Altman Z-Score Models and predicting financial distress: Empirical study of delisted mining stocks on the Johannesburg Stock Exchange.

By

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Abstract

The aim of the study is to measure the predictive prowess of Altman's Z-score models when used to predict financial health and subsequent delisting of mining and metal companies listed on the Johannesburg Stock Exchange (JSE) from 1994 till 2021. The study applied the Altman's Z-score model as well as the Z double prime model to the financials of JSE listed mining companies to measure the predicted status of companies in a year, two years', and three years' time against the actual listing status of each company in the sample over the corresponding time horizons. Key findings indicate that both models reliably predict delisting of mining companies on the JSE when the horizon is only a year in the future. Additional analysis shows that individual factors of the model may not necessarily be a proxy for the Z-scores and that the entire model needs to be considered in its entirety as a measure of financial health.

Key words: Mining, Altman Z-Score models, Financial health, Financial distress, Delisting, Johannesburg Stock Exchange.

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Abbreviations

BE	Book Equity
CA	Current Assets
CL	Current Liabilities
EBIT	Earnings before interest and tax
EMS	Emerging Market Score
GDP	Gross Domestic Product
IFRS	International Financial Reporting Standards
JSE	Johannesburg Stock Exchange
LTD	Long-Term Debt
MVE	Market Value Equity
RE	Retained Earnings
SENS	Stock Exchange News Service
TA	Total Assets
TL	Total Liabilities

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1. Chapter 1: Introduction and background

Mathematical modelling along with the availability of large data pools have birthed statistical techniques that result in models capable of predicting the possibility of future events based on input variables whose relationship with specific outcomes has been measured over time. In as much as the past does not always represent the future, one can use such models to at least predict the chance of future events or outcomes that are highly probable in the absence of any unforeseen factors such as a financial crisis or global pandemic. The Altman Z-score uses discriminant analysis and company financials to predict financial distress and has been widely used for over 50 years (Altman, 2018). This study aims to examine the Z-score model as a measure to predict financial distress that leads firms to bankruptcy and subsequent delisting from the Johannesburg Stock Exchange (JSE).

The failure to meet financial obligations may not be the only motivation to delist. Firms could delist due to the benefits of delisting outweighing those of remaining listed. This generally happens when the costs of listing and adhering to the JSE requirements become burdensome while the benefits of access to a public share capital financing platform diminish. Such scenarios may lead to mergers, acquisitions or simply delisting to go private or cease operations altogether. The focus of this study is to examine mining firms that delist due to financial distress and cease to exist entirely using Altman's models.

The study will analyse the delisting of mining stocks since 1994 with a focus on mining as a sector and the changes to the JSE because of metal and mining companies delisting. An analysis of the different Z-score financial distress models will be conducted to determine the model with the most accurate prediction of financial distress and the subsequent delisting of mining stocks on the JSE. An analysis of the distress models will also be conducted in a bid to explore possible factors that could play a significant role in affecting the predictive prowess of the Z-score models for the South African mining context.

A brief look into the delisting of JSE stocks will also be conducted as a means of setting the background for the study. This is to identify whether there has indeed been a delisting trend due to financial distress of companies or other factors such as mergers and acquisitions. The motivations for delisting will be highlighted before zoning in on the mining stocks whose delisting were because of financial distress.

1.1 SA Mining Sector and origins of Johannesburg Stock Exchange

The mining sector in South Africa has contributed largely to the economic development of the country. Apart from the mineral resources that boost exports, the mining sector has also played a key role in the development of equity markets. In this section, a brief background of mining in South Africa will be conducted to contextualise the sector and its contribution to the JSE and subsequently this study.

According to Minerals Council of South Africa, the first diamond named the Eureka, was discovered near Hopetown in what is now known as the Northern Cape province of South Africa in 1867. Since that discovery and the diamond rush that followed, South Africa became the major producer of diamonds overtaking Brazil and India and the company formed by Cecil John Rhodes in 1888 has continued to lead the global diamond market. Even though there has been over a 100 years of mining diamonds, the deposits in the country are estimated to yield the resource for the next 25 to 50 years (Minerals Council of South Africa, 2019).

The discovery of gold in the mid to late 1880's in the Witswatersrand basin gave rise to rapid industrialisation in the region creating a shift in focus from agrarian activities on farms in the area to mining in that region. Mining created opportunities for migrant labour and economic development as establishment of housing, food supply, health care facilities and transport networks were essential to the mining projects. (Minerals Council of South Africa, 2019). Coal and other metals that flourished under this industrialisation of the country along with the gold rush led to the establishment of the JSE in 1887 by Benjamin Wollan (JSE, 2021). The stock exchange would provide much needed funding for mining companies to meet ever increasing global demand at the time. According to the JSE, DRD Gold Ltd which listed in 1895 is the oldest listing to date, indicative of the strong mining roots of the equity markets in South Africa.

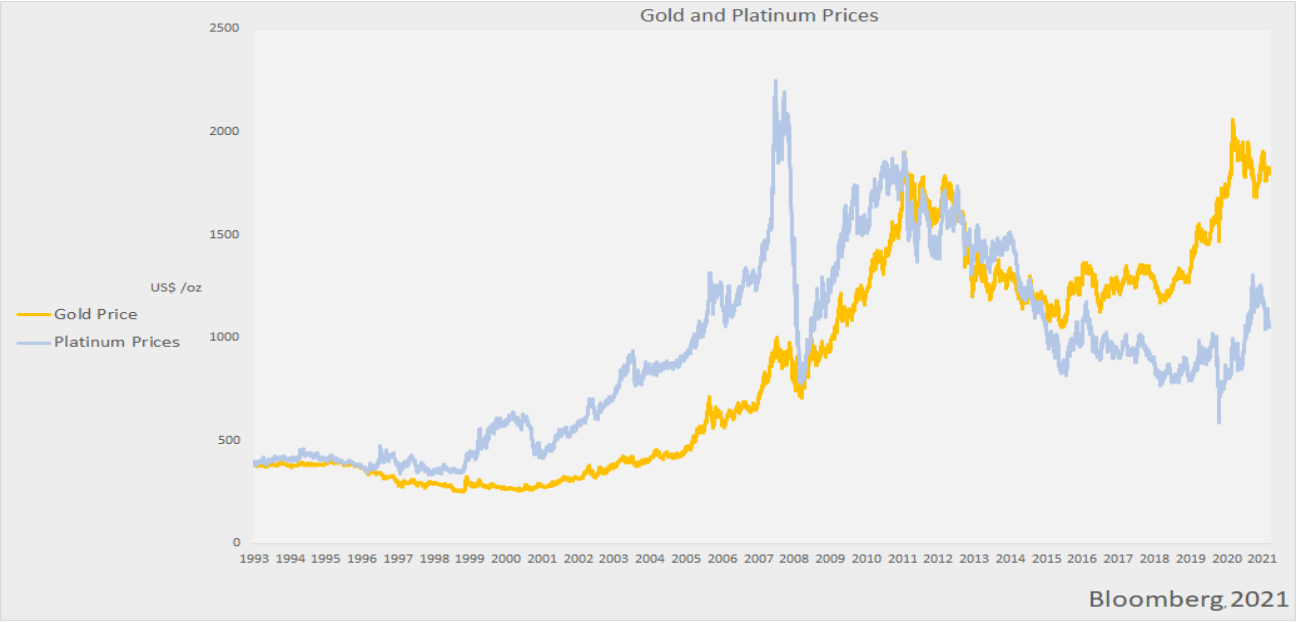
Research conducted in the post-apartheid era revealed that mining companies have made use of equity markets to fund their speculative moves, offset the reduction in profits from mining activities through profit from financial assets and accumulate highly liquid assets so as to cover operational losses for new and growing firms yet to establish sound productive operations (Karwowski, 2015). Established firms that had been operating for considerable periods of time were found to be seeking funds from equity markets in a bid to extend the commercial viability of the existing mines and managing the exhaustion of mineral resources. Exploration mining firms on the other hand have used equity markets to counter the lack of regular cash flows as

well as mitigate risks of the ever-changing global mineral prices. The explorative model is highly dependent on speculation of future mineral prices (Karwowski, 2015). Uncertainty regarding the ability of these firms to start having positive cash flows from operations, while having to cover myriads of operational expenses, necessitates for keeping of large sums of cash. Karwowski found that some mining firms went beyond the precautionary reasons for keeping cash to the investment of financial assets using the excess cash. These mining companies used the equity markets as financial investors would to generate income that would offset the dwindling returns from actual mining operations.

1.2 Commodity Prices and Demand

According to data retrieved from Bloomberg on gold and platinum prices, there has been a rally of gold and platinum prices for the last 5 years. The prices of these commodities previously peaked around the time of the global financial crisis in 2007-2008 and according to the data seems to be heading toward the peak once again.

Figure 1: Gold and Platinum Prices 1994 to 2021



Commodities such as gold seem to be a haven for investors during times of crisis. During the global financial crisis (GFC) as well as the global pandemic, Covid-19, research conducted showed that the highest mean returns with less volatility on average during the peak periods of the turmoil in the financial markets of both GFC and Covid-19, were achieved by the commodity index citing gold as the biggest contributor (Kinateder, et al., 2021). In general, mining companies, given the rising commodity prices, have managed to weather the storm in

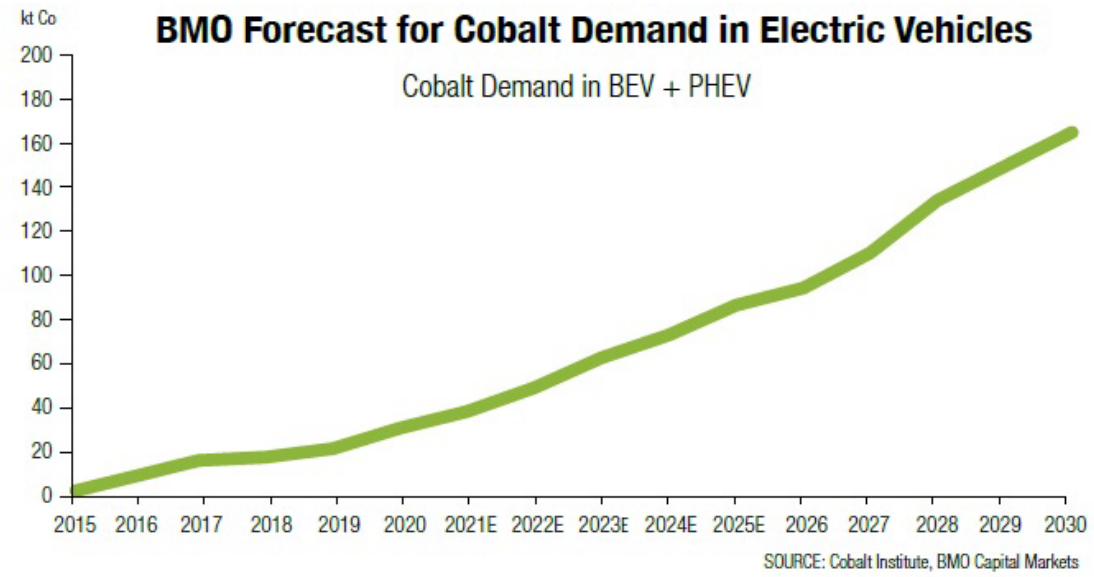
times of crises making the sector a tried and proven investment opportunity (Kinateder, et al., 2021).

Gold was also seen to be a haven in recent times during the Chinese financial crisis that started in June 2015 and ended at the end of February the following year (Ming, et al., 2020). While the various sectors of the stock markets fell by more than a third in value, gold futures only lost 2.4%. This was also an indication that gold was a haven in times of financial market uncertainly.

The realisation of a need to curb the effects of climate change also has a part to play in the way mining as an industry is viewed by investors. Ed Stoddard, a contributor to the Mining Yearbook, points out this fast-approaching reality that was thrust into contemplation by the Australian fires in early 2021, brings new challenges as well as opportunities for mining globally (Mining MX, 2021). The motor industry for example will potentially see an increase in demand of copper as more car manufacturers switch from petroleum to battery power for their new cars.

An increase in demand for copper for the battery components will also be accompanied by an increase in demand for other metals such as platinum that are used in the infrastructure for electric and fuel cell vehicle development. While copper is good for developing fuel cells, scientific innovation has found that cobalt can be a good substitute. Research by BMO Capital predicts that there would be an increase for the demand in Cobalt as shown in Figure 2 below:

Figure 2: Forecast of Demand for Cobalt

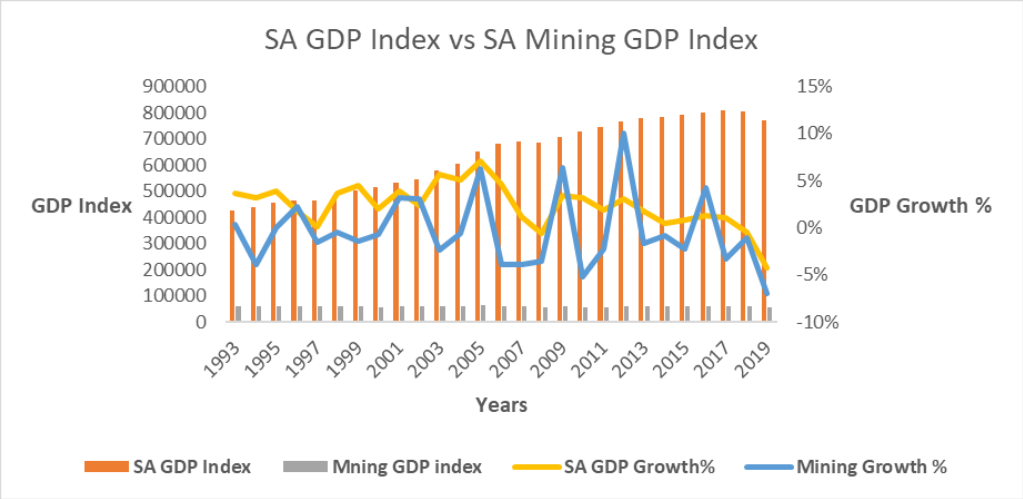


Research at the Florida International University conducted by Dr. Bilal El-Zahab has found that platinum group metals, specifically palladium and platinum are key in improving the efficiency of lithium oxygen and lithium sulphur battery technology to improve range for electric vehicles as well as the charging speeds (Evans, 2020). Although South Africa is not a major producer of cobalt, the demand for palladium and platinum could soar leading to even higher levels of exploration and mining and ever-increasing prices for the commodity.

The increase in demand for these minerals, the haven attributes of gold as well as the rallying of prices may seem to be a perfect ground for the mushrooming of new entrants into mining. However, the exploration and start-up costs for new entrants make mining a complex and at times risky venture. While new mining exploration companies have been expected to mushroom during the commodity boom, there have been no major new entrants into mining (McLachlan, 2021). McLachlan points out that unlike other sectors where a boom would lead to new companies entering the industry and listing, mining tends to move much slower as exploration by new entrants takes a long time before benefits are monetized and when potential is realized, bigger conglomerates usually swoop in to buy these firms before they can list. However, the steadfast nature of mining firms as investment opportunities during periods of crises makes the understanding of the survival of existing, listed mining companies important for national GDP, employment and resourcing secondary industries that contribute to the economy.

The South African economy has shifted from having mining as the major contributor to GDP. The following graph shows the dwindling contribution to GDP growth that mining has made to the South African economy especially in the post-apartheid era. One could attribute this to the growth of other sectors in the economy such as financial services and government (StatSA, 2017). According to GDP index data from Bloomberg, mining has clearly had negative real growth in the contribution to national GDP in recent years. This trend is below the overall growth rate in GDP for South Africa. This shows the diminishing contribution to GDP from mining in recent times.

Figure 3 : SA GDP index vs SA Mining GDP Index



Data Source: Bloomberg.

1.3 Problem Statement

In a fast-paced economic environment, it is important for stakeholders to be fully aware of the financial position or health of a business whose continued survival would be of great interest to them. Whether it be shareholders having an interest in future returns through capital growth and/or dividends, or suppliers and employees of the firm whose livelihoods are paramount, the survival of the firm is crucial. Creditors also have a special interest in the firm as its ability to meet financial obligations directly impacts their operations.

An empirical study of the delisting of metal and mining stocks will be conducted to measure the efficacy of employing Altman's Z-score as well as the Z Double Prime models in predicting financial distress in the South African mining context. As the delisting trend of companies on the JSE in various sectors continues, it would be prudent to determine which of the Altman models more accurately predicts financial distress. This farsighted approach would allow stakeholders to plan accordingly whether it be a future with a distressed firm or seeking remedies to counter the impending financial distress as predicted by the models. The study will also strive to examine the financial ratios used by the two models to explain the Z-scores of the outliers. The use of financial ratios internally gives an indication of financial conditions of the different firms over time, as well as how they compare against peer firms in the sector. Ratios make otherwise incomparable firms due to specific business, age, market capitalization and time listed on a stock exchange, comparable.

The study will establish the model with the highest accuracy in predicting bankruptcy and subsequent de-listing thereof. The ratios with greatest significance to financial distress will also be determined for the mining sector in the South African post-apartheid context. An analysis of the time horizon from point of examination to the eventual delisting will be conducted along with the survival age of listed mining firms. The study will also reflect on the changes to the mining sector in the period as well as the impact to the JSE. The outcomes of the study should contribute to the development of early warning signals for listed mining firms in South Africa. A quantitative method will be employed by analysing financial data of mining stocks listed on the JSE from 1994 to 2021. A discriminant analysis approach using Altman's Z-score and the double prime models will be used to separate firms in good health and those with predicted financial distress and then compared with empirical evidence to determine accuracy of the models.

1.4 Research question

The study aims to investigate the following research question: Can Altman's Z-score and Z' score models accurately predict the financial distress and subsequent delisting of mining companies listed on the Johannesburg Stock Exchange (JSE) at a statistically significant level? If so, which of the two models has greater predictive ability and over what time horizon is the prediction most accurate? By examining the performance of both models in predicting financial distress and delisting, and identifying the most effective time horizon, this study aims to contribute to the understanding of the effectiveness of Altman's Z-score and Z' score models in predicting financial distress and delisting of mining companies on the JSE.

1.5 Overview

This chapter will be followed by the theoretical framework that underpins the study. A background of mining in South Africa will be conducted that highlights the origins and significance to the JSE. The foundational knowledge used in the study will include existing research conducted around the globe in various sectors that used similar techniques to predict financial distress and forecast delisting risk. The various statistical methods would also be discussed to shed light on the advantages and disadvantages of the various techniques. The

Altman models will be highlighted in that regard as the focal point of the study given their extensive use over time.

The research methodology chapter that follows will discuss the empirical research technique used in the study. The data for the study comprises of JSE listed mining firms from 1994 to 2021 sourced from JSE as well as financial data sourced from Bloomberg. The chapter will highlight potential areas that may need further investigation as well as limitations in the study. That chapter will be followed by the analysis of the study which will provide the findings and results. Further areas of potential investigation will also be highlighted. The final chapter will be the conclusion of the study and potential areas of application as well as further research.

2. Chapter 2: Literature Review

2.1 Introduction

Predicting financial distress or bankruptcy that could cause delisting from a stock exchange is vital for all stakeholders of a business. It is important to note that delisting from a stock exchange and bankruptcy that leads to complete shutdown of operations are not always the same event. It is possible to delist from a stock exchange but maintain operations. This study aims to explore the scenarios in which financial distress has led to delisting where companies have ceased operations. The models used to predict financial distress will transitively be used to forecast delisting of firms that cease operations. The empirical study will examine the efficacy of the Altman Z-score models to predict delisting of mining firms on the JSE in the post-apartheid era.

This chapter will firstly delve into the existing research on the mining sector and the emergence of equity markets in South Africa. A discussion using available literature on financial distress, bankruptcy and delisting across the globe will follow. As the background of the study has been contextualised in the previous chapter, this chapter will discuss the research on predicting financial distress and bankruptcy. This section will include the various types of models used. The chapter will end of with a focus on the Altman models and the motivation for their use in this study.

2.2 Mining and equity market

The JSE has seen a decline in mining listings and Table 3 shows the current JSE listing weights of the mining industry as a percentage of market capitalization as well as a percentage of total number of companies in the post-apartheid era as of 2021. Mining, the once dominant sector on the exchange, has seen so many miners delisting for various reasons which this study aims to highlight.

The table below shows the current number of companies listed on the JSE grouped into the 10 industries according to the Industry Classification Benchmark (ICB) way of grouping companies based on their operations (ListCorp, 2021). According to their website, the Basic Materials sector, which would encompass the listed mining companies, makes up about 16% of the total number of listed companies and about 17% of the equity market based on market

capitalization. The mining sector comes second only to Consumer Goods sector which has 24% based on market capitalization despite having the third highest number of listed companies at 54 after the Financials sector with 124 companies and Industrials with 59 companies.

Table 1: JSE Sectors

JSE Sectors	Companies	% of Total	Market Cap	% of Market Cap
Oil and Gas	4	1,16%	222,9	7,91%
Basic Materials	54	15,65%	477,04	16,94%
Industrials	59	17,10%	340,43	12,09%
Consumer Goods	20	5,80%	680,86	24,17%
Health Care	10	2,90%	41,55	1,48%
Consumer Services	47	13,62%	214,21	7,60%
Telecommunications	6	1,74%	50,55	1,79%
Utilities	0	0,00%	0	0,00%
Financials	124	35,94%	332,78	11,81%
Technology	21	6,09%	456,41	16,20%
	345		2816,73	

Source: ListCorp, 2021

The 54 basic materials companies can be further broken down into 6 Chemicals, 6 Industrial and Mining, 39 Mining and 3 Forestry and Paper companies. It should be noted that as of August 2021, three mining companies have delisted namely Rockwell Diamonds Incorporated, African Oxygen Limited, and Unicorn Capital Partners Limited (ListCorp, 2021). Middle East Diamond Resources has not been delisted but was suspended from trading on 6 December 2016 (Sharedata, 2021).

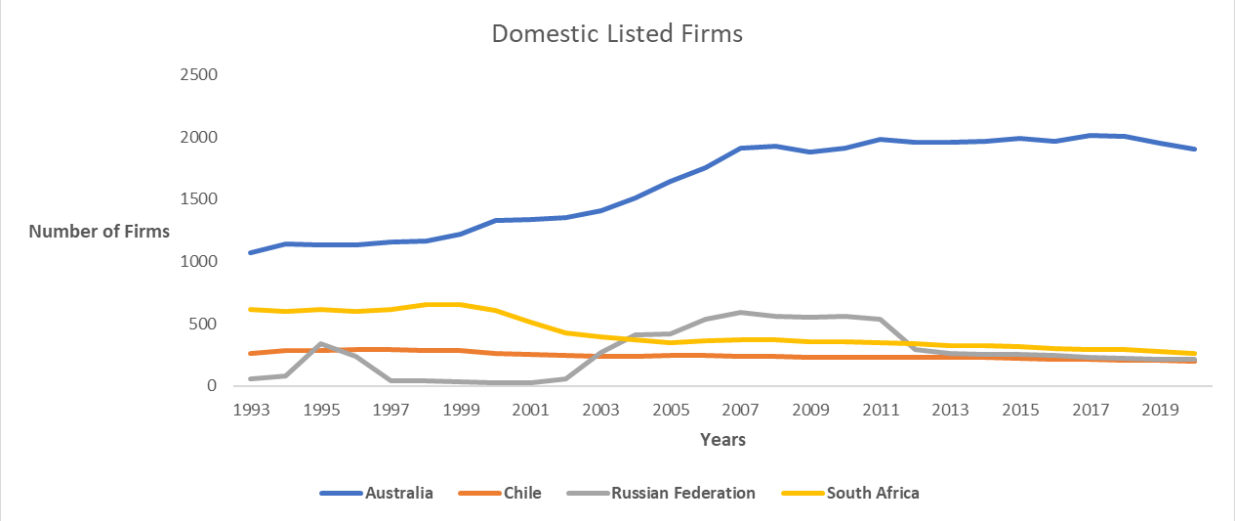
2.3 Delisting of companies

An exploration of World Bank data of some of the major mining countries' domestic listings, namely Australia, Russia, Chile, and South Africa, shows that the number of domestic companies listed on the countries' exchanges have been slowly dwindling in the last 10 years (World Bank, 2022). The same data shows that while there has been a decline in the number of listed companies in the last 10 years, the overall picture from 1994 is slightly different. Australia rose from 1144 to 1902 domestic listed companies and Russia went from 79 to 213 domestic listed companies. However, Chile and South Africa faced declines over the same

period from 1994 to 2020 of 281 to 194 and 600 to 264 respectively according to the data from the World Bank.

As the graph below will show, there seems to be a trend of stock market terminations in the recent past and South Africa has proportionally had the highest decline of the four countries. However, the World Bank data does not break down the listed number of companies into sectors but the inclusion of this trend for all companies portrays a universal trend amongst these mining countries whose equity markets were borne from mining especially in the case of South Africa.

Figure 4: Domestic Listed Companies in Australia, Chile, Russia and South Africa.



Data Source: The World Bank.

There has been a decline in the number of listed mining companies in the post-apartheid era. As at the end of 1994, just over 600 companies were listed on the JSE with 118 of those, about 20%, being mining companies (Miller, 2021). In 2010, there were about 400 listed companies, of which 69 were mining, meaning 17% of the JSE listings were mining companies. This was an almost 3% decrease in the weighting of mining to all other sectors despite a 33% decrease in listed companies from 600 to 400 companies overall. As of 2021, mining companies make up 11% of the JSE listed companies, representing a 6% decline from 2010. Listed companies dropped from about 400 listed in 2010 to 330 in 2021. That is a 17.5% decrease in listings on the JSE for that period. Mining has thus faced a more than proportionate decrease in listings

compared to the nominal decrease of all listings on the JSE given that the percentage of mining listings is declining from 20% in 1994 to 11% in 2021.

According to a report by TimBukOne, the JSE lost 257 listings between 2001 and 2020 with the major factors contributing to the waning of listings including the poor state of the South African economy, mergers and acquisitions, poor performance of the equity market and the lack of growth of small private companies that necessitates a need to list for expansion (Business Insider SA, 2020). The report also highlighted that the all-share gains that were experienced in 2019 were largely due to the mining sector giving an example of Impala Platinum that had gained 290% in that year, once again showing the haven nature of the sector in poor economic times.

Most companies that delist from the JSE are voluntary or because of mergers and acquisitions (Lazanakis, 2020). The voluntary actions of delisting may arise because of high costs of listing and complying with regulatory requirements, outweighing the benefits of access to the stock market. Small and mid-cap shares have had the most voluntary terminations, and this has been attributed to the high cost of listing, reporting standards and other regulatory requirements while having relatively low liquidity as compared to the larger and more established companies. Poor analyst coverage is also a contributing factor to small and mid-cap shares as that undervalues shares and results in low market capitalisation (Bergman, 2019). According to Bergman, the rationale for delisting stems from investors' appetite for large cap stocks that makes it challenging for small cap stocks to raise capital and improve their liquidity. Some of these small cap companies delist in a bid to seek better opportunities to address their BEE ownership echelons in an unlisted environment that is less burdensome for compliance.

2.4 Financial distress, bankruptcy, and delisting

In financial literature, the terms financial distress and bankruptcy have been used to describe corporate failure or the health status of failing companies that may lead to suspension or delisting from a stock exchange. There has been a modification in the understanding of corporate failure away from the traditional legal description to a more all-inclusive economic and accounting definition (Manzaneque, et al., 2016). The lack of sufficient liquidity, liquid capital and equity as well as the default of debt can be seen as early warning signs of financial distress (Carmichael, 1978).

While the term bankruptcy is widely used to indicate a state of financial distress in which legal remedies such as liquidation of assets are put in motion by courts to recover what is owed to creditors, insolvency, which is a term used more in the UK usually referring to firms, is regarded as the stage of financial distress when a company or individual can no longer meet their debt obligations as they become due (Rees, 1995). According to the Bank of England, some of the possible causes of insolvency may include deteriorating profits, inability to eradicate actual or potential loss-making business actions, poor management of working capital and increasing dependence on short term borrowing (Bank of England, 1980).

Financial statement data on companies as well as financial market data, reflecting share price performance, are sources of determining the financial health of a company. However, it is important to note that the period between the availability of financial statements and the assessment of financial health can become problematic when assessing the current financial distress state of the company. While share price data from financial markets has less of a lag compared to financial statements, there are macroeconomic factors that can influence the performance of a company that may need to be considered when gauging the level of financial distress.

2.5 Predicting financial distress

The practice of developing prediction models for financial distress stems from the need to create opportunities for corrective action to address probable failure. An early warning system of failure stimulates preventative measures that seek to curb further losses for all parties (Van Frederikslust, 1978). External factors such as recessions, crises like the Covid 19 pandemic, supply chain deficiencies such as those arising from the Russian invasion of Ukraine and general changes in consumer tastes amongst other factors, may be significant contributors to a firm's failure. However, there are internal factors such as poor management that lead to misallocation of resources that can be addressed to counter failure or reduce losses in the event of apparent failure. These measures could include a shift in policies on financial structure, procurement practices, expansion decisions, product line up etc…to reduce the trajectory towards failure or could be in the form of hastening the shutting down of loss making aspects of the firm or liquidation to curtail the duration in which the firm is distressed (Van Frederikslust, 1978).

Statistical techniques have been used to identify indicators from accounting information that signal failure by examining financial ratios of both failed and surviving companies. The general

approaches used are univariate analysis, multiple discriminant analysis, logit analysis, probit analysis as well as the more recent methods of recursive partitioning and neural networks (Zhou & Elhag, 2007). The following section will give an overview of the various financial distress prediction models. This section will also highlight the reasons why the multiple discriminant analysis model by Altman will be used for this study as well as why the others were not considered for this study.

2.6 Univariate analysis

Beaver in 1966 employed a ratio analysis method to predict financial distress and though he initially started off with the use of 30 ratios, his findings were that cash flow to total debt was the most important indicator for financial distress (Beaver, 1966). The 30 ratios were categorized into six groups namely, cash-flow ratios, net-income ratios, debt to total asset ratios, liquid asset to total asset ratios, liquid asset to current debt ratios and turnover ratios, and it was found that the cash-flow ratios gave a more accurate prediction of failure.

The limitations to the ratio analysis using a single attribute, in this case cash-flow is that not all potential factors are considered simultaneously. Beaver also highlights limitations in the classification of outcomes as the dichotomous choice fails to consider the magnitude of distance to or away from the cut-off point set for classification. Lastly, the cut-off points set using the sample are not always applicable for the entire population.

2.7 Multiple discriminant analysis

The introduction of a multi-pronged ratio analysis technique, unlike the univariate technique by Beaver, was aimed at improving the predictive accuracy by applying an analysis based on multiple ratios simultaneously. This statistical approach makes use of regression analysis to come up with a discriminant function whose outcomes are used for dichotomous classification (Irshad, et al., 2018).

The result of the function is termed a Z-score with the following function:

Equation 1: $\mathbf{Z = a + b_1(X_1) + b_2(X_2) + \ldots\ldots b_n(X_n)}$

where ***a*** is a constant, $\boldsymbol{b_1}$ to $\boldsymbol{b_n}$ are coefficients used for analysis and **X1** to **Xn** are independent variables.

During the mid to late 1960s, during a period experiencing diminishing applicability of traditional ratio analysis, Altman sought to bridge a gap between financial information found in ratio analysis and the statistical approach of multivariate discriminate analysis to develop a more accurate financial distress prediction technique (Altman, 1968). The model that became known as the Altman Z model made use of five variables that measured the profitability, liquidity, solvency, sales activity and financial leverage of 66 US listed manufacturing firms. Altman's Z-model classified firms into those that were financially distressed and those that were healthy with a 90% and 86% accuracy for a 1 year and 2-year horizon respectively. Accuracy in predicting longer time horizons diminished with time (Altman, 1968).

Altman's Z-score model equation is as follows:

Equation 2: $$\mathbf{Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5}$$

Where:

X_1 is working capital/total assets

X_2 is retained earnings/total assets

X_3 is earnings before interest and taxes/total assets

X_4 is market value of equity/book value of total liabilities

X_5 is sales/total assets

The cut off scores for the Z model classified firms with a score of 3 and above as healthy, while those with a score less than 1.8 as financially distressed. A score between 1.8 and 3 would thus be regarded as heading for bankruptcy or potentially facing financial distress in the near future.

The original Z model was used to predict bankruptcies for US manufacturing firms so with time, an adaptation was needed for the prediction of private non-manufacturing firms. An iteration of the model was thus developed to apply to unlisted companies without simply substituting the book value of equity with market value for X_4 in the equation (Altman, 2013).

The revised Z-score model was instead redeveloped to produce the following equation:

Equation 3: $\mathbf{Z' = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5}$

with X_4 changed from market value of equity/book value of total liabilities to book value of equity/book value of total liabilities as these companies are not publicly traded and determining a market value would be complex. The cut off points for this revised Z-score would now require healthy firms to have a score of above 2.90 while financially distressed firms would have a score of below 1.23.

A second revision, dubbed the Z double prime model, was adapted to apply to non-manufacturing and particularly non-US firms such as firms from emerging markets. This adaptation removed the industry effect exhibited by the asset turnover of firms. The fifth term in the equation X_5 (sales/total assets) is removed and the coefficients of the remaining ratios were revised yielding the following equation (Altman, 2013):

Equation 4: $\mathbf{Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4}$

With regards to the Z double prime, firms with a score above 2.6 are considered healthy while those with a score below 1.1 are likely to become financially distressed. Given the various ways in which companies finance their assets, the model may incorporate the use of a constant term of 3.25 to standardize the scores (Altman, 2013).

2.8 Other estimation techniques: Logit, Probit, and Neural networks.

In 1980, Ohlson developed the logit model that would predict the probability of financial distress for a company (Ohlson, 1980). This was a non-linear model that would measure the probability of failure using logit regression. Multiple discriminant analysis assumes normal distribution of input variables, so logit regression makes use of cumulative distribution function using logistic distribution as a means of addressing this issue. The model initially incorporated the use of nine variables from financial statements but determined that four were statistically meaningful in finding the probability of failure. These four were size, total liabilities divided by total assets, net income divided by total assets and working capital divided by total assets (Ohlson, 1980). The outcome was a likelihood of failure between 0 and 1 representing the chance of failure. Ohlson used 105 industrial companies that had been listed but eventually went bankrupt between 1970 and 1976. The model was able to predict 88% of the bankrupt companies using a 1-year prediction time horizon. The logit analysis model was also used as a

early warning tool for bank failure before the 1980's (Martin, 1977). Martin used the model to determine a dependent variable which would be a 1 for failed banks and 0 for those that did not fail using multiple independent variables, or what he termed explanatory variables. Martin's study examined the failure of commercial banks in the United States of America from 1970 to 1976. The study observed approximately 5700 banks and made use of 25 financial ratios that were grouped into asset risk ratios, liquidity ratios, capital adequacy ratios and earnings ratios using publicly available financial information of the banks (Martin, 1977).

The origins of probit analysis were not necessarily related to predicting financial distress but rather to developing an effective solution for the use of pesticides to combat a grape farming insect problem (Bliss, 1934). Zmijewski used the probit analysis technique as a financial distress prediction tool (Zmijewski, 1984). He used a sample of 96 distressed companies as well as 3880 healthy companies between 1972 and 1978. The key ratios used were net income divided by total assets, total liabilities divided by total assets and current assets divided by current liabilities, continuing with the theme of measuring profitability, leverage, and liquidity. However, while the probit and logit models are very similar, the logit analysis model makes use of a cumulative distribution function for a logistic distribution, the probit model makes use of a standardized normal distribution leading to marginally different outcomes between the two models (Kliestik, et al., 2015).

2.9 Use of Altman Z models.

Despite the proliferation of other prediction models and the relative simplicity of Altman's models, the Z-score and Z"-score models have proven to be accurate when classifying distressed and non-distressed firms (Boda & Uradnicek, 2016). Boda and Uradnicek applied the Altman's model to predict financial distress of companies in Slovakia. The original Altman model was developed in 1968 for US companies but they proved the predictive merits of applying the model even when used for Slovak companies decades later. This means that the application of the Z-score models transcends geography and time, making its use is valid.

Some key observations from Boda and Uradnicek were that the Z-score model attempts to cover all types of ratios to fully capture the financial activity of a company. Liquidity, profitability, leverage, and activity of the company are captured in the components of the Z and Z"-score calculation. The aspects of a company that cause bankruptcy such as lack of profitability, failure to meet short-term and long-term financial obligations as well as the value of equity are also measured in the model thereby making it useful in the context of defining

and subsequently predicting financial distress. The portability of the model as well as its ease of use explain the widespread adoption of the model globally.

Ravi Kumar and Ravi also allude to the merits of using Altman's derived models referred to as Zeta models, for the prediction of bankruptcy and failure (Ravi Kumar & Ravi, 2007). Their review points out that the models had a 96% accuracy in classifying the status of companies within a year horizon and about 70% for a 5-year horizon (Altman, et al., 1977).

2.10 Conclusion

This chapter has outlined the origins of the JSE because of the advent of mining in South Africa. The emergence of equity markets and the contribution to the South African economy was highlighted along with the impact and growth of the JSE over time as well as the various financial crises that mining has weathered and showed its haven properties during times of uncertainty. The chapter also defined bankruptcy and financial distress and delved into the motivations of listing and those of delisting from a stock exchange. The importance of early warning systems for financial distress were discussed along with the various prediction techniques used namely, univariate analysis, multiple discriminant analysis as well as other estimation techniques such as logit and probit analysis and the multifaceted technique of artificial neural networks.

3. Chapter 3: Methodology

3.1 Introduction

This chapter builds its foundations on the literature discussed in the previous chapter. The research methodology used to measure the predicting prowess of Altman's models for South African mining delistings is outlined in this chapter. The chapter will go on to outline the method of analysis as well as the data sources. This will include the sampling strategy as well as the analysis of data used in the study.

3.2 Sample and data

The data of all listed firms since 1994 was obtained from the JSE helpdesk. This data included all companies that listed between 1994 and 2021 as well as those that were terminated. All mining firms from this data, excluding Oil and Gas, were then identified before the financial data was collected. The financial data was extracted from Bloomberg using the virtual terminal. This data was made up of the income statement, balance sheet and stock value information that included share prices over the period listed, number of shares outstanding and ultimately the market capitalization of each company. No adjustments were made to the financial statements retrieved from the Bloomberg terminal despite the various IFRS changes such as IFRS 6 that dealt with exploration and evaluation of mineral resources amongst others. The changes in reporting of exploration costs would uniformly affect mining companies, which are the core of this study, therefore these changes would not make a material difference in the cross-sectional ratio analysis across the mining industry. Adjustments would need to have been made if the study was looking beyond mining companies for a uniform treatment of capitalized expenses.

A deep dive into news archives was also conducted to get insights into the individual corporate actions especially for those that had delisted, merged or had been acquired and no longer had Bloomberg or JSE announcements on them. Archived SENS announcements were mostly used along with business news publications. These secondary sources of company information are in the public domain.

3.3 Methodology

A quantitative approach was used in this empirical study. The Altman Z-score and Z double prime score (also referred to as Z plus plus or Z") were used to quantify financial distress. The study aimed to find the extent to which the financial distress predicted by Altman's models was a forerunner for delisting as well as which of the Altman models was more accurate in predicting delisting.

The mining sector, as shown in the literature has been a mainstay on the JSE as the stock market's origins were built on the discovery of precious metals in South Africa. Despite losing its dominance on the exchange in recent times, mining has shown to be an important contributor to exports as well as a haven during financial crises. Mining was thus a good sector to analyse due to its multifaceted nature.

Mining companies on the JSE, as the dominant exchange in South Africa were used. These companies were listed on either the main board or Alt-X. Due to the availability of financial data and the ease of capital flows after the collapse of the Apartheid regime, the study analysed financials of mining companies that were listed on the JSE between 1994 and 2021. The study then examined the status of each of these companies and listed them as follows:

i.) Listed/Suspended
ii.) Delisted/Terminated
iii.) Merged/Acquired
iv.) Privatized

The first iteration of the study considered all companies that still had their ticker on the JSE despite being suspended. The suspension could theoretically be lifted once all remedial action was taken by the suspended companies. However, in general, most suspensions led to delisting. Delisting may not only be due to financial distress therefore in the case of companies that were acquired, an analysis of the acquirer's financial health was conducted. Privatized companies in general did not have publicly available financials for analysis so these companies were excluded from the sample.

A total of 41 companies were initially used in the study. The selection was based on including the mining companies that had available financial data in the form of the Income Statement, Balance Sheet as well as stock value information namely the number of shares outstanding along with the share price for each financial period listed after 1994. This data for each

company would be used to retrospectively measure the accuracy of Altman's models for each company over the years of listing on the JSE. Each company needed to have at least 2 or more years of data as a minimum requirement for inclusion.

Notable inclusions in the study are BHP Group which merged with Billiton Plc, DRDGold which acquired Crown Consolidated Gold, as well as Harmony Gold which acquired African Rainbow Minerals. Sibanye Stillwater is another mining giant that had some merger activity after expanding from Sibanye Gold and acquiring Aquarius and DRDGold. An acquired company was included in the study if the financial data for the acquired company was available, otherwise, financial data from the acquiring company would be considered.

An overview of the given company statuses in the sample, before any deeper analysis, yielded the following:

Table 2: Number of companies based on listing status

Status	Number in sample
Listed	**16**
Suspended	**2**
Delisted	**16**
Merged/Acquired	**7**
TOTAL	**41**

The following conditions were refined to create a dichotomous set of Listed and Delisted. Listed would be those companies that still have a ticker on the JSE, excluding the suspended firms, while delisted would indicate those companies that have been terminated from the exchange. This approach yielded 16 listed and 16 delisted companies. Although this brought the number of companies used in the study to 32, it removed the grey areas of uncertainty regarding the distinction between listed and delisted companies.

The motives behind mergers or acquisitions may not have necessarily regarded the financial distress of a viable business but analysis of other factors that potentially played a role were considered beyond the scope of this study. Therefore, the exclusion of merged or acquired firms may be justified to avoid distortion of results when measuring the true prowess of Altman's models for predicting financial distress and subsequent termination from the JSE. Suspended firms alike were also excluded as these firms could still be able to undertake remedial actions to lift the suspension.

3.4 The Altman Z-score and Z”-score models.

Two Altman models, Z-score and Z”-score were used to test their predictive prowess for mining companies listed on the JSE. These multivariate models are designed to predict financial health status of companies over a 2-to-3-year period. This study aims to measure the usefulness of the models beyond predicting financial health but also the likelihood of delisting from a stock market.

Altman’s Z-score model equation is as follows:

$$\mathbf{Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5}$$

X_1 is working capital/total assets. The total current liability figure from each company’s balance sheet was subtracted from the total current asset figure to determine the working capital. This figure was then divided by the total assets for the firm to determine X_1.

X_2 is retained earnings/total assets. The retained earnings for each year were extracted from the balance sheet and divided by the corresponding total asset figure for each financial year to determine X_2.

X_3 is earnings before interest and taxes/total assets. The operating profit from the income statement was divided by the total asset figure for each year to determine X_3.

X_4 is market value of equity/book value of total liabilities. This calculation requires stock value information in the form of stock prices over the period in question as well as the number of shares outstanding. For uniformity, the last price recorded at the end of each reported financial year was used in conjunction with the number of shares outstanding at that same stage. Finding the product of these would give the market capitalization at the end of each financial year end. The total liabilities figure would be extracted from the balance sheet. Dividing market capitalization by the total liabilities would give X_4.

X_5 is sales/total assets. Total revenue in the income statement divided by total assets would give the turnover ratio or X_5.

Once all variables are determined, a substitution into the Z-score equation determines the Z-score for each company for each year of financial data. According to the Z-score, the zones of financial distress are given as follows:

-healthy- score greater than 3,

-facing financial distress in the near future- score between 1.8 and 3,

-bankrupt or in financial distress- score less than 1.8.

The three Z-score cut off zones could seem to create a problem for the dichotomous classification of health status stated earlier for this study. The view taken in this study is that any company scoring between 1.8 and 3 has been forewarned regarding potential impending financial distress. However, seeing as the method includes year to year analysis, the subsequent scores could give an indication of distress if the scores eventually drop below 1.8. Therefore, for the purposes of this study and to remain with a dichotomous nature of the findings, a cut-off point of 1.8 will be used. This means that any firms with a score below 1.8 would be considered distressed. Those scoring above would be considered healthy enough to remain listed.

The second model used in this study is the Z double prime score which is also known as Z plus plus and denoted as Z". According to the literature, the development of this model came about to cater for non-US firms especially those from emerging markets (Altman, 2013). The model was therefore deemed as suitable for this study as the companies in the sample are all listed on a South African stock market. The matter of secondary listings in other countries that may be considered as developed countries, was not considered material for this study given that the major operations in mining are generally within emerging market jurisdictions so the listed miners on the JSE can be considered operating in an emerging market economy and are thus exposed to the similar macro-economic factors as companies on the JSE with or without any other foreign listings.

Altman's Z"-score equation is as follows:

$$\mathbf{Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4}$$

Variables X_1 to X_4 are like the Z-score model variables. The Z"-score removes the impact of turnover and reworks the coefficients in the equation. The X_4 term also changes from market value of equity/book value of total liabilities as in the Z-score to book value of equity/book value of total liabilities for the Z"-score.

The cut off points for Z”-score also changed slightly to the following zones:

-healthy- score greater than 2.6,

-facing financial distress in the near future- score between 1.1 and 2.6,

-bankrupt or in financial distress- score less than 1.1.

Once again, the cut off for the purposes of the study was set to the point of distress. This means that a score of less than 1.1 for the Z”-score would indicate financial distress while a score above 1.1 would indicate that the firm is likely to be financially sound.

The financial health classification of either financially distressed or healthy was crucial for the analysis of whether Altman’s Z and Z”-score models are good predictors of not just financial distress for mining companies but also their delisting from the JSE.

The Z”-score has a variant known as the Emerging Market Score (EMS), which makes use of a constant value of 3.25 to standardize scores for non-US companies that may have varying ways of financing their assets. The Z”-score equation is then adjusted by adding that constant of 3.25 as follows:

$$\mathbf{Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 + 3.25}$$

The cut-off scores for the EMS were adjusted to:

-healthy- score greater than 5.85,

-facing financial distress in the near future- score between 4.35 and 5.85,

-bankrupt or in financial distress- score less than 4.35.

In line with the methodology used for the other models, this study considered financially distressed as scores below 4.35. The following section will outline the steps taken to determine whether Altman’s models can be used to predict South African mining delisting from the JSE.

3.5 Method for analysis.

An outline of the strategy for analysing the data will be outlined in this section. The Z-scores for each company, for each year listed on the JSE were computed and recorded under the three models as Z-score, Z"-score and Z EMS. The classification of either healthy or distressed was input based on the principals of Altman's model of predicting for the near future. For the purposes of this study, the time horizons used were 1 year, 2 year and 3 years in the future. This means that the score for a company in Year *(X)* was used to predict the financial position for that company in:

Year *(X + 1)* for a 1-year prediction,

Year *(X + 2)* for a 2-year prediction,

Year *(X + 3)* for a 3-year prediction,

The process was followed for each of Altman's models. The results of each classification were then compared with the listing status of the company. Two comparisons were used for this empirical process. The first was based on a rolling year to year which compared every year's predicted financial health position to its actual listing status. This was done to measure any trends that the models may or may not have predicted.

The second method of comparison was that of only looking at what the study termed "the terminal point" as the point of analysis. This was considered as the year in which a company delisted or was terminated from the JSE, or if still listed, then the terminal point would be the end period of the study which was October 2022. Although the financial data used was up to December 2021, the listing status for companies till October 2022 was considered as a way of measuring the Z-score models' predictive prowess. The analysis was thus based on looking at the three-time horizons mentioned earlier but only in reverse as follows:

Terminal status of company at year *(x)* compared to1:

i. Classification at year *(x-1)* for a one-year prediction horizon.
ii. Classification at year *(x-1)* for a two-year prediction horizon.
iii. Classification at year *(x-1)* for a three-year prediction horizon.

Repeating these calculations for all three Altman models, for both the year-to-year and terminal point analysis, as well as for each prediction time horizon enabled the determination of which

model was most accurate in predicting a delisting for each method of analysis thereby finding the most accurate model for predicting the likelihood of delisting. The Z" and EMS models were examined and showed identical classifications for the year-to-year as well as for the terminal point perspective. Analysing both methods, which produced identical financial health predictions, was clearly going to be a duplication, so the EMS model was excluded for the rest of the study and focus was placed on the original Z-score and Z"-score models.

Contingency tables were used in measuring the delisting prediction accuracy of each of Altman's models. Each table was a 2 x 2 matrix which showed the number of companies that fell into the following categories:

1. Listed and financially healthy.
2. Listed and financially distressed.
3. Delisted while financially healthy.
4. Delisted while financially distressed.

The exclusion of the EMS model meant that only 6, instead of 9, contingency tables were used to measure the accuracy of the predicted financial classifications. Each of the two models had a table for 1-, 2- and 3-year horizons respectively. The significance of the findings was initially tested using the Chi square test but further revisions to the sample necessitated the use of Fisher's exact test as some of the categorical data fell below 5 companies. Fisher's exact test is used for nonparametric analysis of categorical data where there may be low frequencies due to small sample sizes. This test works best with 2 x 2 contingency tables and can be used to test for independence or association between two categorical variables.

The following hypothesis was consequently developed:

H_o = The Altman Z-score and Z"-score models are not able to predict the delisting of mining shares on the JSE *n* years in the future.

H_1 = The Altman Z-score and Z"-score models are able to predict the delisting of mining shares on the JSE *n* years in the future.

Where *n* is 1,2,3 years.

3.6 Study limitations and considerations.

A key determinant in the selection of mining companies was the availability of financial data. Companies that did not have all the financial data available on the Bloomberg terminal were excluded. The exclusion reduced the sample size. An example of lack of financial data could be unavailable information regarding the stock valuations such as number of shares outstanding for the market capitalization calculation. Having less than two years of financial data also meant that only a 1-year time horizon was possible so companies in this situation were also excluded from the study.

Companies publish their results at differing points in the year. The study recognised the year-end financial statements, whether it be June or December, to be for the year observed. Additionally, the empirical nature of the study considered all corporate actions till October 2022 to measure the accuracy of the predicted financial health of listed companies with 2021 financials.

The years 2020 and 2021 were unprecedented due to the Covid-19 pandemic. This may have contributed to the financial distress status of listed firms that are still on the JSE and are recovering from the effects of the global crisis.

3.7 Conclusion

This chapter has discussed the research strategy of the study. The main features were the process used in determining the companies that were selected for the study, the iterations used in determining the most appropriate way of categorising the companies based on their status on the JSE and the Altman models used to determine the financial health of each company. The chapter also highlighted the data collection, data sources and the limitations faced in this methodology.

The 32 companies that have been split into listed and delisted will each have their financial health and listing status examined using the financial distress models by Altman. A deep dive into news archives will also be conducted were possible to ascertain the reasons for termination on the JSE for the delisted firms. Any reasons not explained by the models, or that are not in line with financial distress, will be highlighted in the analysis of results. Key iterations of sampling will be highlighted to refine the study and improve accuracy of results.

4. Chapter 4: Analysis

4.1 Introduction

The previous chapters have given a background to the study by reviewing the literature on mining as well as financial distress with a focus on Altman's models. The methodology used for the study has also been discussed highlighting the strategy used for collecting, sampling, and analysing the financial data of JSE listed mining companies. This chapter is the implementation of the outlined strategy for analysing the financial data and reporting results.

The chapter identifies the companies used as the sample as well as the listing and financial status of each company. The financial status was determined by using the Altman's Z and Z"-score models for each of the years of listing since 1994 for each company. A 3-year time horizon was used retrospectively to measure the efficacy of each model by comparing the known listing status of each company with the financial status predicted by Altman's models.

Appendix B is a list of the JSE listed mining companies that were listed on the stock market at a given point between 1994 and 2021. The list includes companies that have been suspended as well as those that have been acquired or that have merged during that period. Appendix C is a table showing the last 3 years, where available, of each company excluding the suspended and acquired/merged companies. The table shows the Z and Z"-scores for each of the years thereby predicting the financial distress or health of each company in 1 year's, 2 years', or 3 years' time.

For the purposes of the study, the cut-off points for the scores were 1.8 and 1.1 for Altman Z-score and Z"-score models respectively. The models each recognise the grey zone between 1.8 and 3 for the Z-score model, and 1.1 and 2.6 for the Z"-score model, as zones that predict impending financial distress. However, given that the study is focusing on the prediction of delisting, and that companies found in the grey zone can potentially exercise remedial action to improve the financial status, and are not technically distressed yet, only the scores below 1.8 and 1.1 would be assigned a distress status that could lead to delisting. Table 3 applies the cut-off points to the data in Appendix C to compare the predicted financial status against the JSE listing status.

4.2 Summary of findings

The rigorous journey which started off with the identification of mining companies that listed on the JSE from 1994 to 2021 and then led to the collection of those companies' financials for each year listed in that period, has led to some noteworthy explorative findings. While the study primary had a focus on determining whether Altman's models can be used to predict financial distress and subsequent delisting from the JSE for relatively young mining companies, which could be referred to as "born-frees", there were some interesting findings that may require further exploration.

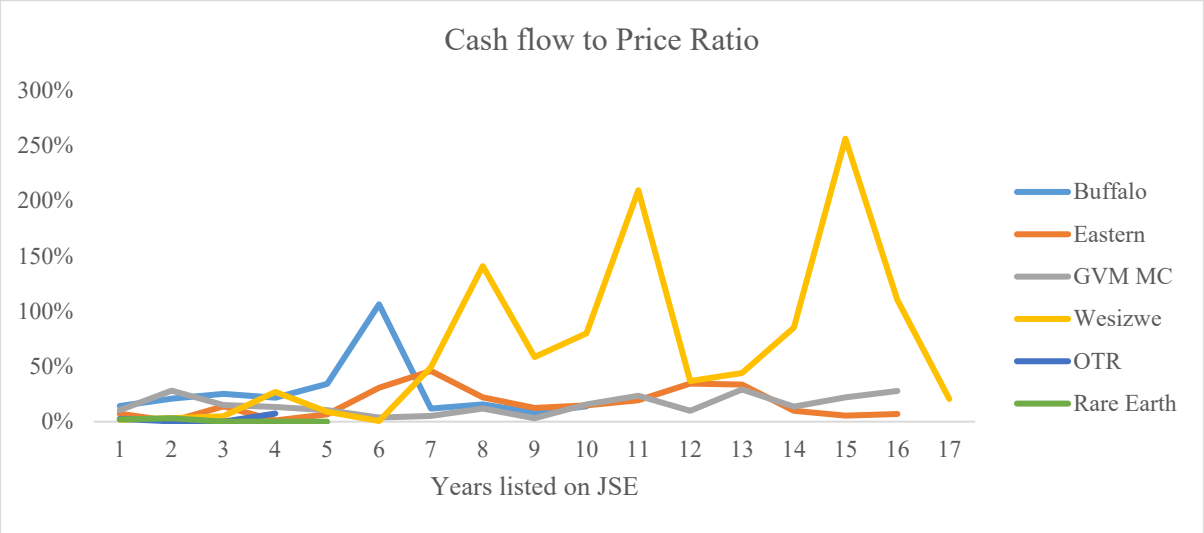
Firstly, regarding the main research purpose, the study was able to determine that both the Altman Z and Z"-score models were able to predict delisting at a statistically significant level for a 1-year time horizon. Investor sentiments of the company can be implicitly captured in the models thus leading to a more accurate view of each company's prospects and ultimately financial health which has a bearing on the listing status of a company.

A notable characteristic of the listed mining companies in general was that mining companies were able to continue operations with little to no revenue. This may be a phenomenon unique to this sector and could present further research opportunities that investigate this anomaly. Little to no revenue leads to poor profitability exhibited by low EBIT to Total Asset ratios.

The lack of revenue for some surviving companies was not the only anomaly as liquidity was also of interest given that the cash flow to price ratios were also not consistent with conventional going concerns. A study by Kruger and Toerien pointed out that the cash to price ratio proved to be the consistent yard stick for JSE companies even in times of crisis (Kruger & Toerien, 2014). Although their study was looking at returns in times of market crisis an adoption of their finding to this study using the outlier companies, which are the financially healthy but delisted and financially distressed but still listed gave some insight into why Altman's models may not have predicted the financial health of these companies accurately.

The Cash flow to price ratio correctly pointed out the companies that should be surviving and those that can be expected to delist with the median of survivors having at least a cash flow to price ratio of 10% and the delisted companies having a ratio below 2%. The number of years listed on the JSE also seemed to work in favour of the survivors as the longer the listing the more likely the company was to survive on the JSE. The figure below illustrates this:

Figure 5: Cash Flow to Price Ratio of Outliers



The applications for Altman's models along with the findings by Kruger and Toerien could be far reaching as the robustness of the financial health prediction of JSE companies, albeit for only a year horizon, would enable credit providers to assess the risk of offering short term debt products. The robustness of the technique stems from the fact that the variables used in Altman's models attempt to capture the relevant factors affecting the business and implicitly capture the macroeconomic environment through investor perceptions reflected in the market versus book value of equity components of the Z-score models.

Table 3: Sample Company list and Predicted Health Status vs Listing Status

			Financial Status Z score			Financial Status Z"Score		
	Company name	**Status**	**1 year**	**2 year**	**3 year**	**1 year**	**2 year**	**3 year**
1	Afgem Limited	**Delisted**	Distressed	Distressed	Distressed	Distressed	Distressed	Distressed
2	Alphamin Resources	**Listed**	Healthy	Healthy	Distressed	Healthy	Healthy	Distressed
3	Bauba Resources	**Listed**	Distressed	Distressed	Healthy	Distressed	Distressed	Healthy
4	BHP Group	**Listed**	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
5	Buffalo Coal	**Listed**	Distressed	Distressed	Distressed	Distressed	Distressed	Distressed
6	Central Rand Gold	**Delisted**	Distressed	Distressed	Distressed	Distressed	Distressed	Distressed
7	Chrometco	**Listed**	Distressed	Distressed	Distressed	Distressed	Distressed	Distressed
8	Diamond Core Resources	**Delisted**	Healthy	Healthy	Healthy	Healthy	Healthy	Distressed
9	DRD Gold Ltd	**Listed**	Healthy	Healthy	Distressed	Healthy	Healthy	Distressed
10	Eastern Platinum	**Listed**	Distressed	Distressed	Distressed	Distressed	Distressed	Distressed
11	GVM Metals/MC Mining	**Listed**	Distressed	Distressed	Distressed	Distressed	Distressed	Distressed
12	Harmony Gold	**Listed**	Healthy	Distressed	Distressed	Healthy	Distressed	Distressed
13	JCI Ltd	**Delisted**	Distressed	Distressed	Distressed	Distressed	Distressed	Distressed
14	Jubilee Metals Group	**Listed**	Healthy	Distressed	Distressed	Healthy	Healthy	Healthy
15	Kumba Iron Ore	**Listed**	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
16	**Noble Minerals**	**Delisted**	Distressed	Distressed		Distressed	Healthy	
17	Oakbay Resources	**Delisted**	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
18	Orion Minerals	**Listed**	Healthy	Distressed	Distressed	Healthy	Distressed	Distressed
19	OTR Mining	**Delisted**	Healthy	Distressed	Healthy	Healthy	Distressed	Distressed
20	**Pamodzi Gold**	**Delisted**	Distressed	Distressed		Distressed	Distressed	
21	Pan African Minerals	**Listed**	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
22	**Platfields**	**Delisted**	Distressed	Distressed		Distressed	Distressed	
23	Rare Earth Extraction Co	**Delisted**	Healthy	Distressed	Distressed	Healthy	Healthy	Distressed
24	Royal Bafokeng Platinum	**Listed**	Healthy	Healthy	Distressed	Healthy	Healthy	Healthy
25	S&j Land Holdings Ltd	**Delisted**	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
26	South 32 Limited	**Listed**	Healthy	Distressed	Healthy	Healthy	Healthy	Healthy
27	South African Coal Min	**Delisted**	Distressed	Distressed	Distressed	Distressed	Distressed	Distressed
28	Southern Mining Corp Ltd	**Delisted**	Distressed	Healthy	Healthy	Distressed	Healthy	Healthy
29	Thabex Exploration	**Delisted**	Distressed	Healthy	Distressed	Distressed	Distressed	Distressed
30	Tharisa PLC	**Listed**	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy
31	Wescoal Holdings	**Listed**	Distressed	Distressed	Distressed	Distressed	Distressed	Healthy
32	Wesizwe Platinum Ltd	**Listed**	Distressed	Distressed	Distressed	Distressed	Distressed	Distressed

Table 3 results yield 16 listed companies and 16 delisted companies. The financial health status of each can then be categorized into contingency tables that can be used for the statistical analysis. The tables are a 2 x 2 matrix with the following groups repeated for each time horizon as well as each Altman model:

Listed and Healthy

Listed and Distressed

Delisted and Healthy

Delisted and Distressed

The following contingency tables represent the data at each prediction time horizon for both the Z-score and Z" models:

Table 4: Contingency Tables excluding suspended and merged/acquired companies

Altman Z-score 1-year horizon			
	Listed	Delisted	Total
Distressed	7	9	16
Healthy	11	5	16
Total	18	14	32
p value: 0.2851			

Altman Z"-score 1-year horizon			
	Listed	Delisted	Total
Distressed	7	9	16
Healthy	11	5	16
Total	18	14	32
p value: 0.2851			

Altman Z-score 2-year horizon			
	Listed	Delisted	Total
Distressed	11	9	20
Healthy	7	5	12
Total	18	14	32
p value: 1			

Altman Z"-score 2-year horizon			
	Listed	Delisted	Total
Distressed	9	8	17
Healthy	9	6	15
Total	18	14	32
p value: 1			

Altman Z-score 3-year horizon			
	Listed	Delisted	Total
Distressed	12	6	18
Healthy	6	5	11
Total	18	11	29
p value: 0.6964			

Altman Z"-score 3-year horizon			
	Listed	Delisted	Total
Distressed	9	8	17
Healthy	9	3	12
Total	18	11	29
p value: 0.2731			

It should be noted that the reason the 3-year horizon differences of 29 total companies versus 32 in 1-year and 2-year horizons was a result of 3 companies namely, Noble Minerals, Pamodzi and Platfields that delisted before 3 years of listing on the JSE. Their inclusion was beneficial at the 1- and 2-year prediction horizon and showed the impact of age on the JSE, financial health and delisting. This will be discussed in more detail in the following sections.

The nature of the study necessitated for multiple iterations of sampling to find statistically significant results. The first iteration of analysis attempted to use the Chi-square test to find P-values for statistical significance. However, the 3-year horizon contingency table for the Z"-score had a data point that was less than 5, comprised of the 3 companies that were Healthy but Delisted. This meant that the Chi square test was no longer appropriate to test for statistical significance for all time horizons for both models. Fishers exact test allows for statistical significance testing where categorical data points are below 5 therefore it was used to test the hypotheses.

Fisher's exact test was used to find the P values using the formula below:

$$p = \frac{(a+b)!\,(c+d)!\,(a+c)!\,(b+d)!}{a!\,b!\,c!\,d!\,n!}$$

where a contingency table is structured as follows:

a	b	$a + b$
c	d	$c + d$
$a + c$	$b + d$	n

and p = p value

a,b,c,d = categorical data in the contingency table

n = total frequency

Given that this calculation would have to be computed 6 times for each of the contingency tables, the following code in R was employed to improve the ease of adjustment of the categorical data: >ContingencyTable=matrix(c(*a,b,c,d*),c(*x*,*y*))

>fisher.test(ContingencyTable)

where *a,b,c,d* would be numeric values for the categorical data and *x* and *y* rows and columns respectively for the matrix.

The fisher's exact test yielded the p values below and that were highlighted above under each contingency table for the first iteration:

Table 5: P values using Fisher's Exact test (first iteration)

Horizon	Z-score	Z"-score
1-year	0,2851	0,2851
2-year	1	1
3-year	0,6964	0,2731

The p-values indicate that the data fails to reject the null hypothesis for all six scenarios being tested. This means that there is no certainty at a 95% confidence level that Altman's Z-score model nor the Z"-score can predict the delisting of mining companies listed on the JSE for this

sample data at a statistically significant level. This required further analysis into the individual companies to review the sample before any inferences.

4.3 Sample data review

An updated analysis of the status of the mining companies needed to be carried out given material developments that may have taken place since the beginning of 2022. The rational for this was that, though the financial data collected was up to December 2021, an empirical approach for this prediction model would include observations on the status of companies in 2022 to measure the accuracy of the model. Some corporate actions necessitated a review of the various companies in the initial sample of 32 JSE mining companies. This review led to a revision of the sample and ultimately adjusted the contingency tables. This section will discuss these adjustments as well as the motivation for each revision of the sample.

In August of 2022, Bauba Resources went through an acquisition by Raubex Group Limited which led to the delisting from the JSE (Bauba Resources, 2022). This means that Bauba was excluded from the sample as it was acquired by another company and in this case, a company whose core business is not metals and mining but rather infrastructure development and construction.

Chrometco is another company that was removed from the sample as it was suspended in July 2022 (Gernetzky, 2022). According to the article on the Business Day website, Chrometco suffered substantially due to the covid-19 disruptions to operations at the Black Chrome Mine which subsequently had to go into a business rescue process. This led to a late submission of financials to the JSE which prompted the suspension.

Diamond Core Resources was also excluded from the sample as its termination from the bourse was due to an acquisition by Canadian company BRC Diamond Corporation. Although the company had listings on the TSX and JSE, the JSE listing BCD, which was later renamed to DelRand Resources (DRN) opted to delist voluntarily from the JSE in 2016 (Sharenet, 2016).

Wescoal Holdings announced a name change to Salungano Group in March 2022 with the intention of moving away from a purely coal mining company to one that aims to diversify into a climate change conscious energy company (Salungano Group, 2022). Though the coal mining arm has been performing well due to the Russia-Ukraine conflict, the company seeks to distance itself from coal to becoming a company looking into providing cleaner energy. While the name change is not technically a termination or delisting from the JSE, the change of focus

from a metal and mining company to one that aspires to be an energy company prompted the exclusion from the sample for this study.

Oakbay Resources was a company mostly owned by Oakbay Investments which gave a 93% ownership to the Gupta family and though listed on the JSE, the shares of Oakbay Resources were infrequently traded and controversies surrounding the operations of the company and its political connections led to the delisting from the JSE (Van Niekerk, 2016). The exclusion from the sample arises from the controversies surrounding the company that appear to have given the company unwarranted lucrative contracts that may have artificially boosted the financial health of the company. Including Oakbay would therefore potentially distort results given that this would appear to be a financially healthy company that delisted from the JSE.

S and J Land holdings, though initially focused on mining property, became another candidate for exclusion from the sample as further investigation revealed that prior to delisting from the JSE, the company had sought other property investments that would shift the company focus from mining property to a wider property portfolio (News 24, 2008). The company was suspended for failure to comply to listing requirements and delisted in April 2010.

The exclusion of the above companies gave rise to a revision of the categorised data set into new contingency tables before testing for statistical significance and measuring the use of Altman's models to predict delisting for South African mining companies listed on the JSE. The revision yielded the following mosaic plot and contingency tables:

Figure 6: Mosaic Plot and Charts for Contingency tables

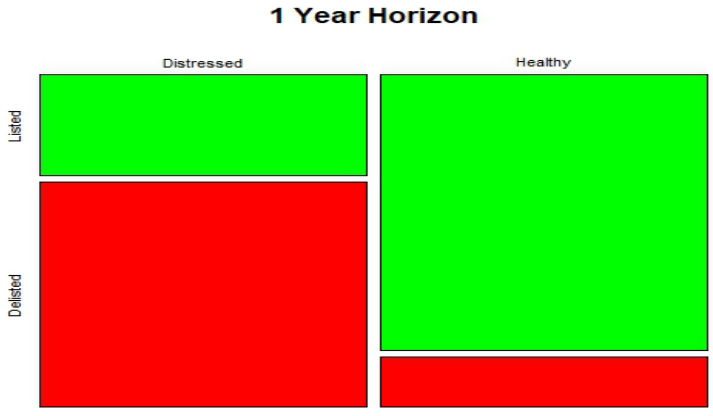


Table 6: Contingency tables using revised sample of mining companies

Altman Z-score 1-year horizon			
	Listed	Delisted	Total
Distressed	4	9	13
Healthy	11	2	13
Total	15	11	26
p value: 0.01542			

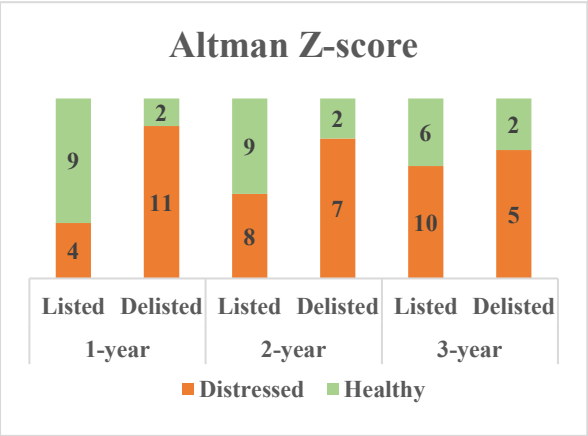
Altman Z”-score 1-year horizon			
	Listed	Delisted	Total
Distressed	4	9	13
Healthy	11	2	13
Total	15	11	26
p value: 0.01542			

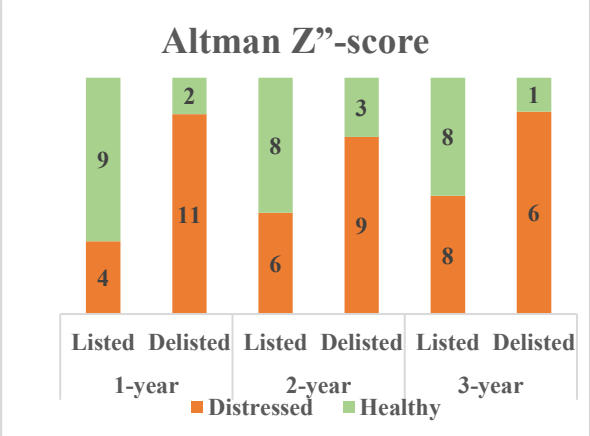
Altman Z-score 2-year horizon			
	Listed	Delisted	Total
Distressed	8	7	15
Healthy	9	2	12
Total	17	9	26
p value: 0.2167			

Altman Z”-score 2-year horizon			
	Listed	Delisted	Total
Distressed	6	9	15
Healthy	8	3	12
Total	14	12	26
p value: 0.1302			

Altman Z-score 3-year horizon			
	Listed	Delisted	Total
Distressed	10	5	15
Healthy	6	2	9
Total	16	7	23
p value: 1			

Altman Z”-score 3-year horizon			
	Listed	Delisted	Total
Distressed	8	6	15
Healthy	8	1	9
Total	16	7	23
p value: 0.176			





The charts above show how the predictive prowess of Altman’s models when used to predict delisting diminish in accuracy as the prediction horizon increases. It is only at the 1-year horizon that both models more accurately classify the mining companies based on their financial health and listing status. The mosaic plot showing the 1-year horizon represents both the Z and Z” models as the contingency tables for the two models are identical for the 1-year horizon. The plot shows the least errors in classification of listed companies that were distressed and delisted companies that were deemed healthy.

Table 7: P values using Fisher's Exact test (second iteration)

Horizon	Z-score	Z"-score
1-year	0,0152	0,0152
2-year	0.2167	0.1302
3-year	1	0,176

4.4 P values

The p values for the adjusted sample reject the null hypothesis only at a 1-year horizon. This means that there is an almost 98% probability that the Altman models' predictions are not coincidental or due to chance when looking at the 1-year horizon. The 2- and 3-year prediction horizons are less reliable for this data set as the p values are substantially above 5% for both models. These results could be unique to mining companies on the JSE, but the findings are beneficial to financial distress prediction and prediction of delisting of mining companies on the JSE that were listed post 1994 and are consistent with the findings in literature of the use of Altman's models. Although the results are not statistically significant at the 2-and 3-year horizons for both models, the Z"-score model seems to have more accuracy as compared to the Z-score model.

4.5 Observations from outlier companies.

The identification of Type I and Type II errors was done to determine reasons for the outlier companies that were not correctly predicted by the two models. For the purposes of this study, Type I errors which can be referred to as false positives, would refer to the companies that are predicted to be healthy and should be listed but turn out to have delisted. For the purposes of this study, we could refer to these as "fallen warriors." Two companies were found to be in this category of fallen warriors companies namely, OTR Mining and Rare Earth Extraction.

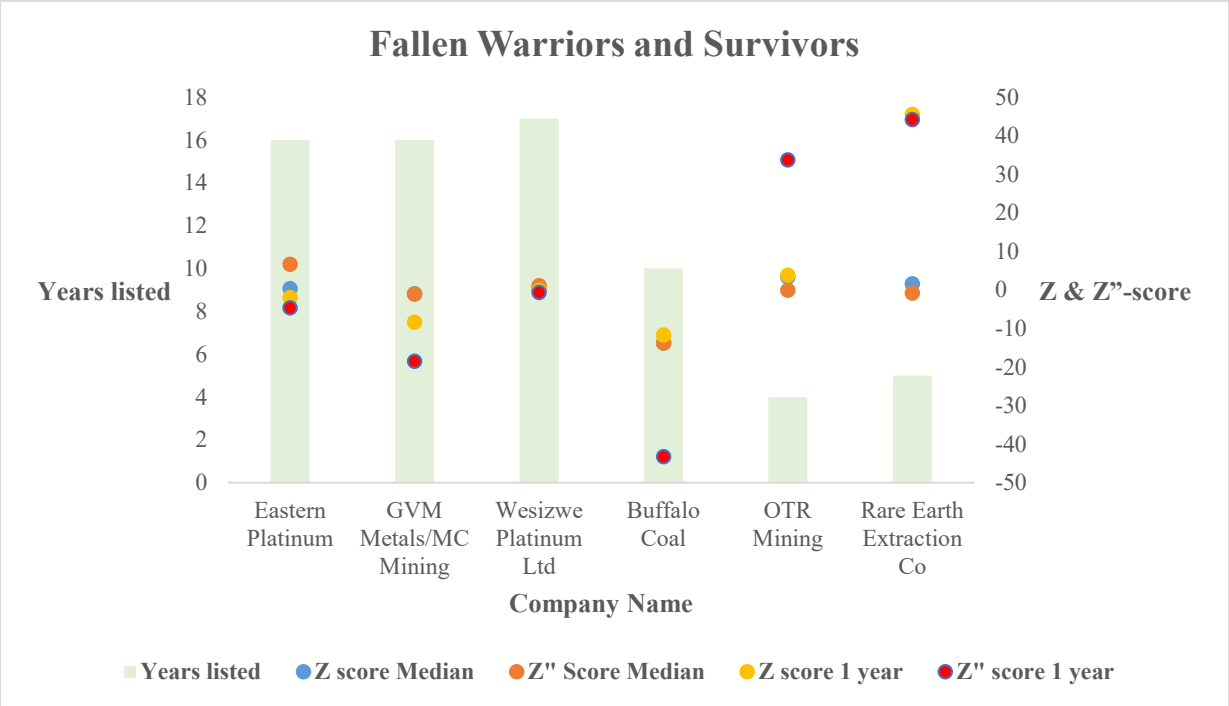
According to the Z and Z"-score models, these companies all had scores that predicted financial health using the 1-year horizon with very healthy scores of 3.8 and 45.5 respectively for the Z-score model and 33.7 and 44.2 for the Z"-score model. Median scores over the duration of listing on the JSE for each company were 3.3 and 1.6 for the Z-score and -0.1 and -0.8 for the Z"-score model. The two companies were listed for 4 and 5 years respectively and in comparison, with the other group of outlier companies, which are those that are listed but were predicted to have been distressed, the duration listed is relatively shorter. This suggests that junior miners may have greater difficulty remaining on the JSE. The nature of the mining sector, for example in the case of mining exploration firms, exhibits large periods of low to no

revenue, high input costs that push up the total asset base, low liquidity, and volatile share prices due to the commodity price fluctuations of the associated minerals, affect the financial health of the companies.

Further analysis reveals that OTR Mining and Rare Earth Extraction both delisted due to failure to comply to JSE regulations. The considerable differences in medians between the Z-score and Z"-score emanate from the market value versus book value aspects of the models and the sometimes-conflicting predictions of financial health. The lower number of years listed also mean that the medians alone may not paint a clear picture of the overall status of the companies so the failure of the models' predictions for these outliers can be attributed more to the failure to comply to JSE regulations which is not captured by the models in the prediction of financial health and delisting.

The following figure shows the companies for the "Fallen Warriors" and "Survivors."

Figure 7: Outlier companies



Type II error, or false negatives refer to the companies that were predicted to be in distress and would delist within a year but turned out to still be listed on the JSE. This study would like to refer to these as "Survivors." Eastern Platinum, MC Mining, Wesizwe Platinum and Buffalo Coal could be considered in that regard. These companies were listed for at least 10 years and as of October 2022 continue to show compliance and ability to remain listed despite showing signs of distress for most of the time listed. This could once again reflect the nature of the mining industry in that companies can be listed for years without any revenue while traded shares on the JSE often result in increased market value.

Eastern Platinum, which is a PGM and exploration company, has had a flattened share price since 2017 after peaking in 2008. As with most other exploration firms, the company continues to operate pursuing prospects of acquisitions in the future from senior miners with financial muscle to embark on the extraction of minerals. Wesizwe Platinum's share price also peaked in 2008, dropped and flattened ever since. These two companies were directly exposed to the global platinum commodity prices that peaked in 2008 at about $2000 per ounce and have declined to current levels just under $1000 per ounce of platinum.

MC Mining which is involved in coal mining has seen its share price lose 58% of value over the last 5 years. The company has been in distress for 11 out of the 16 years it has been listed on the JSE when using the Z-score 1-year prediction, while 10 out of 16 years when using the Z"-score 1-year prediction. The other coal miner, Buffalo Coal has also seen a decline in its share price. The global shift to cleaner energy sources may be contributing to the poor performance of these companies. However, these companies seem to be resilient and continue to be listed on the JSE. The Eskom crisis as well as the Russia-Ukraine war could see coal prices rally due to the shortages and boost these struggling survivors.

4.6 Further analysis

The following section of results will attempt to discuss some of the key observations from the individual financials companies used in the study. This section will strive to uncover any contributing factors to the listing status of each of the companies used in the study using their financial health status, as determined by Altman's Z double prime model, with a focus on examining the following characteristics of size based on market capitalisation, the age of each listing, revenue, and profitability trends. This section will also attempt to determine the key variables with the highest contribution to the listing status of each highlighted company.

Firstly, the table below categorises the companies based on Altman's Z double prime score using a 1-year horizon as well as the actual listing status. The 1- year horizon will be the focus as it was the only predictive time horizon that proved to be statistically significant. Although the Z-score and Z double prime score models were both statistically significant at the 1-year time horizon, the Z double prime model will be used for this further analysis as its origin was intended to cater for non-US, emerging markets. This section will discuss some of the companies listed and highlight key issues that may be of interest especially for further research into mining listings.

Table 8: Categorised companies based on financial health and listing status.

Listed		**Delisted**	
Healthy	**Distressed (Survivors)**	**Healthy (Fallen Warriors)**	**Distressed**
Alphamin	Buffalo Coal	OTR Mining	Afgem
BHP	Eastern Platinum	Rare Earth Extraction	Central Rand Gold
DRD Gold	MC Mining		JCI Ltd
Harmony Gold	Wesizwe Platinum		Noble Minerals
Jubilee Metals			Pamodzi Gold
Kumba Iron Ore			Platfields
Orion Minerals			South African Coal Mine
Pan African Minerals			Southern Mining Corp
Royal Bafokeng Platinum			Thabex
South 32			
Tharisa			

4.7 Insights from no/low Revenue but Healthy Listed Companies.

As discussed previously, there appears to be a healthy status even for companies with significant periods of low to no revenue. Three companies that experienced this phenomenon were namely Alphamin Resources, Jubilee Metals and Orion Minerals. These companies sparked interest because they all had consecutive years of no revenue but remained listed while having a healthy status according to Altman's Z"-score.

The revenues, or lack thereof had a direct bearing on the profitability of each of the companies and an analysis of this required two-pronged approach that involved a time series analysis of the individual company's sales and earnings while also analysing the age of listing, that is the number of years listed and the market capitalisation of the company. The second approach considers the individual company's ratios and trends with the peer companies in the same group. While the group can initially be just the companies that have a healthy status and are still listed, the results of the comparison can be extended to the entire sample of companies to include the de-listed while distressed, the "survivors" and the "fallen warriors" as defined earlier.

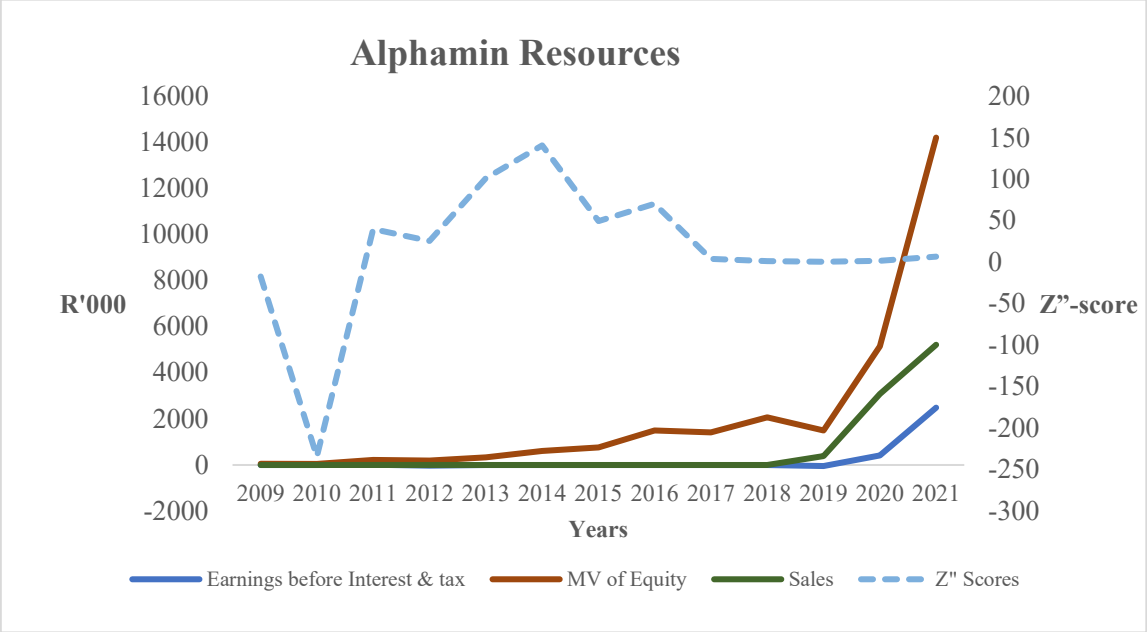
4.7.1 Alphamin Resources APH

Alphamin Resources (APH) is a company that focuses on the mining and exploration of tin. According to the company's website the company has operations in the Democratic Republic of Congo, and it is held to have the highest grade of tin in the world. The company is listed as AFM in Mauritius and as APH on the JSE AltX. The following chart shows the commodity price movement of tin.

Figure 8: Tin Prices

Source: Business Insider

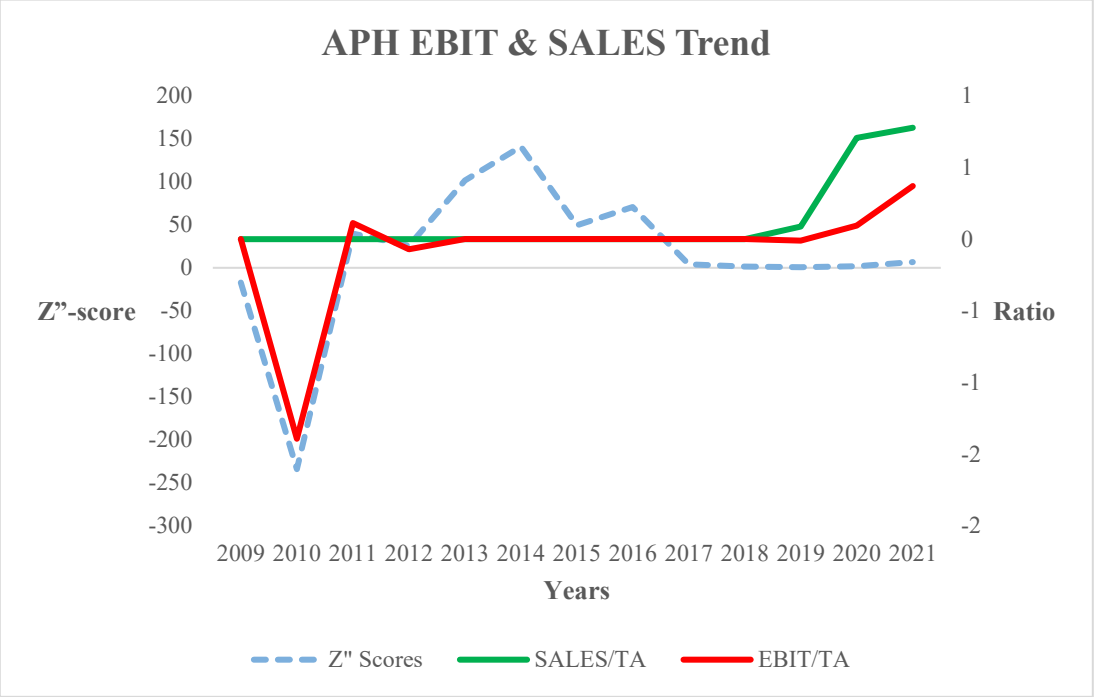
Figure 9: Alphamin Z”-scores, Sales, Market Value and Earnings



Figures 8 and 9 show the increase in market value along with increased sales and subsequent increase in earnings almost as the mirror image of the commodity price movements. The increase in tin prices seems to have catapulted sales and share prices hence the increased market value. APH had no revenue in the form of sales for the first 10 years of listing. Sales seem to coincide with the rise in commodity price of tin. The lack of sales for young companies appears to be commonplace for mining companies on the JSE. It is worthwhile investigating the correlation between listing age and the generating of sales and or earnings for the healthy and listed firms.

The latest Z”-score used in the study of 6.8 on the other hand, though currently stable above the cut-off of point of 1.1 to signify financial health and listing status, has been much higher over the 13 years of listing for APH with a median score of 6.8, highest score of 141 and lowest of -234 putting the current score at exactly the 50-percentile point. Figure 10 below paints a picture that there seems to be a correlation between revenue, earnings, and tin prices in Figure 8, but there is very little correlation with the Z”-scores over the period of listing for APH. The big swings in the Z”-scores could be attributed to the teething stage of the company as the Z”-scores have remained stable from 2017.

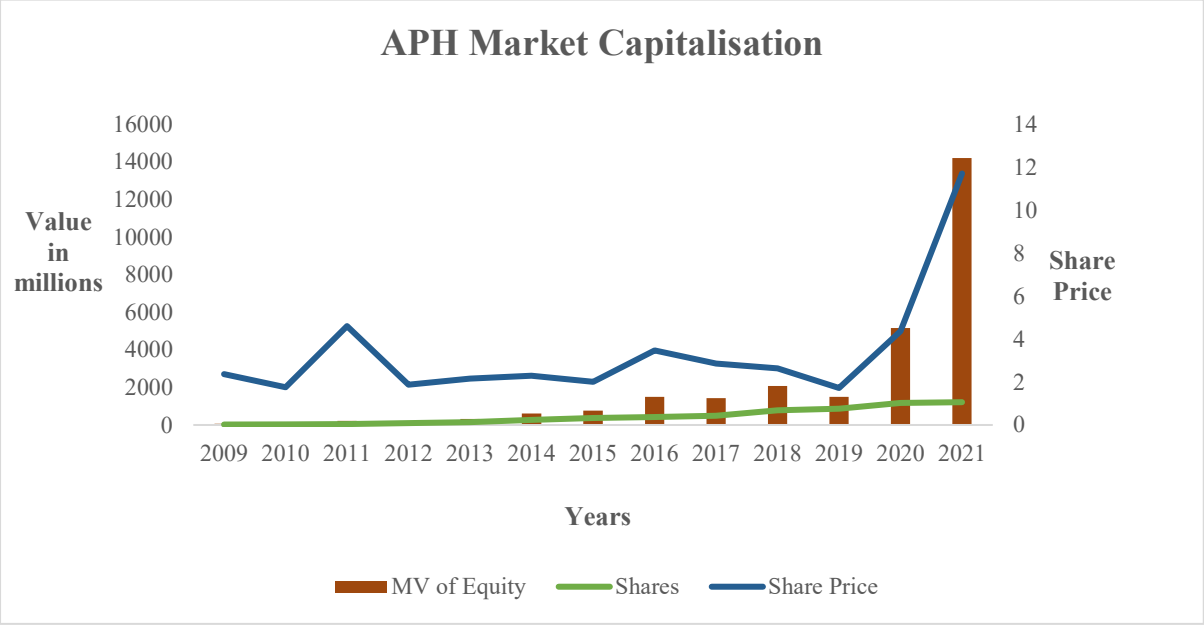
Figure 10: Earnings and Sales for Alphamin Resources



The health status of APH according to Altman's model as well as its listing status, could primarily be due to the investors showing confidence in the company especially from around the end of 2019. The Tin prices began to rally along with the share price of APH. The company's market capitalisation grew significantly from 2019 as the number of shares outstanding increased from 24 million shares in 2009 to 866 million in 2019 and 1.2 billion shares as at the end of 2021.

As discussed in the literature, mining has been considered a haven during times of crises so this could be another example of that. The financial turbulence caused by the Covid-19 epidemic may have pushed commodity prices up, in this case Tin prices, and investors may have flocked to what they considered as undervalued stocks, such as APH. The demand for the shares inevitably push prices up and those periods of no to low revenue are soon forgotten as sales pick up amidst a booming tin market. Figure 11 below gives a picture of this. Given that the Z-score model makes use of the market value of equity instead of the book value ratio used in the Z"-score model, the two models capture current market outlook for the company and in APH's case could explain the continued healthy and listed status of the company despite the years of no revenue and profitability.

Figure 11: APH Market Capitalisation



4.7.2 Jubilee Metals Group JBL

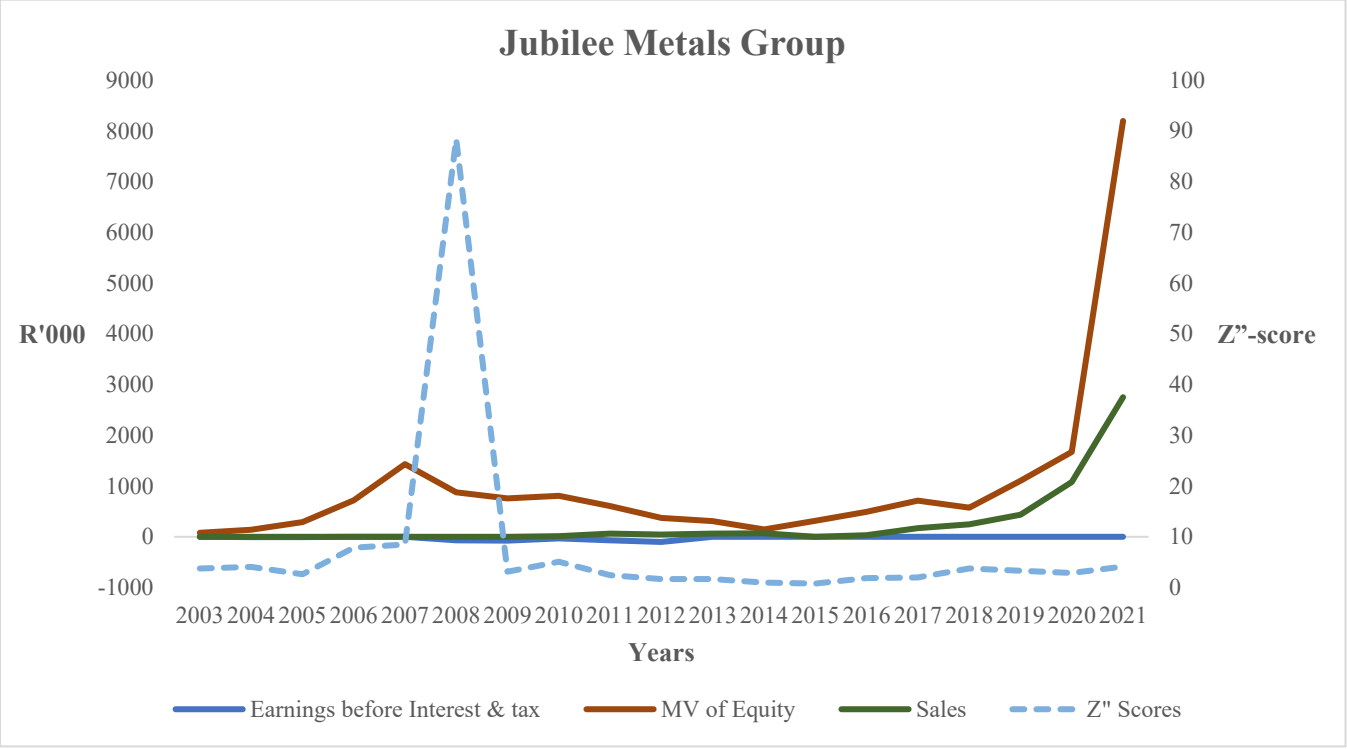
Jubilee Metals Group (JBL) is a company that focuses on extracting PGM metals from discarded mine waste. The company's approach is to have a less capital-intensive approach to processing minerals on the surface of used mines unlike the mainstream way of mining that requires huge capital investment for exploration and extraction of minerals from the deep within the ground. The company's approach has expanded to other minerals such as lead, cobalt, zinc, and copper (ListCorp, 2023).

As stated earlier, JBL is one of the companies that the Z"-score predicted to be financially healthy and should continue to be listed. However, just like APH, the company went through some years of no revenue. The company had no revenue for 8 out of the 19 years of being listed on the JSE. Interestingly, it was only found to be in distress, according to Altman's models, for 2 of those 19 years. The median Z"-score was 3.13 with a 2021 score of 4.14. JBL's score only fell below the 1.1 cut-off twice with scores of 0.99 and 0.78 in 2015 and 2016 respectively. This begs the question, how is JBL able to survive on the JSE with no to low revenue. Figure 12 below shows the movement of the main commodity that JBL focuses on which is platinum.

Figure 12: Platinum Prices

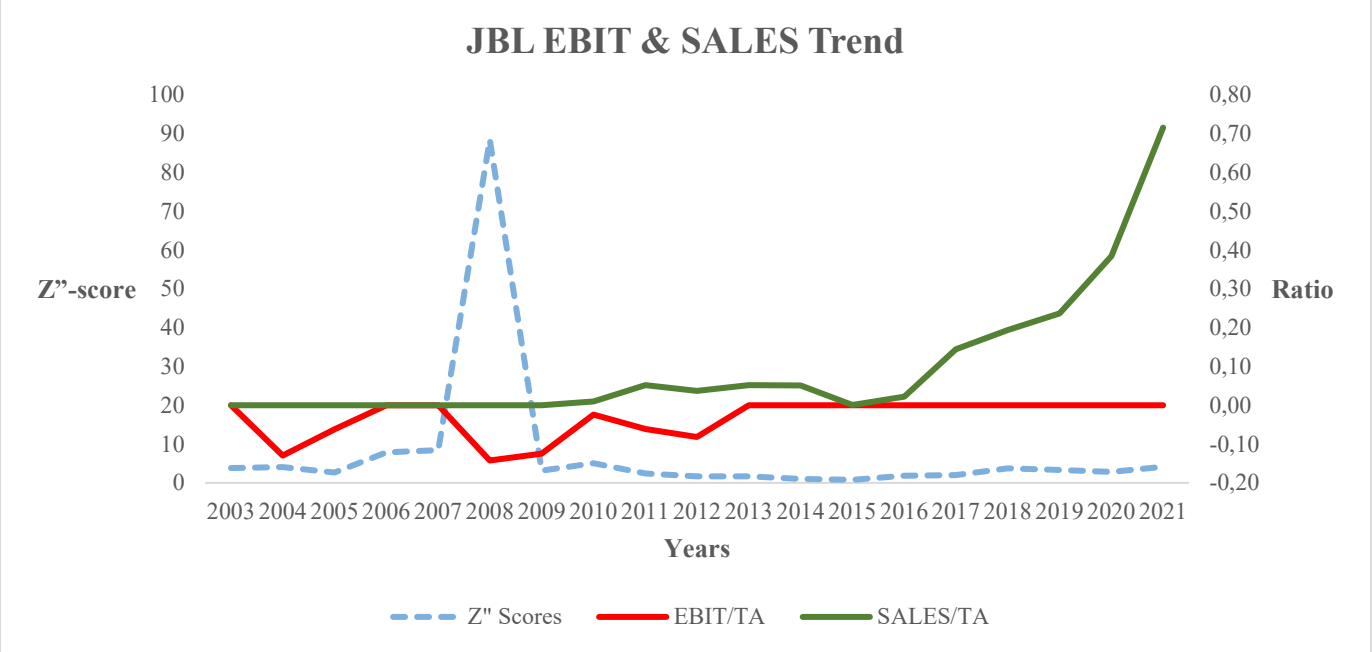
A visual comparison of the platinum price in Figure 12 and Figure 13 below, showing JBL's Z"-score, earnings, sales and to some extent market value, shows little to no correlation. Although sales started to pick up from 2016, earnings have continued to be non-existent.

Figure 13: Jubilee's Z"-scores, Sales, Market Value and Earnings



At a quick glance, this seems like a strange phenomenon. The Z"-score has been steady since 2009 and just like was observed with APH, no revenue for the initially years of listing eventually improved from the later parts of 2018 and 2019 with sharp increases after 2019 to all time revenue highs as at 2021. However, unlike APH, earnings for JBL did not rise with the increased sales despite a stable Z"-score. Figure 14 below depicts this picture and highlights the unexpected flat earnings ratio given the sharp increases in sales and slight pick up of commodity prices during the Covid-19 epidemic.

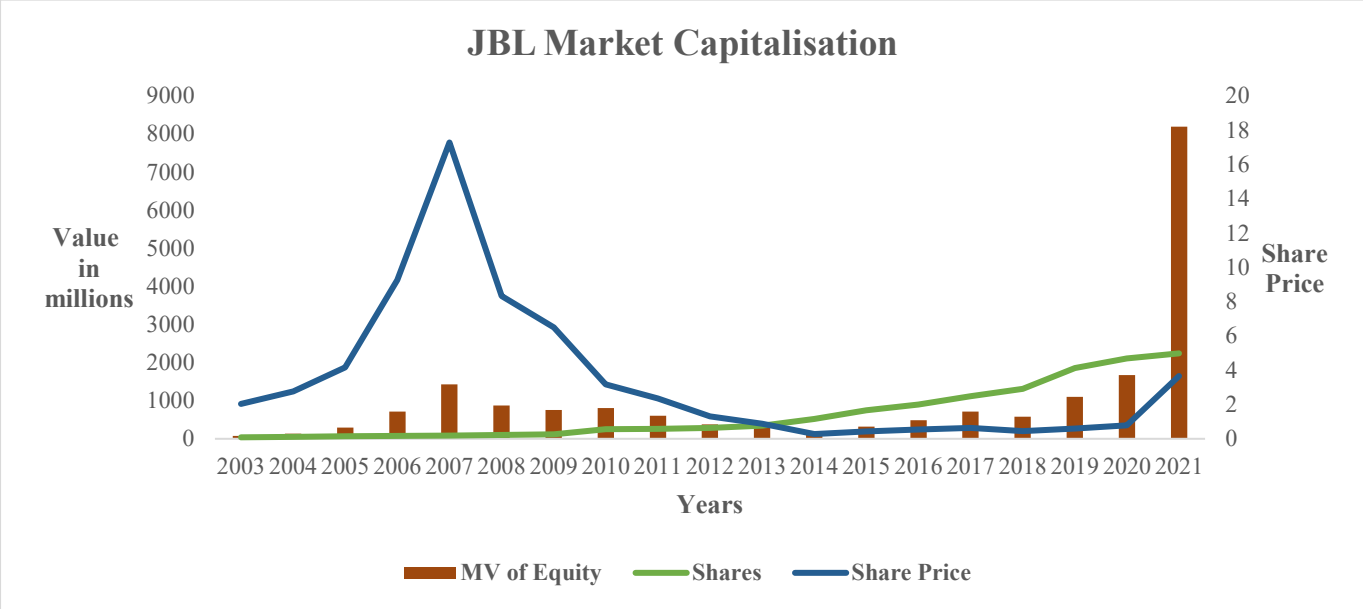
Figure 14: Earnings and Sales for Jubilee Metals Group



The bewildering aspect of the flat earnings is further compounded by the increase in shares outstanding and to some extent a rise in share price. Questions such as, "what are investors seeing in this no-earnings company that is drawing them to JBL?", or "are investors only interested in capital gains and are not concerned about dividends?", immediately come to mind. The Z"-score has generally been stable with only an unusual variation occurring in 2008 when current liabilities were significantly reduced from 47.31 million in 2007 to 5.88 million. This may have contributed to the sharp increase in Z"-score in 2008. An investigation into the capital structure of these highlighted companies and their peers could be pursued as an extension of this study. However, for the purposes of this study, the ratios in Altman's models capture the essence of the financial position of these companies.

Figure 15 below shows the changes in market value of JBL, changes in shares outstanding, as well as the share price movements.

Figure 15: JBL Market Capitalisation



JBL's share price peaked in 2007 at R17.28 but the value of the company was no way near the 2021 levels. The all-time high valuations in 2021 were because of an increase in the number of shares outstanding having risen from 2007 numbers of 82 million shares to 2.2 billion shares at R3.66 per share. One could conclude that this had a direct bearing on the Z"-score and the healthy status. However, given that the Z"-score has been generally stable throughout the listing period, the low debt obligations also play a role in the stability of the company and maintaining a healthy status according to Altman's models.

4.7.3 Orion Minerals (ORN)

Orion Minerals is an exploration and development company that focuses on copper and zinc. The company is relatively young especially compared to the companies being analysed here, that is those with no-to-low revenue but healthy and listed, having only listed in 2017. The age of listing appears to be significant to this portion of the analysis because the earlier companies, APH and JBL also went through periods of no revenue before having substantial increases in sales from 2019 till the terminal point of the study of 2021. One could place ORN as a company in its infancy and could follow the same path the two companies analysed above carved.

ORN has been in financial distress for every year it has been listed except for 2021 when it got a Z"-score of 10.48. Below is a table summarising the key financials for ORN.

Table 9: ORN Financial Summary Table

Year	CA	CL	TA	RE	EBIT	Shares	Price	MVE	TL	LTD	Sales	Z"-scores
2017	42,88	11,81	221,42	-800,77	-79,47	917,42	R0,25	229,91	108,19	-	-	**-12,18**
2018	83,80	156,40	415,36	-888,64	-62,22	1481,60	R0,41	602,79	214,11	-	-	**-8,14**
2019	21,23	117,11	472,77	-950,16	-88,88	2003,35	R0,32	634,08	182,79	-	-	**-7,48**
2020	17,53	111,53	788,26	-1349,81	-83,73	2899,56	R0,18	520,79	131,69	-	-	**-1,84**
2021	229,20	32,50	1051,44	-1222,79	-107,90	4317,12	R0,36	1575,45	74,67	-	-	**10,48**

ORN appears to be wholly financed using equity, so the low debt obligations make it less risky for investors who seem to be buying up the shares. Cash injected from equity financing is sustaining the business until the company can start generating revenue. As stated earlier, 5 years of listing means the company is still in the early stages of exploration and developing a viable mine. News archives highlight the company investing in the Prieska Copper and Zinc mine so that could soon provide much needed revenue and earnings.

The healthy status in 2021 is a result of the lower current liabilities that improve the working capital, the gradually increasing share price and the increase in the number of shares outstanding that are boosting the market value for Altman's model calculation of Z"-score. The negative retained earnings and earnings before interest and tax as well as the absence of any revenue would ordinarily write this company off as a distressed company that could soon delist but as has been the theme, some mining companies on the JSE still offer value to investors despite the red flags. This observation along with those outlined above in the cases of APH and JBL, could lead to further research into the size and age of listing and the impact thereof on the financial health and listing status of South African mining companies on the JSE. A summary of the components of Altman's model are tabled below for all the healthy companies that remained listed on the JSE.

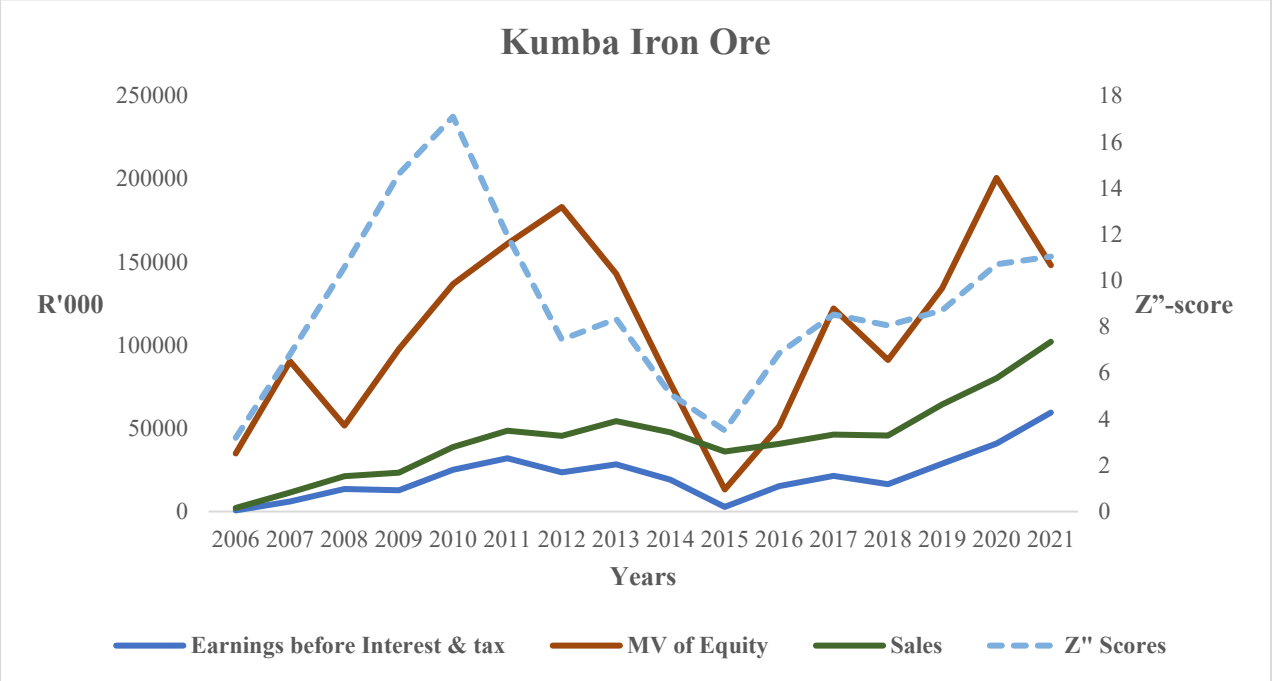
Table 10: Healthy and Listed companies.

	Z" Score			YEARS LISTED				EBIT/TA			SALES/TA		
	Current	Median	Median ALL	AGE	Distressed	Healthy	Median	2021	Median	Median ALL	2021	Median	Median ALL
APH	6,80	6,80	2,99	13	3	10	15	0,37	0,00	0,03	0,78	0,00	0,54
BHG	4,90	3,59	2,99	28	2	26	15	0,27	0,13	0,03	0,60	0,57	0,54
DRD	6,76	-0,66	2,99	23	18	5	15	0,29	0,01	0,03	0,83	0,79	0,54
HAR	2,42	2,42	2,99	27	3	24	15	0,10	0,01	0,03	0,86	0,50	0,54
JBL	4,14	3,13	2,99	19	2	17	15	0,00	0,00	0,03	0,72	0,02	0,54
KIO	11,03	8,43	2,99	16	0	16	15	0,73	0,55	0,03	1,25	1,07	0,54
ORN	10,48	-7,48	2,99	5	4	1	15	-0,10	-0,15	0,03	0,00	0,00	0,54
PAN	4,30	1,40	2,99	15	2	13	15	0,25	0,00	0,03	0,82	0,67	0,54
RBP	6,76	4,79	2,99	12	0	12	15	0,21	0,02	0,03	0,47	0,16	0,54
S32	2,77	3,08	2,99	7	0	7	15	0,02	0,03	0,03	0,45	0,45	0,54
THA	6,05	4,28	2,99	8	3	5	15	0,25	0,13	0,03	0,83	0,76	0,54

Apart from the analysis above on healthy companies that remained listed despite having little to no revenue and profitability, Table 9 provides some other insights worth noting. Kumba Iron Ore (KIO), Royal Bafokeng Platinum (RBP) and South 32 (S32) have not had a period of distress since listing with ages of listing on the JSE of 16, 12 and 7 years respectively. No significant correlation between the age of listing and Z"-score or financial health could be determined. However, the sound financials of each of these speak volumes.

KIO has ticked the boxes of all aspects that make up a financially sound company. Share prices and number of shares outstanding have not been the only contributors to achieving a healthy Z"-score. Instead, the company has generated sales consistently and the asset turnover shows great efficiency and utilisation of resources. Sales between 2019 and 2021 have been R64 billion, R80 billion and R102 billion respectively Earnings have been generated every year and have increased from R684 million in 2006 to almost R60 billion in 2021. The company has reinvested copiously over the years with figures of R34 billion, R46 billion and R42 billion from 2019 till 2021 alone as retained earnings. The company has relatively low long-term debt obligations, something that seems to be prevalent amongst the mining companies in the sample. However, it makes use of short-term liabilities that are easily covered by the current asset base, making it a perfect recipe for success through sound working capital management. The ratio of long-term debt to total assets could be contributing to investor confidence as they would consider such a company as having less solvency risk.

Figure 16: Kumba's Z"-scores, Sales, Market Value and Earnings



Despite the dips in Z”-scores and market value of equity, KIO has maintained its healthy status as shown in Figure 16 and Table 9. RBP and S32 were also found to have consistent sales and earnings just like KIO, with steadily increasing share prices and consequently growing market valuations of equity that contributed to both their healthy Z”-scores as was the case with KIO.

In summary, financially healthy mining companies that continue to be listed on the JSE could remain listed because of continued investor confidence in the companies that sees more shares being issued into the market, thus signalling expansion along with rallying share prices and underlying commodity prices that foster positive outlooks for the companies. Lack of sales at earlier stages of the business seem to come with the territory for these healthy firms and could be considered typical of the mining sector in South Africa. Earnings seem inevitable with time with eventual growing sales. Altman’s Z” model seems to capture these dynamics well enough to correctly predict delisting at statistically significant level for a 1-year horizon.

4.8 Insights from Age of listing and Debt Ratios.

In this section of further analysis of the sample data, an analysis of the number of years a company has been listed along with the number of periods a company has been found to be in distress will be conducted. The aim will be firstly to determine if there is any correlation between the number of years a company has been listed and the Z’ score, followed by an analysis of whether the ratio of distressed years to total years listed of each company has any correlation to the Z”-score. The section thereafter will look at the levels of indebtedness of each of the companies in the sample to see whether that could be a contributing factor to the financial health and listing status of the companies in the sample.

4.8.1 Years Listed, Healthy and Distressed

Figure 17 below paints a picture of the impact of the number of years a company is listed on the JSE affects its health and listing status. A visual analysis of the graphs shows that companies that were found to be healthy by Altman’s Z”-score and remained listed on the JSE, had the highest median age of listing of 15 years compared to the distressed and delisted with a median of 6 years. Interestingly, survivors, those that were distressed but remained listed, had a median age of listing of 16 years.

Figure 17: Healthy vs Distressed Years

The lowest age of listing for firms that were still listed on the JSE was 5 years, which was Orion Minerals. ORN had 4 years of distress before achieving a Z"-score above 1.1 to signify health. DRD Gold had 18 years of distress out of the total 23 years of listing. These two companies out of the 11 that were healthy and listed were the only ones with a distressed status for more than 50% of their life on the JSE.

When considering the survivors along with the healthy listed companies from the sample, the graphs seem to show that the longer a company is listed, the more likely it will remain listed and have more periods of a healthy status. The lower median years of listing for distressed and delisted firms shows that the companies were listed for a relatively shorter time on the JSE and most of the periods they were listed were enduring financial distress.

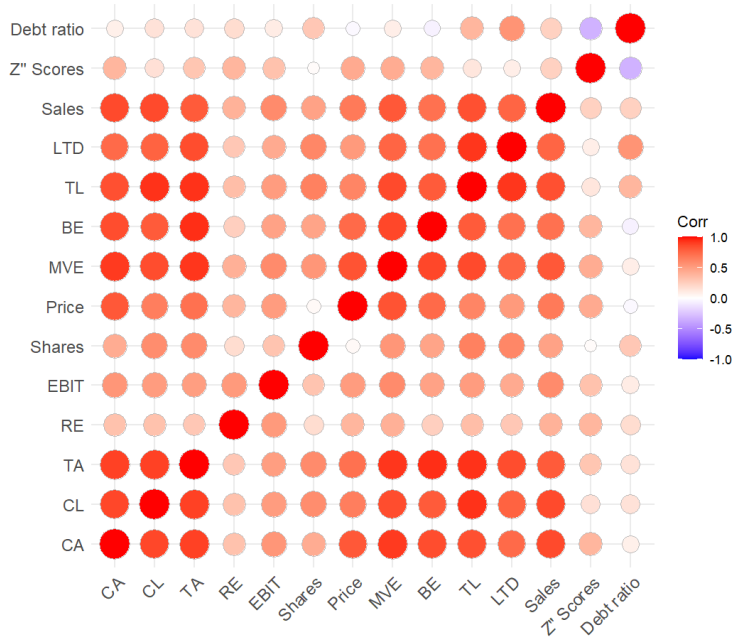
The fallen warriors, those with a healthy status but delisted, were healthy for less than half the time they were listed. OTR Mining had its final year on the JSE as the only year out of 4 years, that was healthy. Rare Earth Extraction had 2 financial healthy years out of 5 years of listing. Given that the Z"-score model used to determine the health status was statistically significant at a 1-year horizon, companies that happened to get a healthy score in the without considering the other years appear to be healthy despite delisting. This analysis shows that the Z"-scores in

the build up to that terminal point were correctly predicting potential before that abnormal Z”-score like in the case of OTR Mining and Rare Earth Extraction.

4.8.2 Debt Financing.

An investigation of the relationships between the inputs used in the Altman models and the Z”-scores highlighted that most individual factor correlations did not have a high enough magnitude to be noteworthy indicating that each factor, on its own, was not necessarily a good proxy to use for measuring financial health of a JSE listed mining company. Figure 18 below visualises this finding in a correlation matrix.

Figure 18: Correlation Matrix of Factors used in Altman’s model.



Although the exercise of finding the correlations between various factors did not yield significant findings in terms of noteworthy correlations, a factor that stood out and was worth conducting further analysis was the relationship between the Z”-score and the debt ratio as it was the only negative relationship with a correlation coefficient of -0.335 with a p-value of 4.216E-09. This may suggest that as companies become financially stable as measured by the Z”-score, the proportion of debt used decreases. Alternatively, but in the same vein, as debt ratio increases, the financial health of a company as determined by the Z”-score diminishes. Figure 19 below portrays this by picking a single company from each of the four categories used in the study namely, a healthy and listed, a distressed and delisted, a healthy but delisted and a distressed but listed company.

Figure 19: Sample company Debt ratios vs Z”-scores

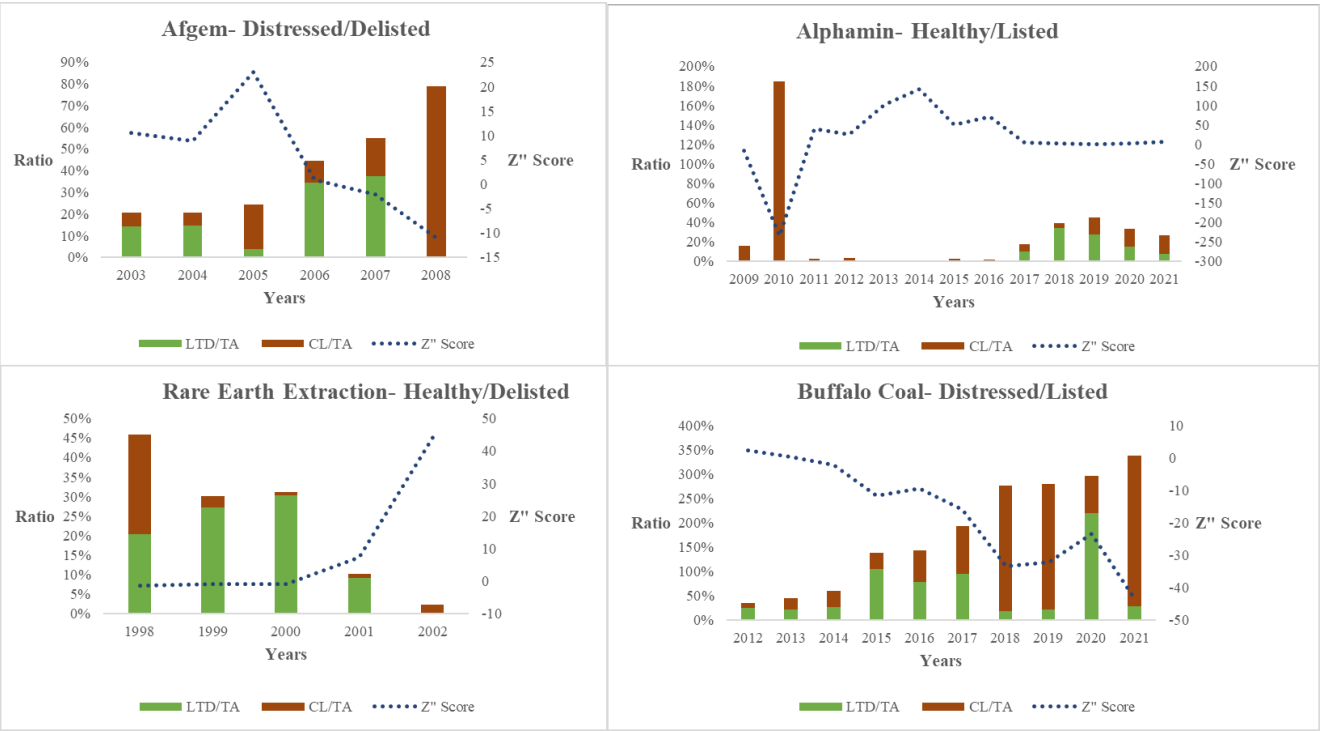


Figure 20 above consists of four companies, with each company being selected from the four groups of companies as per their financial health. A common thread from the graphs shows that Z”-scores were generally higher in periods where the companies had a smaller proportion of debt financing. Interest bearing debt, denoted in the graphs as LTD for long term debt, as a percentage of total assets appears to have a negative relationship with the Z”-score. Periods with lower LTD/TA have higher Z”-scores and this could be useful to investors or credit providers.

Additionally, the graphs show how mining companies make extensive use of short term debt financing for their operations. Short term liabilities denoted in these graphs as CL/TA (current liabilities over total assets) are used at some point during the listing period of the companies as the main source of debt financing for these mining companies. Overall, this supports the negative relationship between debt and Z”-scores that was highlighted in figure 18.

4.9 Conclusion

This chapter discussed the analysis conducted for the study. The iterative process of analysing each company's financials as well as corporate actions and relevant current news necessitated a need to review sampling and examining results multiple times to have up to date and accurate information as of October 2022. After a review of the initial sample, results show that Altman's Z-score and Z" models exhibit a high level of predictive prowess when predicting a company's financial health and listing status 1 year into the future. An analysis of the fallen warriors and survivors showed that those that were deemed distressed but were still listed had a track record of distress during the 10 or more years of listing on the JSE that they endured while the companies that were deemed healthy by the model but delisted, terminated their listing due to other factors such as failure to comply with JSE rules and regulations.

The application of Altman's models for predicting distress and subsequent delisting were found to be consistent with literature on bankruptcy prediction models and research conducted all over the globe. The mining sector in South Africa showed that despite potentially having periods of low to no revenue, low liquidity and profitability, the model was found to be robust at a 1-year horizon. At the 1-year horizon where the predictive prowess was found to be strongest, both the Z-score and Z"-score models yielded the same predictions. However, as the time horizon increased, the Z"-score model proved to be exhibit more predictive prowess than that of the Z-score model although not statistically significant at the 2- and 3-year horizons for both models.

Further analysis showed that the individual factors on their own cannot be used as a proxy for the Z"-score and financial health status. Altman's models require the comprehensive use of all factors in the model to achieve a score and a measure for financial health status. The absence of sales or earnings on their own does not necessarily translate to financial distress and subsequent delisting. Sample data used shows that mining companies tend to go for multiple periods without revenue and earnings while continuing to be listed and are even able to issue additional shares. The commodity prices seem to play a role in the investors' outlook, and this is evidenced by the rising market capitalisations driven by share prices and the increases in outstanding shares. The one factor that appears to warrant further investigation on a bigger sample of companies is the proportion of debt used by companies. The debt ratio has proven to have a somewhat small but worth noting negative relationship with the Z"-score.

5. Chapter 5: Conclusion

The study endeavored to examine the predictive prowess of Altman's Z-score and Z"-score models in predicting the delisting or termination of mining companies from the JSE. The equity markets in South Africa came about because of the discovery of precious minerals and this empirical study was based on mining companies that listed on the JSE from 1994 to observe the nature of mining companies in South Africa without the effect of global sanctions and during the period of democracy. The study in line with research from across the globe in various sectors found that Altman's models showed high levels of reliability when predicting financial distress and delisting for a 1-year horizon when compared with the 2-year and 3-year horizons for mining companies in South Africa that listed after 1994. Findings from Fisher's exact test were considered for significance testing given the smaller sample size.

The study further investigated the classification errors made by the models and found that the companies that were erroneously predicted to fail due to financial distress and were still listed on the exchange, the survivors, may have been due to the above average number of years of listing and nature of mining sector especially for exploration companies that operate for years with low to no revenue and consequently poor profitability and low liquidity. The other set of companies, the fallen warriors, those companies that were considered healthy but terminated their listing from the JSE, had a common thread of JSE regulation compliance failure that led to their termination. As discussed, the liquidity of these firms as well as the number of years listed on the JSE explain their demise and possibly their failure to comply and meet obligations.

Further analysis delved into attempting to explain the findings above. An analysis of revenues showed that the mining sector appears to have low to no revenues especially at early stages of the operation. This ultimately affects profitability and liquidity. However, these factors seem not have major negative impacts on the Z"-score when each factor is observed in isolation. Over time the addition of outstanding shares into the market as well as rising share prices appear to sustain the mining companies until they reach periods of generating sales and becoming profitable. Debt ratio was found to have a small but notable negative relation with the Z"-scores. Z' scores of the sample data used showed a decrease with an increase with the proportion of debt to total assets.

A limitation of the study was that the impact of the Covid-19 pandemic, Ukraine-Russia war as well as the ongoing Eskom crisis in South Africa were not specifically considered

extensively. However, one of the mining sector characteristics is that the investors consider mining sector as a haven during times of crises. The rise in commodity prices as well as the need for reliable energy played a role in cushioning the impact of the lockdowns as well as the energy crisis on mining. An area of study that could be included in further related research in that regard could be the analysis of the impact of these crises on all companies that delisted in the corresponding periods across all sectors.

An aspect that was not included in the study but could add value to the body of knowledge in the future is a comparison of the predictive prowess of multiple discriminant analysis models applied by Altman with the adaptive-learning, or machine learning artificial neural networks' prediction systems which depend on valuable extensive amounts of data to achieve correct predictions. As more companies focus on big data and analytics, the meaningful data needed for input into the artificial neural networks will improve and lead to better learning systems with better outputs. Any additional company data apart from the yearly or semi-annual financial data provided by companies could prove useful in building predictive models that reduce the lag created by the sole use of published company financials.

6. Appendix

Appendix A: Mining contribution to South African GDP

Year	SA GDP Index	Mining GDP Index	Mining %
1993	410256,80	60748,80	14,8%
1994	425440,50	60999,20	14,3%
1995	439060,50	58597,30	13,3%
1996	456146,70	58581,00	12,8%
1997	464147,30	59912,30	12,9%
1998	464840,90	58976,70	12,7%
1999	482119,00	58690,40	12,2%
2000	503742,00	57836,20	11,5%
2001	513696,80	57401,00	11,2%
2002	533852,60	59219,10	11,1%
2003	546662,20	61020,10	11,2%
2004	577633,70	59600,50	10,3%
2005	606683,80	59260,00	9,8%
2006	649809,30	62966,70	9,7%
2007	680111,90	60502,80	8,9%
2008	687853,90	58136,10	8,5%
2009	684145,90	56086,80	8,2%
2010	707477,40	59694,20	8,4%
2011	730145,80	56621,40	7,8%
2012	743902,80	55369,80	7,4%
2013	766855,50	60945,70	7,9%
2014	780278,70	59902,10	7,7%
2015	783757,50	59410,20	7,6%
2016	790482,00	58084,30	7,3%
2017	801180,10	60547,80	7,6%
2018	809635,30	58512,00	7,2%
2019	805965,30	57898,50	7,2%
2020	771924,90	53869,10	7,0%

Source: Bloomberg, 2021

Appendix B: Mining Companies listed on the JSE from 1994

Ticker	Board	Main Instrument Name	Status

1	AEA	AltX	AFRICAN EAGLE RES PLC	Suspended
2	AFG*	Main	African Gem Resources	Delisted
3	AOD*	Main	African Rainbow Miner Gm (Harmony)	Merged/Acquired
4	APH*	AltX	Alphamin Resources Corp	Listed
5	AML	Main	Amalia Gold Min & Explor	Delisted
6	APS1*	Main	Anglo Am Plat Corp Ltd	Merged/Acquired
7	ARQ	Main	Anooraq Resources Corporation	Privatized
8	AQP*	Main	Aquarius Platinum Ltd	Merged/Acquired
9	BAU*	Main	Bauba Resources	Listed
10	BIL2*	Main	Billiton Plc	Merged/Acquired
11	BRE	Main	BRAEMORE RESOURCES PLC	Merged/Acquired
12	BCD	Main	BRC DIAMONDCORE LTD	Delisted
13	BUC*	Main	Buffalo Coal	Listed
14	CRD*	Main	Central Rand Gold Ltd	Delisted
15	CNY	Main	Century Carbon Mining Ld	Delisted
16	CMO*	AltX	Chrometco Ltd	Listed
17	CAM2	Main	Consolidated African Min	Delisted
18	CRO2*	Main	Crown Consolidated Gold (DRDGold)	Merged/Acquired
19	DMR*		Diamond Core Resources	Delisted
20	DMC	Main	DIAMONDCORP PLC	Delisted
21	EPS*	Main	Eastern Platinum Ltd	Listed
22	ELD	Main	Eland Platinum Hldgs Ltd	Merged/Acquired
23	FCR	Main	Ferrum Crescent Limited (Europa Metals)	Listed
24	FIU	Main	First Uranium Corp	Privatized
25	GIY	AltX	Giyani Gold Corporation	Privatized
26	GLN	Main	Glencore Xstrata plc	Listed
27	GFL*	Main	Gold Fields Ltd	Merged/Acquired
28	GBG	Main	Great Basin Gold Ltd	Delisted
29	JCG	Main	Jci Gold Ltd	Merged/Acquired
30	JCD*	Main	Jci Ltd	Delisted
31	JBL*	Main	Jubilee Platinum plc	Listed
32	KGL	Main	Kalahari Goldridge Min	Merged/Acquired
33	KEH*	Main	Keaton Energy Hldgs Ltd (Wescoal)	Merged/Acquired
34	KBO*	AltX	KIBOMINING PLC	Listed
35	KCM	AltX	KIMBERLEY CONS MINING LD	Delisted
36	KWR	Main	KIWARA PLC	Merged/Acquired
37	KNT	Main	Knights Gold Min Co Ltd	Delisted
38	KPM2	Main	Kroondal Platinum Mines	Merged/Acquired
39	KIO*	Main	KUMBA IRON ORE LTD	Listed
40	KMB	Main	Kumba Resources Ltd	Merged/Acquired
41	MZL	Main	Mazal Mining and Explore	Delisted
42	MCZ*	Main	MC Mining (GVM Metals)	Listed
43	MMH*	Main	Miranda Mineral Hldgs Ld (UAT Minerals)	Suspended
44	NBL2*	Main	Noble Minerals Ltd	Delisted
45	ORL*	Main	Oakbay Res and Energy Ltd	Delisted
46	OPT	Main	Optimum Coal Hldgs Ltd	Delisted

47	ORN*	Main	Orion Minerals NL	Listed
48	OTR*	Main	Otr Mining Ltd	Delisted
49	PZG*	Main	PAMODZI GOLD LTD	Delisted
50	PAN*	AltX	PAN AFRICAN RESOURCE PLC	Listed
51	PLL*	Main	Platfields Limited	Delisted
52	PLN	Main	PLATMIN LTD	Privatized
53	RCO*	Main	Rare Earth Extraction Co	Delisted
54	RSG*	Main	Resource Generation Ltd	Suspended
55	RDI	Main	ROCKWELL DIAMONDS INCOR	Delisted
56	RBP*	Main	Royal Bafokeng Platinum Ltd	Listed
57	SJL*	Main	S&j Land Holdings Ltd	Delisted
58	SGL*	Main	Sibanye Gold Limited	Merged/Acquired
59	SAH*	Main	SOUTH AFRICAN COAL MIN	Delisted
60	S32*	Main	South32 Limited	Listed
61	SMC*	Main	Southern Mining Corp Ltd	Delisted
62	UUU	Main	Sxr Uranium One Inc	Merged/Acquired
63	TAW	Main	Tawana Resources Nl	Delisted
64	TEL	Main	Teal Explore and Min Inc	Delisted
65	TBX*	Main	Thabex Exploration Ltd	Delisted
66	THA*	Main	Tharisa plc	Listed
67	WCC	AltX	The Waterberg Coal Co Ltd	Delisted
68	WSL*	AltX	Wescoal Holdings Ltd	Listed
69	WEZ*	Main	Wesizwe Platinum Ltd	Listed
70	WGR*	Main	Witwatersrand Cons Gold	Merged/Acquired
71	YBA	AltX	Yomhlaba Resources Ltd	Delisted
72	ZPL	Main	Zambezi Plat RF Ltd Pref	Delisted

Source: JSE

Appendix C: Z and Z”-scores for Listed and Delisted Sample

Company name		Year	Code	Listing Status	Z-score	Z”-score

Afgem Limited	3	2006	AFG	Listed	0,942	0,866
Afgem Limited	2	2007	AFG	Listed	-0,858	-2,160
Afgem Limited	1	2008	AFG	Delisted	-3,881	-11,021
Alphamin Resources	3	2019	APH	Listed	0,294	0,687
Alphamin Resources	2	2020	APH	Listed	2,849	1,893
Alphamin Resources	1	2021	APH	Listed	7,097	6,803
Anglo American Platinum Ltd	3	2019	AMS	Listed	7,352	5,388
Anglo American Platinum Ltd	2	2020	AMS	Listed	5,830	5,486
Anglo American Platinum Ltd	1	2021	AMS	Listed	7,682	8,255
Bauba Resources	3	2019	BAU	Listed	2,518	5,552
Bauba Resources	2	2020	BAU	Listed	0,473	1,060
Bauba Resources	1	2021	BAU	Listed	1,028	0,809
BHP Group	3	2019	BHG	Listed	3,501	4,328
BHP Group	2	2020	BHG	Listed	2,835	3,629
BHP Group	1	2021	BHG	Listed	4,262	4,896
Buffalo Coal	3	2019	BUC	Listed	-7,975	-32,228
Buffalo Coal	2	2020	BUC	Listed	-7,372	-23,429
Buffalo Coal	1	2021	BUC	Listed	-11,670	-43,240
Central Rand Gold	3	2014	CRD	Listed	-17,198	-43,623
Central Rand Gold	2	2015	CRD	Listed	-23,830	-60,421
Central Rand Gold	1	2016	CRD	Delisted	-27,068	-67,705
Chrometco	3	2019	CMO	Listed	0,721	-1,386
Chrometco	2	2020	CMO	Listed	0,250	-2,041
Chrometco	1	2021	CMO	Listed	0,271	-2,968
Diamond Core Resources	3	2005	DMR	Listed	6,727	-3,358
Diamond Core Resources	2	2006	DMR	Listed	4,116	9,899
Diamond Core Resources	1	2007	DMR	Delisted	7,200	7,038
DRD Gold Ltd	3	2019	DRD	Listed	1,169	0,307
DRD Gold Ltd	2	2020	DRD	Listed	9,616	4,158
DRD Gold Ltd	1	2021	DRD	Listed	6,954	6,763
Eastern Platinum	3	2019	EPS	Listed	-2,065	-4,218
Eastern Platinum	2	2020	EPS	Listed	-2,004	-4,948
Eastern Platinum	1	2021	EPS	Listed	-1,969	-4,658
GVM Metals/MC Mining	3	2019	MCZ	Listed	-6,648	-14,798
GVM Metals/MC Mining	2	2020	MCZ	Listed	-9,342	-20,020
GVM Metals/MC Mining	1	2021	MCZ	Listed	-8,377	-18,458
Harmony Gold (African Raindbow Min)	3	2019	HAR	Listed	0,831	0,398
Harmony Gold (African Raindbow Min)	2	2020	HAR	Listed	1,590	0,696
Harmony Gold (African Raindbow Min)	1	2021	HAR	Listed	2,149	2,424
JCI Ltd	3	2002	JCD	Listed	-0,898	-3,264
JCI Ltd	2	2003	JCD	Listed	0,003	-1,746
JCI Ltd	1	2004	JCD	Delisted	-0,405	-2,434
Jubilee Metals Group	3	2019	JBL	Listed	1,377	3,339
Jubilee Metals Group	2	2020	JBL	Listed	1,485	2,859
Jubilee Metals Group	1	2021	JBL	Listed	5,332	4,139
Kumba Iron Ore	3	2019	KIO	Listed	7,544	8,711

Kumba Iron Ore	2	2020	KIO	Listed	9,737	10,707
Kumba Iron Ore	1	2021	KIO	Listed	8,505	11,033
Noble Minerals	2	1999	NBL2	Listed	0,744	3,594
Noble Minerals	1	2000	NBL2	Delisted	-0,867	-0,073
Oakbay Resources	3	2015	ORL	Listed	2,775	4,132
Oakbay Resources	2	2016	ORL	Listed	3,184	3,908
Oakbay Resources	1	2017	ORL	Delisted	3,806	3,280
Orion Minerals	3	2019	ORN	Listed	-1,596	-7,480
Orion Minerals	2	2020	ORN	Listed	-0,518	-1,844
Orion Minerals	1	2021	ORN	Listed	10,917	10,481
OTR Mining	3	1999	OTR	Listed	2,765	-0,911
OTR Mining	2	2000	OTR	Listed	-4,378	-21,749
OTR Mining	1	2001	OTR	Delisted	3,838	33,709
Pamodzi Gold	2	2006	PZG	Listed	0,199	-2,969
Pamodzi Gold	1	2007	PZG	Delisted	-0,738	-4,661
Pan African Minerals	3	2019	PAN	Listed	2,161	2,296
Pan African Minerals	2	2020	PAN	Listed	3,275	3,031
Pan African Minerals	1	2021	PAN	Listed	3,802	4,301
Platfields	2	2011	PLL	Listed	-1,080	-7,360
Platfields	1	2012	PLL	Delisted	-4,210	-9,976
Rare Earth Extraction Co	3	2000	RCO	Listed	-0,445	-0,837
Rare Earth Extraction Co	2	2001	RCO	Listed	1,696	7,185
Rare Earth Extraction Co	1	2002	RCO	Delisted	45,485	44,162
Royal Bafokeng Platinum	3	2019	RBP	Listed	1,447	3,047
Royal Bafokeng Platinum	2	2020	RBP	Listed	2,447	5,191
Royal Bafokeng Platinum	1	2021	RBP	Listed	4,495	6,756
S&j Land Holdings Ltd	3	2005	SJL	Listed	12,411	57,485
S&j Land Holdings Ltd	2	2006	SJL	Listed	23,980	97,493
S&j Land Holdings Ltd	1	2007	SJL	Delisted	11,502	44,770
South 32 Limited	3	2019	S32	Listed	2,271	3,420
South 32 Limited	2	2020	S32	Listed	1,446	3,081
South 32 Limited	1	2021	S32	Listed	1,966	2,767
SOUTH AFRICAN COAL MIN	3	2013	SAH	Listed	-1,335	-3,530
SOUTH AFRICAN COAL MIN	2	2014	SAH	Listed	-1,988	-5,461
SOUTH AFRICAN COAL MIN	1	2015	SAH	Delisted	-3,316	-8,661
Southern Mining Corp Ltd	3	2001	SMC	Listed	33,485	34,762
Southern Mining Corp Ltd	2	2002	SMC	Listed	13,505	26,617
Southern Mining Corp Ltd	1	2003	SMC	Delisted	0,566	-0,189
Thabex Exploration	3	2009	TBX	Listed	0,417	-3,405
Thabex Exploration	2	2010	TBX	Listed	15,562	-1,919
Thabex Exploration	1	2011	TBX	Delisted	-2,714	-2,887
Tharisa PLC	3	2019	THA	Listed	2,680	3,724
Tharisa PLC	2	2020	THA	Listed	2,679	4,923
Tharisa PLC	1	2021	THA	Listed	3,216	6,052
Wescoal Holdings	3	2019	WSL	Listed	1,744	1,318
Wescoal Holdings	2	2020	WSL	Listed	0,976	-0,481

Wescoal Holdings	1	2021	WSL	Listed	1,080	-0,250
Wesizwe Platinum Ltd	3	2019	WEZ	Listed	-0,029	0,092
Wesizwe Platinum Ltd	2	2020	WEZ	Listed	-0,047	-0,151
Wesizwe Platinum Ltd	1	2021	WEZ	Listed	-0,102	-0,627

Appendix D: Outliers: Fallen Warriors and Survivors.

Company name	Status	Median		Avg while listed		Last 3 yrs avg		Years distressed		Years listed
		Z score	Z" Score	Z score	Z" Score	Z score	Z" Score	Z score	Z" Score	
Eastern Platinum	Survivor	0,35	6,64	0,83	5,31	-2,01	-3,52	12	4	16
GVM Metals/MC Mining	Survivor	-0,98	-1,07	9,19	4,00	-8,12	-17,76	11	10	16
Wesizwe Platinum Ltd	Survivor	0,24	1,13	11,40	7,72	-0,06	-0,23	10	8	17
Buffalo Coal	Survivor	-13,79	-13,79	-4,27	-16,91	-9,01	-32,97	10	9	10
OTR Mining	Fallen Warrior	3,30	-0,11	6,05	2,94	0,74	3,68	1	3	4
Rare Earth Extraction Co	Fallen Warrior	1,55	-0,84	9,65	9,63	15,58	16,84	4	3	5

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