33–55.

Ngwenya, S. (2018). Assessing the State of Financial Distress of Listed Gold and Platinum Mining Companies in South Africa. Acta Universitatis Danubius., 14(4), 655–677.

Ofori, E., & Gvozdanovic, I. (2017). Exploring the financial performance of listed companies on the Ghana Stock Exchange and Johannesburg Stock Exchange using the Altman Z-score model. International Journal of Economics, Commerce and Management United Kingdom, 10. http://ijecm.co.uk/

Ohlson, J. A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. In Source: Journal of Accounting Research (Vol. 18, Issue 1).

Oz, I. O., & Simga-Mugan, C. (2018). Bankruptcy prediction models' generalizability: Evidence from emerging market economies. Advances in Accounting, 41, 114–125. https://doi.org/10.1016/j.adiac.2018.02.002

Ozili, P., & Arun, T. (2023). Spillover of COVID-19: impact on the Global Economy. In Managing Inflation and Supply Chain Disruptions in the Global Economy. IGI Global, 41–61.

Pham Vo Ninh, B., do Thanh, T., & Vo Hong, D. (2018). Financial distress and bankruptcy prediction: An appropriate model for listed firms in Vietnam. Economic Systems, 42(4), 616–624. https://doi.org/10.1016/j.ecosys.2018.05.002

Platt, H. D., & Platt, M. B. (2002). Predicting Corporate Financial Distress: Reflections on Choice-Based Sample Bias. Journal of Economics and Finance, 26(2).

Platt, H. D., & Platt, M. B. (2006). Understanding differences between financial distress and bankruptcy. Review of Applied Economics, 2(2), 141–157. http://ageconsearch.umn.edu

Pretorius, M. (2008). Critical variables of business failure: A review and classification framework. South African Journal of Economic and Management Sciences, 11(4), 408–430.

Richardson, S. A., Sloan, R. G., Soliman, M. T., & Tuna, I. (2005). Accrual reliability, earnings persistence and stock prices. Journal of Accounting and Economics, 39(3), 437–485. https://doi.org/10.1016/j.jacceco.2005.04.005

Salim, M. N., & Ismudjoko, D. (2021). An Analysis of Financial Distress Accuracy Models in Indonesia Coal Mining Industry: An Altman, Springate, Zmijewski, Ohlson and Grover Approaches. Journal of Economics, Finance and Accounting Studies (JEFAS), 3(2). https://doi.org/10.32996/jefas

Schilit, H. (2003). Financial Shenanigans, Center for Financial Research Analysis.

Schilit, H. M., & Perler, Jeremy. (2010). Financial shenanigans. McGraw-Hill.

Sloan, R. G. (1996). Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings? In Source: The Accounting Review (Vol. 71, Issue 3).

Sun, J., Li, H., Huang, Q. H., & He, K. Y. (2014). Predicting financial distress and corporate failure: A review from the state-of-the-art definitions, modeling, sampling, and featuring approaches. Knowledge-Based Systems, 57, 41–56. https://doi.org/10.1016/j.knosys.2013.12.006

Suresh, S. P. (2022). Predicting financial distress of Omani Tourism Companies during COVID-19 using Zmijewski model. https://www.researchgate.net/publication/360457849

Taffler, R. J. (1983). The Assessment of Company Solvency and Performance Using a Statistical Model. Accounting and Business Research, 13(52), 295–308. https://doi.org/10.1080/00014788.1983.9729767

Talab, H., Flayyih, H. H., & Ali, S. I. (2017). Role of Beneish M-score Model in Detecting of Earnings Management Practices: Empirical Study in Listed Banks of Iraqi Stock Exchange Accounting. International Journal of Applied Business and Economic Research. www.serialsjournals.com

Tavlin, E. M., Moncarz, E. S., Dumont, D., Tavlin, E. M. ;, & Moncarz, E. S. ; (1989). Financial Failure In the Hospitality Industry. In Hospitality Review (Vol. 7, Issue 1). https://digitalcommons.fiu.edu/hospitalityreviewAvailableat:https://digitalcommons.fiu.edu/hospitalityreview/vol7/iss1/7

The British Accounting Review. (2022). Special Issue: New Perspectives on Financial Distress and Corporate Risk Management. Elsevier. https://www.journals.elsevier.com/the-british-accounting-review/call-for-papers/special-issue-new-perspectives-on-financial-distress-and-corporate-risk-management

King IV Report on Corporate Governance for South Africa, (2016). http://www.iodsa.co.za/?page=KingIVEndorsers

University of Cape Town. (2022). Finance and Tax Library Guide: Databases. https://libguides.lib.uct.ac.za/c.php?g=182278&p=1201503

WHO. (2022). Coronavirus disease (COVID-19). World Health Organisation. https://www.who.int/emergencies/diseases/novel-coronavirus-2019/question-and-answers-hub/q-a-detail/coronavirus-disease-covid-19

Wilcox, J. W. (1973). A prediction of business failure using accounting data. Journal of Accounting Research, 163–179.

Zmijewski, M. E. (1984). Methodological Issues Related to the Estimation of Financial Distress Prediction Models. In Studies on Current Econometric Issues in Accounting Research (Vol. 22).