Testing the accuracy of the Emerging Market Scoring Model for measuring and predicting financial distress for South African firms

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Abstract

This study investigated the accuracy of the Emerging Market Scoring Model (EMS model) for measuring and predicting financial distress for South African firms. The EMS model was applied to a 62-firm sample composed of two independent groups of 31 firms each, known as the extender and non-extender groups, for the period ranging from the financial years ended 2017 to 2020. Firms in the extender group extended the release of their financial results for the financial year ended 2020, signalling possible financial distress. For comparison, these were matched with 31 firms that did not extend the release of their financial results for the financial year ended 2020. The accuracy with which the EMS model predicted the financial distress of the extender group firms over the period was tested, by categorising firms into a financial health zone known as the EM score. A t-test was conducted to test whether a statistically significant difference existed between the mean EM scores of the two sample groups. The Fisher's exact test was conducted to test for the existence of a statistically significant non-random relationship between the two sample groups and the EMS model's categorical outputs. The EMS model displayed low predictive accuracy over the period, largely attributed to the limitations of the study. The t-test found a statistically significant difference between the extender and non-extender sample groups' mean EM scores over the period, while the Fisher's exact test did not find a statistically significant relationship between the two sample groups and the EMS model's categorical outputs. The study's results were therefore inconclusive that the EMS model is an accurate measure and predictor of financial distress for South African firms, although the results were promising enough to warrant future research. The study seeks to fill a methodological gap by testing a model that has enjoyed limited usage in South Africa, with the potential to aid stakeholders in proactively identifying and improving the financial health of firms, thereby alleviating the societal costs of business failure.

Key words: Altman Z-score, EMS model, financial distress, financial health, South Africa

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1. Introduction

Successful and sustainable firms are the progressive engine of the global economy. The World Bank's Ciani, Hyland, Karalashvili, Keller & Tran (2020) posited that successful large firms will make one of the greatest contributions to economic restoration and job creation in the post-pandemic global economy. Ciani et al. (2020) believed that the macro development of successful economies is greatly determined by sustainable large firms, because their productivity is great enough to have a significant effect on aggregate economic output and welfare.

The existence of successful large firms is therefore vital. Equally vital is enabling the growth of potential high-growth firms and safeguarding the sustainability of existing firms. Successful large firms have the advantages of economies-of-scale, in that they have the power to influence wages and decrease raw material and manufacturing costs. Large firms have access to greater monetary capital reserves with which to invest more into research and development, and to make productive investments that allow more efficient growth than less stable start-up firms. Large firms also have access to the best human capital, which gives them access to cutting edge business intelligence to serve their markets (Ciani et al., 2020). In addition, well-functioning economies have much of their labour force in successful large firms that provide mass employment to the populace, compared to slow-growing and sluggish economies (Ciani et al., 2020).

Nevertheless, large firms experience a lot of volatility and uncertainty, especially in the emerging markets, and their continued success and growth into sustainable firms is pivotal to the growth and stability of emerging market economies. Ciani et al. (2020) suggested that stakeholders must facilitate the sustainable growth of firms that are financially healthy. Those that are financially unhealthy or face financial distress should be remedied effectively to safeguard their sustainability and ensure their survival and growth into stable large firms (Ciani e al., 2020). Cassim & Swanepoel (2021) added that these firms' financial health should be continuously and thoroughly evaluated, as proactive identification of financial distress - which allows management to apply effective remedies to restore a firm's financial health - can ensure their growth and sustainability.

This necessitates the need for an effective measure and predictor of the financial distress of firms. According to empirical studies, financial distress prediction models can predict a firm's financial condition and its susceptibility to financial distress, bankruptcy, and failure, which allows for the proactive application of effective remedial action to safeguard the firm's financial health. History teaches that firm failure metes out severe consequences that effect many stakeholders within an economy. Stakeholders such as employees, creditors, banks, and governments are impacted heavily by firm failure through the loss of income, revenues, and assets (Cassim & Swanepoel, 2021). For this reason, applying financial distress prediction models to firms on a regular basis can act as an early warning sign to detect inbound financial distress. This facilitates the proactive implementation of remedial action to avoid firm failure.

This is particularly important in South Africa, where firms were under increasing strain owing largely to the slow growth of the domestic economy following the global financial crisis (Venter & Wolhuter, 2023). Successful South African firms contribute greatly to the gross domestic product of the nation through investment, job creation, domestic capital accumulation, and overall economic welfare. But South African firms face a challenging operating environment that severely impacts on their ability to remain sustainable going concerns (Venter & Wolhuter, 2023). In addition, Inflationary pressures and rising interest rates, political and regulatory policy uncertainty, and the emergence of unforeseen global shocks such as pandemics and war, are some of the main challenges (Venter & Wolhuter, 2023). The idea for this study was borne out of this environment. The study investigated the accuracy of a particular financial distress prediction model to measure and predict financial distress for South African firms, namely the Emerging Market Scoring Model (EMS model) (Altman, 2005). The EMS model was created for use in the emerging markets and considers their unique characteristics in its methodology. It is also the first of its kind and is recognised as a benchmark for predicting the financial distress of emerging market firms (Cassim & Swanepoel, 2021).

The study's sample was selected from the Johannesburg Stock Exchange which was comprised of 397 publicly listed South African firms, as at the financial year (FY) ended 29 February 2020. From this population, 40 firms were identified that extended the release of their financial results past the agreed due dates of issue for the FY ended 2020, signalling possible financial distress. Nine financial services firms were excluded from the 40 because of their characteristically opaque nature (high leverage and off-balance sheet financing), which could skew the EMS model's results. 31 firms therefore constituted the sample of firms that extended the release of their financial results. Economics literature posits that firms delay the release of their financial results for several reasons, a major one being financial distress (Agyei-Mensah, 2018; Lukason & Camacho-Miñano, 2019; Nurquran, 2023). This study therefore made the assumption that all 31 of these firms experienced financial distress in the FY ended 2020. These 31 firms therefore acted as the study's proxy for financially distressed firms, since the relatively small size of the South African capital market did not provide a full sample of bankrupt firms in the study's period with which to test the EMS model. For comparison, each of these 31 firms were matched with firms that did not extend the release of their financial results for the FY ended 2020, bringing the total sample of firms to 62. These two independent samples were termed the *extender* and *non-extender* groups. FY 2020 is the *'year of financial distress'* in this study, and the focal point in the study period when the extender group firms were expected to experience financial distress. The year end information relating to FY 2020 is calendar year 2019. FY 2020 is also the year from which the preceding year end periods' financial condition is relatively observed and measured. This denotes FY 2019 as the *'one-year prior to distress'* mark, and all other years as prior to FY 2020 following the same sequence. The following research question and sub-questions are answered:

1) Is the EMS model an accurate measure and predictor of corporate financial distress for South African firms?
    a) Does a statistically significant difference exist between the mean EM scores of the two sample groups - extender and non-extender?
    b) Is there a statistically significant non-random relationship between the sample groups (extender/non-extender) and the EMS model's outputs related to the firms' financial condition (distressed/safe)?

To answer the main research question 1), The accuracy with which the EMS model predicted the financial distress of the extender group firms (and for comparison the non-extenders) over the period was tested, by categorising firms into a financial health zone known as the

EM score. The EM score places a firm into a financial health zone, namely: distressed, grey, and safe. To answer sub-question a), the t-test was conducted to test whether a statistically significant difference existed between the mean EM scores of the two sample groups. To answer sub-question b), the Fisher's exact test was used which is a statistical methodology used to establish if there are non-random associations between two categorical variables (Jung, 2014). In this study, the fisher's exact test was used to gauge for the existence of a statistically significant non-random relationship between the two sample groups and the EMS model's categorical outputs related to the firms' financial health zone. The EMS model predicted financial distress for the sample with low accuracy rates, one-year, two years, and three years prior to the year of financial distress in FY 2020. However, the t-test found a statistically significant difference between the extender and non-extender group firms' mean EM scores over the study period. Conversely, the Fisher's exact test found that the relationship between the two sample groups and the EMS model's categorical outputs related to the firms' financial condition was not statistically significant. Nonetheless, the EMS model detected that the occurrence of distressed firms was greater in the extender group than in the non-extender group. The EMS model was able to distinguish and show that extender group firms would experience greater financial distress than non-extender group firms over the period. The study's results were therefore inconclusive that the EMS model is an accurate measure and predictor of financial distress for South African firms, although the results were promising enough to warrant future research. The literature review section delves into the history and literature of financial distress prediction models. Research conducted in developed and emerging markets using Altman's models and other methodologies are discussed. The data methodology section outlines the research design and the sample criteria, and the EMS model's variables are explained. The results section discusses the output of the EMS model on the 62-firm sample. For comparison, the extender and non-extender groups are closely examined via descriptive statistics and ratios, and the research questions are revisited and answered. Lastly, the study's limitations and areas for further research are outlined, and the work is concluded. The study seeks to fill a methodological gap by testing a model that has enjoyed limited usage in South Africa, with the potential to aid stakeholders in proactively identifying and improving the financial health of firms, thereby alleviating the societal costs of business failure.

2. Literature review

This section explores the literature of financial distress prediction models and the preceding development of traditional ratio analysis as a method to evaluate and predict a firm's financial distress and its probability of bankruptcy. The history and development of Altman's financial distress prediction models are surveyed and discussed, with a special focus on the Emerging Market Scoring Model (EMS model) (Altman, 2005). Research conducted in South Africa and other emerging markets using Altman's suite of models and other financial distress prediction models are surveyed and discussed.

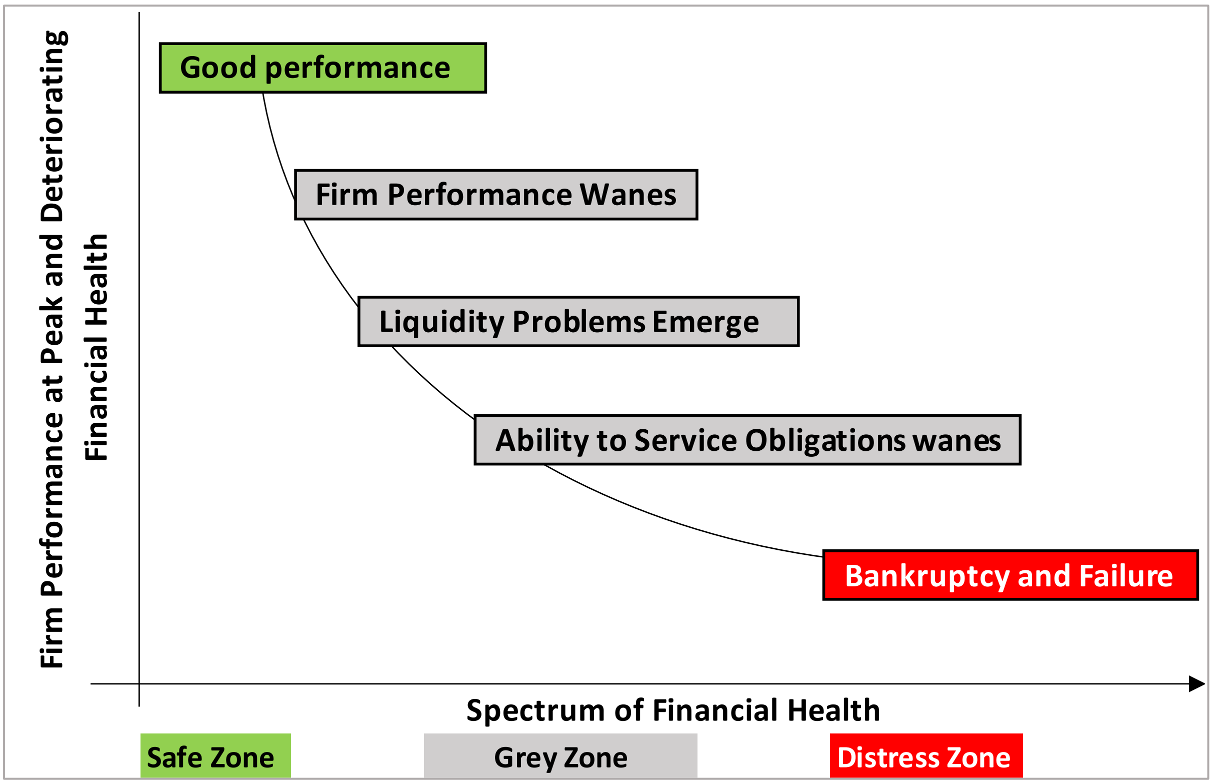
In its methodology, the EMS model outputs a score, the EM score, that is convertible into a similar United States (U.S.) corporate bond rating - known as the 'bond rating equivalent' (BRE) (Altman, 2005). The BRE is comparable to the ratings given by credit rating agencies (CRAs) to similar U.S. corporate bonds and can be used in lieu of or in addition to the ratings provided by CRAs (Altman, 2005). Therefore, the history and track record of CRAs is briefly discussed. Considering the latter, the literature encourages the use of financial distress prediction models as additional tools to measure and safeguard the financial health of firms, and briefly outlines other applications of financial distress prediction models.

2.1 Financial Distress

Financial distress is defined differently by various authors throughout the history of financial literature. The expressions financially distressed, financially unhealthy, insolvent, bankrupt, and failure are used synonymously in finance literature (Sabela, Brummer, Hall & Wolmarans, 2018). These terms do not ordinarily mean the same thing in a technical sense. A firm can experience financial distress and not become insolvent or enter bankruptcy. Bankruptcy and failure are at the extreme end of the spectrum as shown in figure 1, where a firm has experienced ongoing financial distress without remedy which progresses into a state of insolvency and consequent bankruptcy and failure.

Section 128 of the South African Companies Act of 2008 defines financial distress as an inability by a firm to service its liabilities as they become payable within the subsequent six months and/or the probability that a firm will become insolvent within the subsequent six months (*Companies Act, No. 71 of 2008*, 2009:s128). Elloumi & Gueyie (2001) agreed, stating that financial distress occurs when a firm deteriorates to the extent that it is unable to service its liabilities.

Figure 1: Spectrum of financial health



Source: Prepared by the author

According to Beaver (1966), firm failure occurs when a firm becomes derelict in paying its bonds, has an overdrawn bank account, fails to pay its preferred stock dividend, or has entered bankruptcy. Beaver (1966) defined firm failure as the incapability by a firm to honour its financial obligations as they become due. Ngwenya (2018) defined firm failure as unrelieved financial distress that could result in bankruptcy. Both authors see financial failure as present even before a firm technically exits the market.

These definitions imply that financial distress may be transitory and treatable, in that when distress is detected early enough it allows firms to take remedial action to avoid insolvency and bankruptcy. When financial distress is detected too late or not remedied effectively, it may lead to firm failure, thus the use of 'probability' of bankruptcy in the literature. Beaver

(1966) agreed with the latter, noting that the ability to identify the financial illnesses of firms implied the possibility that several firms' 'illnesses' *are* proactively identified, and effective remedies applied before firm failure happened. Beaver (1966) noted that ratio analysis was recognized as far back as 1966 as having the potential to save a firm from failure before it occurred, via its predictive mechanism that acted as a diagnostic tool to identify financial illnesses in need of remedy.

Carmichael (1978) prescribes four scenarios that might result in financial distress. These are inadequate liquidity, failure to meet debt obligations, inadequate equity, and inadequate liquid capital. Conversely, Doumpos & Zopounidis (1999) posit that failure to pay debt obligations is not sufficient to classify a firm as financially distressed, and that a firm truly reaches the failed state when its total debt surpasses its total assets.

Another interesting addition to the financial distress debate is the phenomenon of firms extending the release of their financial results. Since the early 1980's, most conventional economics literature theorized that any delay in financial reporting by firms signalled the possibility of brewing financial distress (Whittred & Zimmer, 1984). Contemporary literature also finds evidence to support the latter for the most part, implying that the delay of financial results may indicate underlying financial distress, or may be caused by other factors (Lukason & Camacho- Miñano, 2019) (Nurquran, 2023). Extend and delay are used synonymously to denote the act of firms not releasing their financial results on the originally agreed due date of issue.

Whittred & Zimmer (1984) sought to answer this question by assessing whether reporting intervals vary between healthy and distressed firms. Whittred & Zimmer (1984) investigated the association between the timeliness of financial reporting and the probability of financial distress on a sample of Australian firms listed on the Sydney Stock Exchange. The authors used their own multiple discriminant analysis model on two independent samples; 37 failed firms matched with 37 firms that did not fail. The model used financial ratios and found that significantly longer delays of financial results were observed in several firms that experienced financial distress two years prior to failure. The authors found financial ratios to be more accurate predictors of financial distress than merely observing lags in financial reporting. In other words, though firms lagging in releasing their financial results signal possible financial distress, prior periods of reporting lags have little predictive ability for the future. Whittred & Zimmer (1984) therefore noted that information on reporting lags prior to firm's experiencing distress did not increase the ability of the authors to predict financial distress even when using distress prediction models fed by financial ratios. This is because delays in financial reporting can happen for reasons other than preceding or current financial distress (Whittred & Zimmer, 1984).

Lukason & Camacho-Miñano (2019) investigated the interconnectivity between Estonian firms' annual financial reporting delays and bankruptcy risk, and financial determinants. The study period was 14 years from 2000 to 2014, and the sample included roughly 90% of the active firm population in Estonia. The authors used Altman's (1968) Z-score model to evaluate the probability of financial distress of the sample. Lukason & Camacho-Miñano (2019) found that firms with greater bankruptcy risk had a greater likelihood of extending the release of their financial results. They also found that firms with lower profitability and liquidity were likelier to extend the release of their financial results. In their study, Lukason & Camacho-Miñano (2019) warned stakeholders to practice caution when extending credit to firms that extend the release of their financial results, as the latter could signal poor financial health and a higher probability of bankruptcy. Lukason & Camacho-Miñano (2019) believed that the association between financial distress and information disclosure is a pivotal and evolving area for research that warrants further inquiry.

Nurquran (2023) conducted a study to analyse how financial distress affects financial reporting delays in firms listed on the Indonesian Stock Exchange from 2014 to 2020. The study found that the likelihood of a firm extending its financial results is directly related to the degree of financial distress experienced by the firm. Like Lukason & Camacho-Miñano (2019), Nurquran (2023) advised investors and regulators to practice prudency when decision-making regarding firms that extend the release of their financial results. This implies that the delay of financial results may or may not imply financial distress, but that the likelihood of firms extending their reporting is higher when they are experiencing financial distress.

Agyei-Mensah (2018) investigated the effects that financial reporting delays has on firms. Agyei-Mensah (2018) examined the impact of financial reporting lags and governance on the financial health of listed Ghanian firms from 2012 to 2014. The study found that firm performance is negatively affected by lags in financial reporting, and that this relationship is statistically significant. In addition, Agyei-Mensah (2018) stated that firms are often eager to report good performance and less eager to report bad performance. The implications of reporting lags negatively affect a firm's reputation, making it difficult to attain capital (Agyei-Mensah, 2018). Irrespective of the reasons that firms extend the release of their financial results, the consequences are often material and can negatively affect the firm (Agyei-Mensah, 2018).

There are other reasons why firms extend the release of their financial results which does not imply financial distress, such as audit delays (Lukason & Camacho- Miñano, 2019). Regardless of the reasons, financial literature concedes that extending the release of financial results indicate financial distress to some degree and is indeed a major market event that has consequences that are largely financial in nature (Lukason & Camacho- Miñano, 2019) (Nurquran, 2023). For example, a loss of investor confidence could spark a sell-off of the firm's stock and result in a share price depreciation. Consequently, a firm can incur monetary penalties from regulatory bodies for failure to release financial results on time, which can result in a firm incurring difficulties in raising additional money in the capital markets. The latter can impair a firm's present and future financial health and overall firm performance.

In South Africa, non-compliance to the Johannesburg Stock Exchange (JSE) regulations on the release of financial results can be penalised by suspension of a firm's listing on the exchange. During the Covid-19 pandemic, the JSE was very strict on the timeliness of results. Firm's that sought an extension were considered on a case-by-case basis and the same penalties would be enforced on non-compliance. Nevertheless, 40 firms listed on the JSE extended the release of their FY ended 2020 financial results in FY 2020.

Regardless of the divergence in the nomenclature, history has shown that firm failure metes out severe consequences that effects many stakeholders in an economy. Stakeholders such as employees, creditors, banks, and governments are severely impacted by firm failure through the loss of income, revenues, and assets (Cassim & Swanepoel, 2021). For this reason, applying financial distress prediction models to firms on a regular basis can act as an early warning sign to detect financial distress requiring treatment. This facilitates the implementation of proactive remedial action for firms to improve their financial condition and avoid failure.

Ngwenya (2018) and Cassim & Swanepoel (2021) agreed that timeous discovery of financial distress is pivotal to the survival of firms. Since the year 2000, many large firms have gone bust because of financial troubles not being dealt with timeously. Some of these include South African firms 1Time Holdings and Velvet Sky, and large U.S. firms Lehman Brothers, American International Group (AIG), and Chrysler (Cassim & Swanepoel, 2021). Sabela et al. (2018) agreed with this view, that early identification of financial distress is pivotal for safeguarding economic and social value and can potentially assist in preventing and mitigating losses to investors and stakeholders.

2.3 Theoretical framework

Quantitative studies on financial distress prediction models have their genesis in the 1930's (Bellovary, Giacomino & Akers, 2007). These works investigated the utility of employing financial ratios that are quotients of two numbers derived from financial statements, to measure the financial health of firms and their likelihood of distress and failure. Financial distress models existed for centuries prior to the 1930's in major economies like the U.S. and Europe and utilized a myriad of methodologies to calculate the financial health of firms. Primitive models deployed categorical variables with little to no analytical study, mostly utilizing qualitative and behavioural aspects such as leadership and governance (Bellovary et al., 2007).

Ratio analysis was young in the 1960's, with corporate creditworthiness measures restricted to one ratio – the current ratio (Beaver, 1968). By this time, the identification of financial distress had begun to forge a strong link with traditional ratio analysis, though little empirical evidence existed about the utility of ratio analysis for decision-making (Beaver, 1966). Beaver (1966) presented one of the first definitive empirical works on the efficacy of employing financial ratios to predict the financial distress of firms. Beaver (1966) tested 30 ratios on a sample of 79 bankrupt and 79 non-bankrupt public U.S. industrial firms. Financial statement data was gathered for a 10-year period from 1954 to 1964. The ratios were chosen based on their prevalence and acclaim in prior literature, their performance in prior literature, or their prior existence as a cashflow ratio. The population of selected firms represented 90% of the market capitalisation of all U.S. industrial firms in 1966. Financial statement data for the failed firms were collected for five years before they failed, starting in 1949, and matched by non-bankrupt firms based on industry and asset size similarities. Beaver (1966) sought to ensure sample homogeneity that would not be impeded by contrasting industries. This was to ensure that identical numerical ratios do not infer different financial conditions on firms in one industry compared to others.

Beaver (1966) used a simple univariate analysis model which investigated the predictive potential of the independent variables (ratios) one at a time. Beaver (1966) nevertheless made three important discoveries. Firstly, the ratio of a firm's cash flow from operations to its total debt was the prime predictor of financial distress (Beaver, 1966). This is intuitive since a firm generating ample cash in proportion to its debt has the liquidity to repay its liabilities and diminishing its risk. Secondly, ratio analysis could predict the probability of financial distress for up to five years in advance (Beaver, 1966). Thirdly and perhaps most importantly, when ratios were employed to proactively detect the financial illness of firms, remedial treatment could be applied to prevent further deteriorating and firm failure (Beaver, 1966).

Beaver (1968) intended his study to be a benchmark for subsequent inquiry into other models for predicting financial distress as well as other forms of presenting and using accounting data. Beaver (1968) championed the use of ratios for uses other than financial distress prediction and his works paved the way for the adoption of more sophisticated models.

2.4 The Original Z-score (1968) model

Prior inquiries heralded subsequent researchers such as American Finance Professor Edward Altman (1968) to develop a multivariate analysis model. The latter was intended as a numerical measurement tool to evaluate the financial health of U.S. manufacturing firms, and to predict their probability of going bankrupt in the next one to five years (Altman, 2018). Altman (1968) theorized that prior works strongly suggested that ratio analysis had the potential to act as a measurement tool for a firm's financial condition. Altman (1968) agreed with previous authors that ratios evaluating liquidity, profitability, and solvency were the most critical barometers to measure firm financial health and performance. Yet Altman (1968) noted that ratio analysis was unappreciated as an analysis method, and that many academics and practitioners despised the relevance of ratio analysis. For this reason, Altman (1968:589) endeavoured to investigate its merits to *"bridge the gap… between traditional ratio analysis and the more rigorous statistical techniques which have become popular among academicians…"*. Altman (1968) also observed that prior studies quoted different ratios within the liquidity, profitability, and solvency spectrum as being relatively more effective, while establishing no order of importance. Thus, no consistency had been established yet.

Altman (1968) further noted that prior works lacked because they employed univariate analysis that was vulnerable to confusion and misinterpretation, since the methodology accentuated singular variables in evaluating financial distress while not accounting for the relationships of the variables to each other. Altman (1968) therefore sought to build upon the findings of prior studies expansively to build a better, multivariate analysis model, that used the multiple discriminant analysis (MDA) statistical technique. MDA categorises objects into two or more categories that are mutually exclusive, where a classification is made in problems where the dependent variable is qualitative, such as 'male or female' or 'bankrupt or non-bankrupt' (Altman, 1968, 590-592). Where univariate analysis examines variables one by one, MDA has the benefit of wholly evaluating all the independent variables including the relationship between the variables. MDA has been used since the 1930's in several disciplines such as biology, behavioural science, and by the economic and financial disciplines since the 1960's (Altman, 1968). The MDA statistical technique was made possible by the advent of computers which became increasingly available by the mid-1960's and allowed for more rigorous statistical analysis. This computing power was utilised to enhance the information content of accounting numbers on financial statements, which facilitated the creation of Altman's first financial distress prediction model in 1968 (Altman's, 1968). By using the MDA statistical technique, Altman (1968) created the Altman Z-score model in 1968 as a predictor of corporate financial distress.

In his original study, Altman (1968: 589) analysed 66 manufacturing firms in the U.S. and divided them into two categories: 33 bankrupt and 33 continuing firms. Mean size was considered, and outliers were eliminated to ensure sufficient homogeneity of the sample, and to reduce the size effect on the results. Altman (1968) however, believed that financial ratios nullified the size effect, and that prior studies in any case did not adequately differentiate between size. Beaver (1968) did not strictly account for asset size but argued contrary to Altman (1968) that asset size changes the correlation between ratios and the outcome of financial distress prediction, which would distort a comparison between large and small firms. In other words, all else equal, a large firm is still more solvent than a smaller firm. Therefore, investigators into this field should consider size.

The data for the bankrupt firm's was chosen five financial years before they filed for bankruptcy, with non-bankrupt firms concurring for the same period - from 1946 to 1965. Altman (1968: 591) initially chose 22 ratios for the analysis and collected income statement and balance sheet data for the sample of firms. Like Beaver (1966), the ratios were collected on the premise of their acclaim in prior literature and their prospective applicability in the study as judged by the author. Altman (1968: 592) trimmed the 22 ratios down to five deemed to be the most effective in predicting corporate financial distress. He argued that certain ratios had larger mutual collinearity and correlation and would therefore cancel each other out (Altman, 1968: 594). This process condensed the predictive independent variables (ratios) into a small yet powerful model that could impart significantly useful information. The five ratios fall into the following categories: Liquidity, profitability, leverage, solvency, and activity ratios. Altman (1968) then attached objectively derived weights (coefficients) to each ratio that was derived via the computer algorithm employed.

The linear discriminant function structure of the original Z-score (1968) model is as follows:

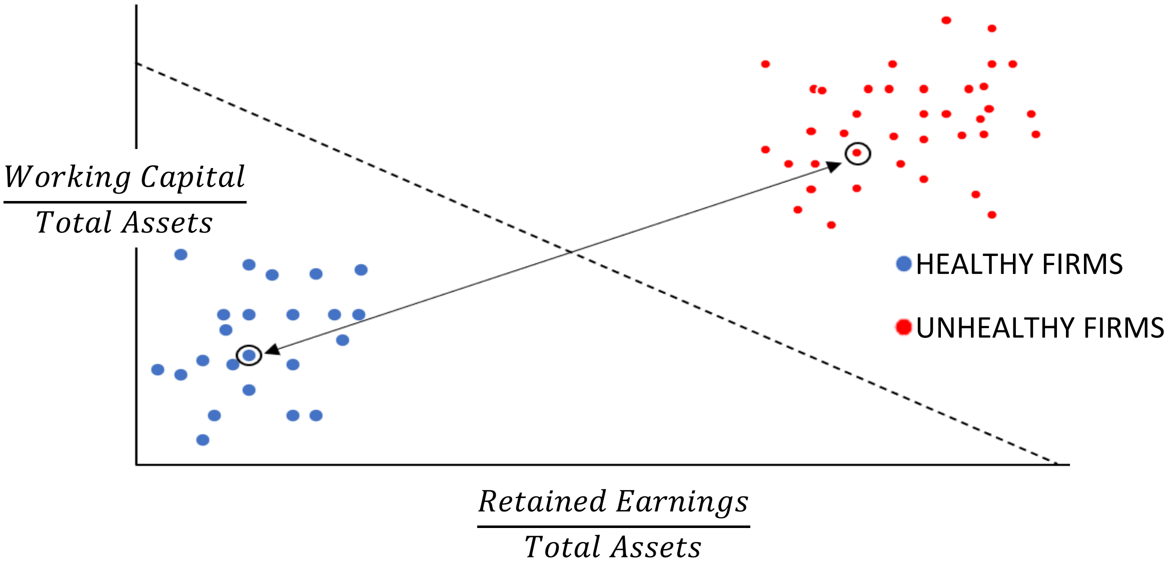
$$\boldsymbol{Z = a_1x_1 + a_2x_2 + a_3x_3 + \ldots + a_nx_n}$$

$Z =$ The $Z -$ score is the discriminant score (dependent variable)

$a =$ The objectively derived weights or discriminant coefficients

$x =$ The five best discriminant independent variables (ratios)

Figure 2: Linear Discriminant Structure



Source: Prepared by the author

The Altman Z-score (1968) model is outlined below:

$$\boldsymbol{Z = 1.2\,x_1 + 1.4\,x_2 + 3.3\,x_3 + 0.6\,x_4 + 1.0\,x_5}$$

$x1 =$ Working capital / total assets

$x2 =$ Retained earnings / total assets

$x3 =$ Earnings before interest and taxes / total assets

$x4 =$ Market value of equity / book value of total debt

$x5 =$ Sales / total assets

Altman (1968: 589) found that by using the MDA statistical technique, the model enhanced the information content of ratios, making it useful as a predictor of financial distress. Altman (1968: 604) found that the Z-score model was 95% and 72% accurate in predicting the bankruptcy of firms one and two years prior to failure, respectively. In addition, Altman (1968) found that the Z-score model was 48%, 29%, and 36% accurate in predicting bankruptcy three years, four years, and five years prior to bankruptcy, respectively.

Altman (1968) observed that an expansion of the time interval prior to bankruptcy reduced the model's predictive accuracy. Altman (1968) therefore posited that the Z-score model is rendered inaccurate post the second year and would henceforth have little statistical significance (Altman, 1968), contrary to the findings of Beaver (1966). The original Z-score (1968) model is among the most popular and employed models to measure and predict the financial health of firms globally (Altman, 2018). Contemporary literature views the Z-score model as an effective short-term financial distress prediction tool, effective at aiding other methods that are effective over a longer time horizon, such as the ratings provided by CRAs (Altman, 1968). After creating his first model, Professor Altman envisioned additions to the Z-score model for suitability to measure non-manufacturing firms and firms outside of the U.S. (Altman, 2005).

2.5 The EMS model (2005)

To internationalise the utility of the original Z-score model beyond the U.S. market, an enhancement to model followed in 1995, called the Z-double-prime model (Altman, 2005). The Z-double-prime model was intended for utility in emerging economies and nonmanufacturing firms, and has been used to evaluate the financial condition of firm's inside and outside of the U.S. This is unlike the original Z-score model which was created mainly for applicability in the U.S. (Altman, 2005).

In 2005, Altman (2005) introduced an enhanced version of the Z-double-prime model called the Emerging Market Scoring Model (EMS model). The EMS model built upon the empirically tested Z-score model of 1968 and Z-double-prime model of 1995 with enhancements that sought to cater for the unique economic characteristics of emerging market firms. The EMS model became a practical methodology to evaluate and predict the financial health of private and public firms in emerging markets (Altman, 2005). Prior to the EMS model, most financial distress models focused mainly on firms in the U.S. In addition, the original Z-score model was unsuitable to measure all emerging market firms since it necessitated that firms be public *and* be engaged in manufacturing (Altman, 2005: 313).

The EMS model's methodology follows a similar approach to the original Z-score model by calculating a firm's 'EM score'. The EMS model goes further than the original Z-score model by translating this EM score into a related bond rating equivalent (BRE) that is comparable to U.S. corporate bond ratings established by credit rating agencies (CRAs) (Altman, 2005: 312). The BRE can be contrasted to actual corporate bond ratings assigned by CRAs and provide additional information for decision making. This makes it possible for market participants to conduct their own independent research and not overly rely on CRAs, especially since CRAs have been found lacking in the past (Gredil, Kapadia & Lee, 2022).

The EMS model is as follows:

$$\boldsymbol{Z = 6.56(x_1) + 3.26(x_2) + 6.72(x_3) + 1.05(x_4) + 3.25}$$

$x1 = \text{Working capital / total assets}$

$x2 = \text{Retained earnings / total Assets}$

$x3 = \text{Operating income / total assets}$

$x4 = \text{Book value of equity / total liabilities}$

Altman (2005: 316) replaced the use of the 'market value of equity' used in the original Z-score model with the 'book value of equity' in the EMS model's formula. This was to render the model useful for evaluating the financial condition of private emerging market firms since the availability of constant equity prices could be unattainable in this case. This was also to account for the illiquidity and inefficiency that is generally thought to characterise emerging market economies. The constant term of 3.25 in the EMS model originated from the Z-double-prime model which is the calculated average Z-scores of bankrupt U.S. firms and is intended to standardize the EMS model's output (Altman, 2005). The EMS model's methodology follows six sequential steps:

Step one calculates the firm's EM score and translates it into a BRE that is comparable to U.S. corporate bond ratings assigned by CRAs (Altman, 2005: 313).

Step two adjusts the firm's BRE to consider its susceptibility to currency shocks. This evaluates a firm's ability to meet its foreign currency denominated liabilities (Altman, 2005: 313). This result could move the BRE up or down.

Step three adjusts the firm's rating according to its industry environment to determine weaknesses or strengths (Altman, 2005: 313). This result could move the BRE up or down.

Step four adjusts the firm's rating according to the firm's competitive stature within its industry by looking at its size, management conditions, and domestic political influence. (Altman, 2005: 313). This result could move the BRE up or down.

Step five examines any distinctive traits of the firm's debt or bonds, by looking at special collateral and guarantor qualities. (Altman, 2005: 313). This result could move the BRE up or down.

Step six contrasts the firm's modified BRE established in step two to six to similar actual U.S. corporate bond ratings assigned by CRAs. If no credit rating exist, the revised BRE can act as a credit quality assessment tool on its own (Altman, 2005: 313).

Note that step one is the only quantitative measure and can be used exclusively to measure a firm's financial condition (Altman, 2005). Steps two to six are qualitative and subjective in nature and are merely designed to augment the findings established in step one (Altman, 2005: 313). This study will only utilize the quantitative output of the EMS model in step one. Altman (2005: 315) affirmed that step one can be applied alone to provide valuable information. Altman (2005: 315) also affirmed that the EMS model can be utilized to measure any emerging market firm's credit quality, irrespective if the firm has outstanding bonds or not.

2.6 Applications of the Altman Z-score model (1968) and the EMS model (2005)

Altman (2005) initially tested the EMS model on 31 Mexican firms that had outstanding Eurobonds, for the year-ended 1994 to 1996. Mexico was experiencing the peso-crisis that commenced because the Mexican government devalued the peso against the U.S. dollar, which caused massive capital flight from Mexico. By the year-ended 1994, only 13 of the 31 firms in the sample were rated by a CRA (Altman, 2005). The EMS model's EM score and the subsequent BRE rated all the firms, and the BRE's for the sample ranged from AAA (good credit quality) to D (bad credit quality).

After the peso crisis of 1994, Altman (2005) noted that the EMS model's EM score detected with significant certainty the recessionary economic and business conditions wrought by the peso-crisis on the sample of firms. These conditions further deteriorated in 1995 with a trough beginning in 1996. By 1996 the Mexican economy had begun a recovery, and this was commensurate with the improvement in the EM scores observed for the sample of firms in 1996, as calculated by the EMS model.

After the initial application of the EMS model for the year-ended 1994, Altman (2005) maintained continuous observance of the sample's EM scores and calculated successive BRE's in 1995 and 1996 for most of the firms in the initial sample. The firms most closely watched were those categorised as CCC (extremely risky) and D (so risky that default is imminent). Of the firms that eventually defaulted, the EMS model clearly detected their debt and financial distress as well as indicated the recovery of the firms that had successfully restructured. Three firms in particular, Grupo Sidek, Grupo Situr, and Grupo Simec had junk bond ratings assigned by the EMS model in 1995. Failed attempts to successfully restructure in 1995 continued to weight on the firms' financial health, and the EMS model assigned these firms a D rating in 1996 prior to their failure (D equates to 'so risky that default is imminent'). The firms later defaulted on their debt in 1996. This proved the predictive ability of the EMS model in an emerging market in its original application.

In South Africa, Ngwenya (2018) evaluated the levels of financial distress faced by publicly listed South African gold and platinum firms for the period of 2011 to 2015. The Altman Z-score and EMS model were utilized to predict the financial distress of the sample of 5 gold and 5 platinum firms. Ngwenya's (2018) study focused on mining firms, citing that the latter have played an integral role in the development of the South African economy since the 1800's, and because most financial distress studies done prior to his have focused mainly on firms in other industries. Ngwenya (2018) found that gold mining firms faced more financial distress than platinum mining firms. Ngwenya (2018) recommended that the management of gold and platinum mining firms carry out consistent ratio analysis to proactively apply the necessary remedial actions to improve their financial health. In addition, Ngwenya's (2018) agreed with Altman (2005) that continuous analysis via ratio analysis, among other tools, is beneficial to the sustainability of firms within an economy.

Rama (2012) empirically tested Altman's (1968) Z-score model on a sample of 227 South African firms listed on the JSE in 2008 to calculate their probability of failure in 2009 and 2010. Rama (2012) found Altman's (1968) Z-score model to be an effective tool for evaluating and predicting firm financial distress. Rama (2012) identified moderate to high financial distress among firms that did not ultimately fail. These firms subsequently showed an improvement in their Z-scores. Rama (2012) therefore asserted that prior discovery of financial distress could enable management to take remedial actions to prevent losses and ensure solvency, in line with the findings of Beaver (1966), Altman (2005) and Ngwenya (2018).

Marias, Soni & Chitakunye (2014) used Altman's (1968) Z-score not to predict the probability of failure, but to predict the probability of success. The authors investigated the Z-score's ability to predict corporate success as well as the financial health and performance on 13 South African firms listed on the JSE, one year after measuring the firm's health using the Z-score model. Diverging from the conventional direction of most studies, Marais et al. (2014) intended to investigate the Z-score's ability to predict firm success one year prior to success. Inconclusive results on the Z-score's capacity to forecast the financial success of firms was found (Marais et al., 2014), although the effort indicated that Altman's (1968) Z-score model could possibly be used to predict a myriad of firms' financial conditions, including success.

Some researchers have attempted to augment financial distress prediction models to enhance their utility. In one study, Sabela et al. (2018) conducted a study that used a three-stage model to predict the financial distress of South African firms listed on the JSE. The authors endeavoured to increase the reliability of existing financial prediction models through the addition of independent variables in each stage of the three-stage model. Stage one used only fundamental firm financial data such as working capital and total debt ratios. Stage two added market-based data such as the price/earnings ratios and share price of firms. The authors found that the addition of step two to step one enhanced the model's accuracy. When adding macroeconomic indicators in stage three, such as gross domestic product and the unemployment rate, Sabela et el. (2018) found no improvement the model's effectiveness to predict financial distress. Note that steps two to six of the EMS model's process utilize the addition of macroeconomic elements to augment the model's output in step one. Sabela et al.'s (2018) study effectively negated the use of subjective macroeconomic variables.

Altman (2018) identified several uses of the original and subsequent Z-score models. The internal applications are introspective in nature. When management gauges the financial status quo, the model can help decide whether remedial action is needed, such as restructuring, spin-offs of unprofitable divisions, or outsourcing. Also, firms that rely on suppliers for goods or raw materials can use the model to decide whether to do business with entities based on their financial health. Scholars interested in particular firms from a case study point of view can employ the models to derive useful information regarding its economic standing.

The external applications are more numerous. Lenders and investors in a firm's bonds can use the models as decision-making tools, to aid in choosing to extend credit or to purchase a firm's debt. This can also aid in deciding suitable interest rates and applicable premiums. This is useful for banks and other providers of credit. The models can also aid in calculating appropriate default probabilities for firms issuing bonds, and therefore aid investors of fixed income assets (Altman, 2018: 1). Investors in a firm's equity can assess a firm's financial health to decide on an investment strategy. A firm with good financial health and positive outlook will likely form part of a long investment strategy where investors seek to gain from a firm's share capital appreciation and dividends. The Z-score models assign such firms a high (safe zone) score. Firms that are in distress with a high probability of default will most likely be included in a short portfolio that seeks to gain from a firm's stock price depreciation or bust (Altman, 2018: 2). Such firms would receive a low Z-score.

Ngwenya (2018) stated that institutional and retail investors, as well as managers of firms can benefit from conducting financial distress and bankruptcy prediction exercises regularly. The latter might illuminate bad financial management such as resource misallocation which can prevent large bankruptcies and large losses. Crucial intelligence is gleaned by assessing the financial condition of firms which can facilitate decision-making by principals and management. Therefore, financial distress prediction can act as a radar to detect financial imprudence within a firm, which can aid the administration of proactive remedial action to enhance a firm's financial health and avoid losses (Ngwenya, 2018). Lastly, disseminators of market information such as S&P and Bloomberg revealed that more equity analysts visit the Altman Z-score page than visits by fixed income analysts (Altman, 2018: 5).

2.7 Credit rating agencies

Financial distress models can curtail the overreliance on external providers of market information, such as that provided by CRAs. This facilitates market efficiency, especially since CRAs have been found lacking in recent years. CRAs became the subject of extensive studies that posit that the conflicts of interest inherent in CRAs arises from 'the issuer-pay model' and competition for clientele. This results in CRAs being disincentivised to issue correct ratings for their clients (Gredil, Kapadia & Lee, 2022). Mainstream negative sentiments on CRAs originated after the dotcom boom and bust and after the 2007 global financial crisis, when ratings were observed to be lagging (or slow) and lacking (or misleading).

This sentiment escalated in the aftermath of the global financial crisis when reporters and law makers identified that inflated ratings were assigned to structured financial products by CRAs. This resulted in the housing market boom leading up to the bust in 2007 (Gredil et al., 2022). The global financial crisis brought renewed scrutiny on ratings agencies when triple-A rated financial products when bust. Altman (2018:3) noted that roughly 22% of all bonds that have defaulted from 1971 to 2017 were rated investment grade by the professional CRAs. 19% of defaulted bonds since the start of the global financial crisis until 2017 were rated investment grade by the CRAs (Altman, 2018:3). The latter necessitates that money managers and investors include additional credit and risk models in their investment decisions. The Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act) was passed in 2010 as a U.S. federal law which made several important changes to financial regulations in the post global financial crisis era (Gredil et al., 2022). The Dodd-Frank Act enhanced consumer safety and financial stability by mandating that law makers refrain from referencing CRAs when drafting regulations, which effectively limited the use of credit ratings in regulations (Gredil et al., 2022). The Dodd-Frank Act further decreased the reliance of investors on CRAs by strongly encouraging investors to conduct independent due diligence (Gredil et al., 2022).

But CRA's are not discarded as credit measurement tools because they are indeed useful insofar as having the ability to predict a firm's financial condition beyond a one-year time interval, which is somewhat better than other measures over the same period. This is because other models, including the Z-score models, become less effective with longer horizons. As noted in the literature earlier, the Altman Z-score model (1968) and Altman EMS model (2005) are most accurate at a one-year prior horizon, slightly less in a two-year horizon but still useful. They become significantly unreliable after a two-year horizon (Gredil et el., 2022). Therefore, ratings by CRAs can be highly complemental to empirically tested statistical models such as the Z-score models.

Considering the above, this study intends to investigate the accuracy of the Emerging Market Scoring Model (EMS model) for measuring and predicting the financial distress of listed South African firms. Although the Z-score (1968) has been applied rigorously in the South African and international markets, the EMS model has enjoyed limited use as a methodology for predicting the probability of default of South African firms.

3. Data and methodology

This section outlines the research design and the sample criteria. The data selection process and study period are discussed, and the EMS model's variables are expounded upon.

3.1 Research design and sample

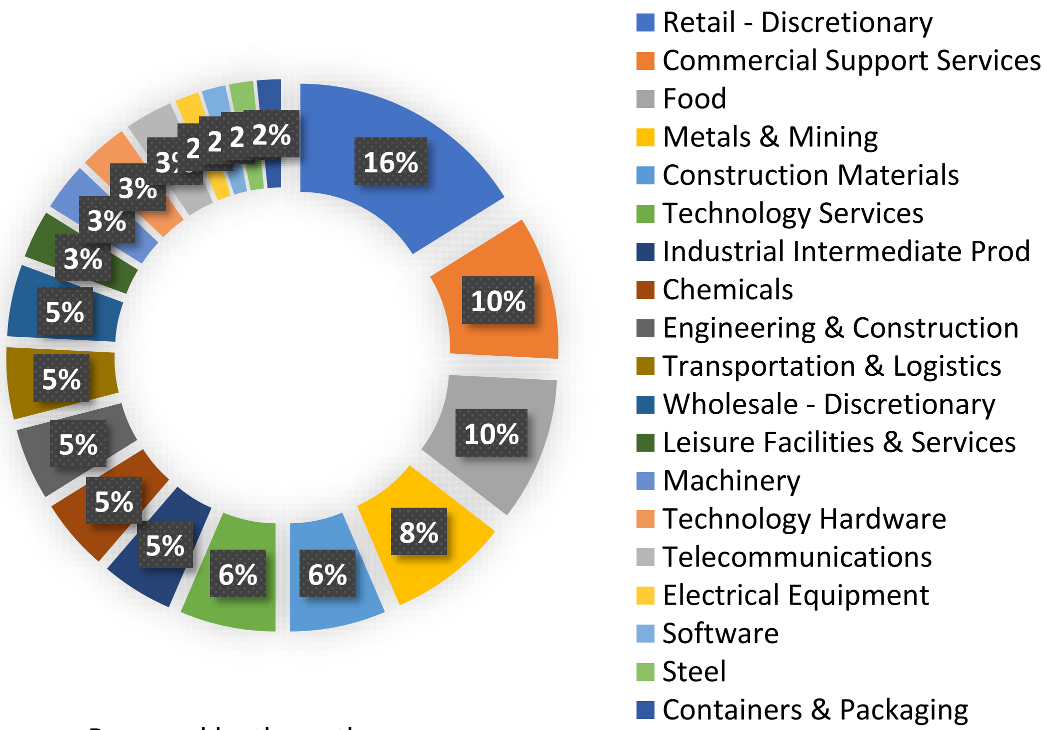
The study's sample was selected from the Johannesburg Stock Exchange which was comprised of 397 publicly listed South African firms, as at the financial year (FY) ended 29 February 2020. From this population, 40 firms were identified that extended the release of their financial results past the agreed due dates of issue for the FY ended 2020, signalling possible financial distress. Nine financial services firms were excluded from the 40 because of their characteristically opaque nature (high leverage and off-balance sheet financing), which could skew the EMS model's results. 31 firms therefore constituted the sample of firms that extended the release of their financial results. This study made the assumption that all of these 31 firms experienced financial distress in the FY ended 2020. These 31 firms therefore acted as the study's proxy for financially distressed firms, since the relatively small size of the South African capital market did not provide a full sample of bankrupt firms in the study's period with which to test the EMS model. For comparison, each of these 31 firms were matched with firms that did not extend the release of their financial results for the FY ended 2020, bringing the total sample of firms to 62. These two independent samples were termed the *extender* and *non-extender* groups.

The non-extender group was chosen based on the following criteria in order of importance: 1) The firm did not extend the release of its financial results for the FY ended 2020, 2) The firm is non-financial in nature and operates in the same sub-industry, industry, industry group, or sector as its extender group peer - as classified by the Bloomberg Industry Classification Standard (BICS). The BICS organises firms into coherent peer groups based on a firm's primary revenue source (Bloomberg, 2014) (see appendix 1). 3) The firm's total assets do not exceed each other more 30 times mutually. This was to minimise the size-effect in the sample. 4) The firm was publicly listed on the Johannesburg Stock Exchange (JSE) during FY 2020. Matching is first attempted via sub-industry and if a match is found, the peer closest in asset size to the extender group firm is chosen. If a peer is not found, the classification is broadened to provide more options, and this process is repeated until a suitable peer is found. Care was taken to ensure adequate homogeneity between the two samples. With the limited depth of the JSE, differences inevitably existed in the sample. This was kept to a minimum and outliers *were* eliminated as far as possible to ensure sufficient sample homogeneity, and to reduce the possibility of size effect distortions on the results. Altman (1968) believed however, that financial ratios nullified the size effect such that comparison is still valid.

Nevertheless, the implication of the JSE's lack of depth on the sample is that one pair of firms, namely Arden Capital Ltd and City Lodge Hotels Ltd, had a large asset size difference of 28.55 times. Note that this is the biggest difference, as the next four biggest asset size differences were no more than 9.90, 8.35, 6.29, and 5.76 respectively. The rest of the sample were much closer related in term of asset size. It is for this reason that the asset size criterion was deliberately loosened to *'firms' asset sizes should exceed each other no more than 30 times mutually'* to accommodate for this one extraordinary case.

The sample was comprised from various industries as displayed in figure 3.

Figure 3: Industry constituents of the sample



Source: Prepared by the author

3.2 Data and study period

All financial statement data was collected from the Bloomberg Terminal's Equity Screening Function. The Bloomberg Terminal is a reputable and global disseminator of financial data and news. The EMS model was built in Microsoft Excel, and the financial statement data was fed into the model to calculate the EM scores for the sample of firms (appendix 2).

This study tested the EMS model for a four-year period from FY ended 2017 to FY ended 2020. Note that FY ended 2020 is the '*year of financial distress*' in this study, and the focal point in the study period when the extender group firms were expected to experience financial distress. The year end info relating to FY 2020 is calendar year 2019. FY 2020 is also the year from which the preceding year end periods' financial condition is relatively observed and measured. This denoted FY 2019 as the 'one-year prior to distress' mark, and all other years as prior to FY 2020 following the same sequence.

3.3 The EMS model

The EMS model's variables are conventional measures of liquidity, solvency, profitability, leverage, and activity. The model's coefficients are computer program determined weightings which were generated when Altman (2005) created the EMS model. The constant term of 3.25 in the model's formula was the median of the Z-scores calculated for the failed U.S. firms in Altman's (2005) pioneering EMS model study. This term serves to standardise the output, acting as a baseline for default EM scores and bond rating equivalents (BREs), so that scores below a certain threshold (<1.75) would be rated a U.S. BRE of D. The EMS model's variables are elucidated upon below:

$x1 = \textbf{Working capital / total assets}$ measures a firm's assets compared to its total capitalisation. Working capital is the surplus of current assets over current liabilities and indicates liquidity. Liquidity is a key element of business success, without which a firm cannot proactively respond to liabilities or opportunities.

$x2 = \textbf{Retained earnings / total assets}$ are the accrued profits over a firm's lifetime relative to its total capitalisation. Retained earnings is a firm's net profits after tax, which was not paid out as dividends, held perpetually or reinvestment in profitable projects. Higher retained earnings reduce the firm's dependency on outside capital and effectively acts as a buffer when market liquidity tightens. This enhances stability and growth.

$x3 = \textbf{Operating income / total assets}$ indicates operational profits earned in relation to assets employed and gauges the firm's ability to effectively deploy its assets productively in the generation of profits. It shows the firm's capacity to create value from its operations and indicates the efficiency of its operations and management.

$x4 = \textbf{Book value of equity / total liabilities}$ indicates the net value of a firm's assets compared to its external debt and indicates to what degree assets can diminish before being exceeded by the firm's liabilities – a situation that could result in firm insolvency. Book value of equity is based on the balance sheet of a firm and is not subject to market psychology.

The EMS model generates a quantitative output that designates a firm into a financial health category, known as the EM score. The EM score thresholds are outlined below:

The Distress Zone: An EM score of ***<1.75 to 4.50*** denotes the distressed zone, where firms face a high probability of financial distress as measured by the EMS model. Urgent remedial action is necessary to ensure a firm's sustainability as a going concern.

The Grey Zone: An EM score of ***4.50 to 5.85*** denotes the grey zone where firms face a moderate probability of financial distress. Prudent financial management is required to prevent the firm from degenerating further into a state of high financial distress.

The Safe Zone: An EM score of ***5.85 to > 8.15*** denotes the safe zone where firms are considered financially healthy, with a very low probability of financial distress in the foreseeable future.

The EMS model goes further than the original Z-score model by translating the EM score into a related bond rating equivalent (BRE) that is comparable to U.S. corporate bond ratings established by credit rating agencies (CRAs) (Altman, 2005: 312). See table 1:

Table 1: EMS model's Bond Equivalent Ratings

EM score	Financial Health Zone	U.S. Bond Equivalent Rating
> 8.15	Safe Zone	AAA
7.60 – 8.15	Safe Zone	AA+
7.30 – 7.60	Safe Zone	AA
7.00 – 7.30	Safe Zone	AA-
6.85 – 7.00	Safe Zone	A+
6.65 – 6.85	Safe Zone	A
6.40 – 6.65	Safe Zone	A-
6.25 – 6.40	Safe Zone	BBB+
5.85 – 6.25	Safe Zone	BBB
5.65 – 5.85	Grey Zone	BBB-
5.25 – 5.65	Grey Zone	BB+
4.95 – 5.25	Grey Zone	BB
4.75 – 4.95	Grey Zone	BB-
4.50 – 4.75	Grey Zone	B+
4.15 – 4.50	Distress Zone	B
3.75 – 4.15	Distress Zone	B-
3.20 – 3.75	Distress Zone	CCC+
2.50 – 3.20	Distress Zone	CCC
1.75 – 2.50	Distress Zone	CCC-
<1.75	Distress Zone	D

Source: Altman (2005)

4. Results

This section discusses the outputs of the EMS model on the 62-firm sample. For comparison, the extender and non-extender groups are closely examined via descriptive statistics and ratios. The accuracy with which the EMS model predicted the financial distress of the extender group firms (and for comparison the non-extenders) over the period was tested, by categorising firms into a financial health zone known as the EM score. The EM score places a firm into a financial health zone, namely: distressed, grey, and safe. Lastly, the research questions are revisited and answered.

Table 2 displays the characteristics of the two samples as at financial year (FY) end 2020, the year of financial distress of the study. The mean asset size of the extender group is slightly larger than that of the non-extender group in for the FY ended 2020. Both samples have sufficiently healthy liquidity as displayed by the average current ratio, with the non-extenders ranking higher. Conversely, both samples have high debt ratios that suggests overleveraging of firms. The latter added to the riskiness of firms for the FY ended 2020.

Table 2: Sample characteristics at time of sampling

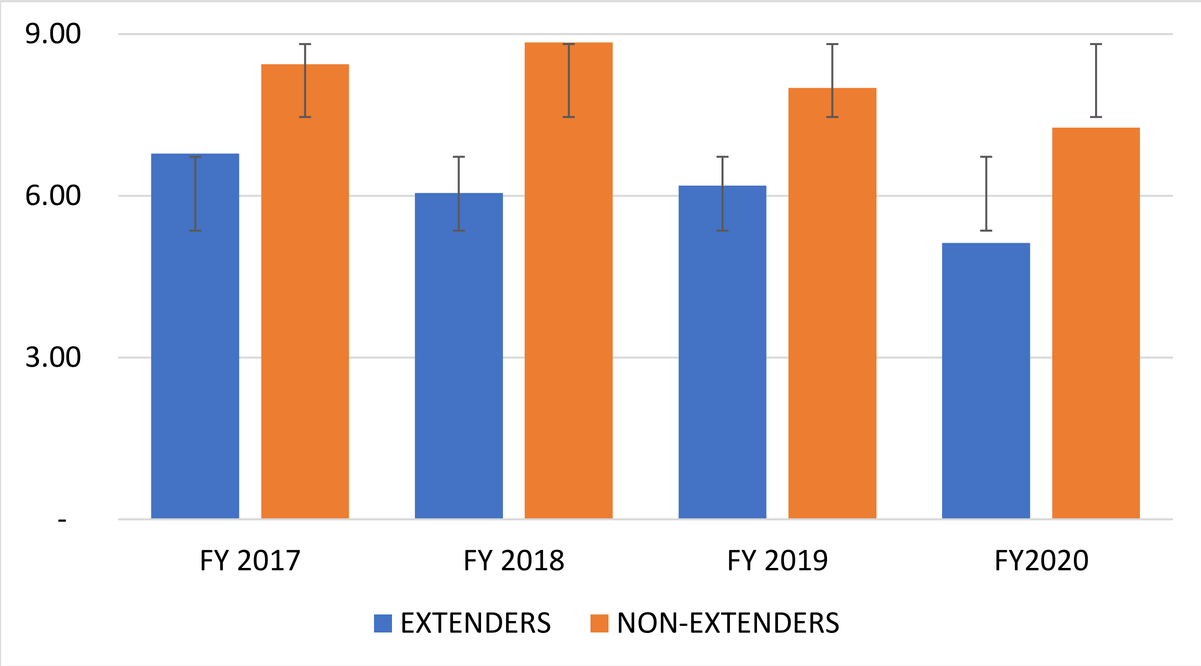
	Extenders	Non-extenders
Mean asset size (000m's)	6821	5521
Liquidity (via current ratio)	1,12	1,43
Leverage (via debt ratio)	0,59	0,60

Source: Prepared by the author

4.1 Descriptive statistics of the full sample

The descriptive statistics in table 3 show a general downward trend in the means and medians of both sample groups, owing to deteriorating EM scores as measured by the EMS model over the period (see figure 4). From FY 2017, the mean and median EM scores get closer to each other in both groups, indicating a more symmetrical but still skewed distribution of the EM scores with less outliers, although outliers are still present. The decrease in the maximum values over the period indicate the waning financial health of firms in both groups, although the decline is worse for the extender group, showing lower maximum and minimum EM scores.

Figure 4: Average EM scores between extender and non-extender sample group



Source: Prepared by the author

Table 3: Descriptive statistics as at the year of financial distress

	EXTENDER GROUP				NON-EXTENDER COHORT			
FY	**2017**	**2018**	**2019**	**2020**	**2017**	**2018**	**2019**	**2020**
Mean	6.78	6.05	6.19	5.13	8.44	8.85	8.00	7.26
Median	7.06	6.98	6.49	5.83	7.65	7.69	7.65	7.10
Std Dev	3.60	4.39	4.41	3.72	4.55	4.35	3.93	4.10
Variance	12.93	19.28	19.42	13.84	20.74	18.91	15.47	16.80
Kurtosis	2.54	5.64	2.95	-0.33	3.23	5.67	4.19	3.96
Skew(x)	-1.02	-1.68	-0.65	-0.63	1.52	1.91	1.56	1.45
Range	17.72	24.36	24.17	14.38	21.49	22.25	19.30	19.56
Min	-4.96	-10.23	-7.69	-3.79	1.87	3.01	2.60	2.19
Max	12.77	14.13	16.48	10.59	23.36	25.26	21.91	21.75
n	31	31	31	31	31	31	31	31

Source: Prepared by the author

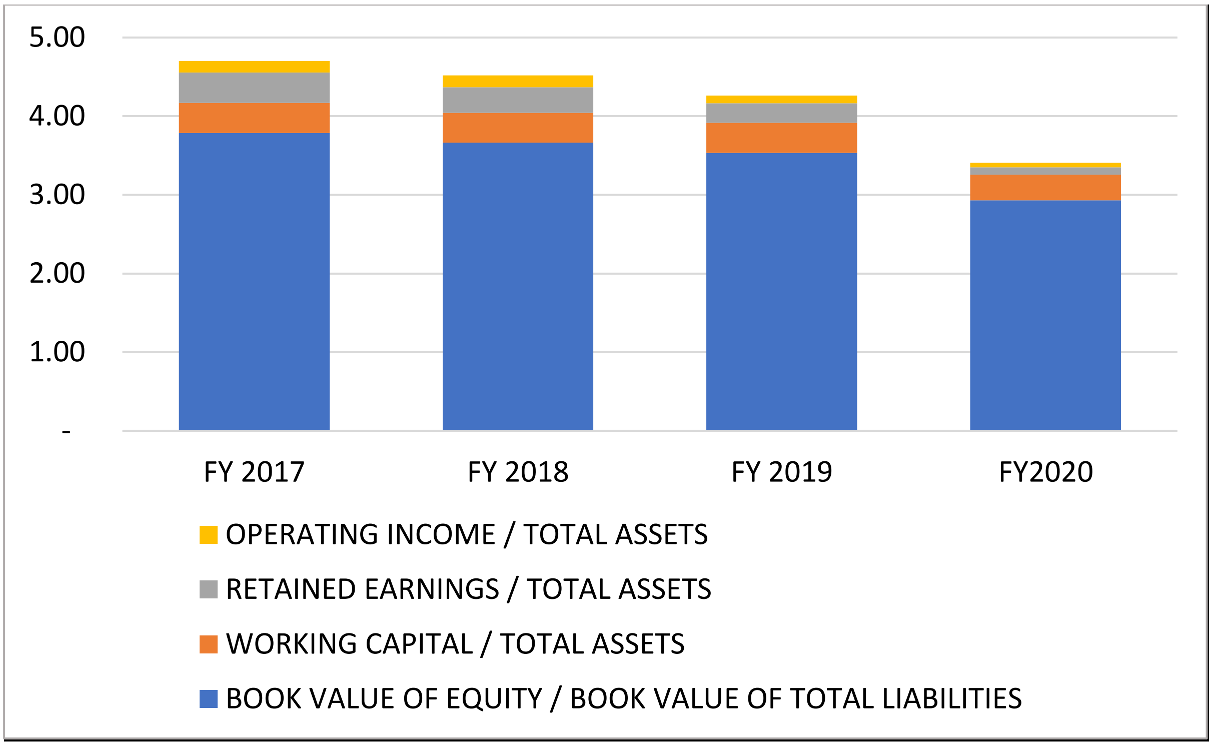
4.1.1 Extender versus non-extender group

The extender group had lower mean and median EM scores than the non-extender group over the period (figure 4 and table 3). Kurtosis is present in the first three years of the period for the extender group, indicating the occurrence of outliers in the data. Both kurtosis and skewness decrease from FY 2018 to FY 2020, indicating the less frequent occurrence of outliers, that is firms with very high or very low EM scores. The decreasing range from FY 2019 to FY 2020 is also indicative of the latter. The standard deviation of the extender group was lower relative to the non-extender group but still high and indicated the spread of EM scores from the mean. In other words, the EMS model scored certain firms very high and others very low. This is evident in the large range value observed over the period. Lastly, the extender group saw a steeper decline in its EM scores, down -24% from FY 2017 to FY 2020; while the non-extenders only saw a decline of -14% over the period. The non-extender group had better financial health over the period relative to the extenders, indicated by a higher mean EM score and median value. No significant difference in standard deviation values is observed, although the non-extenders' are slightly higher indicating more spread of its EM scores from its mean. The non-extenders have positive skewness indicating the existence of firms with large EM scores and an overall financially healthier group. Conversely, the extenders displayed negative skewness which indicates firms with negative EM scores, and lower EM scores over the period and an overall financially unhealthier group.

4.2 EM score and ratios

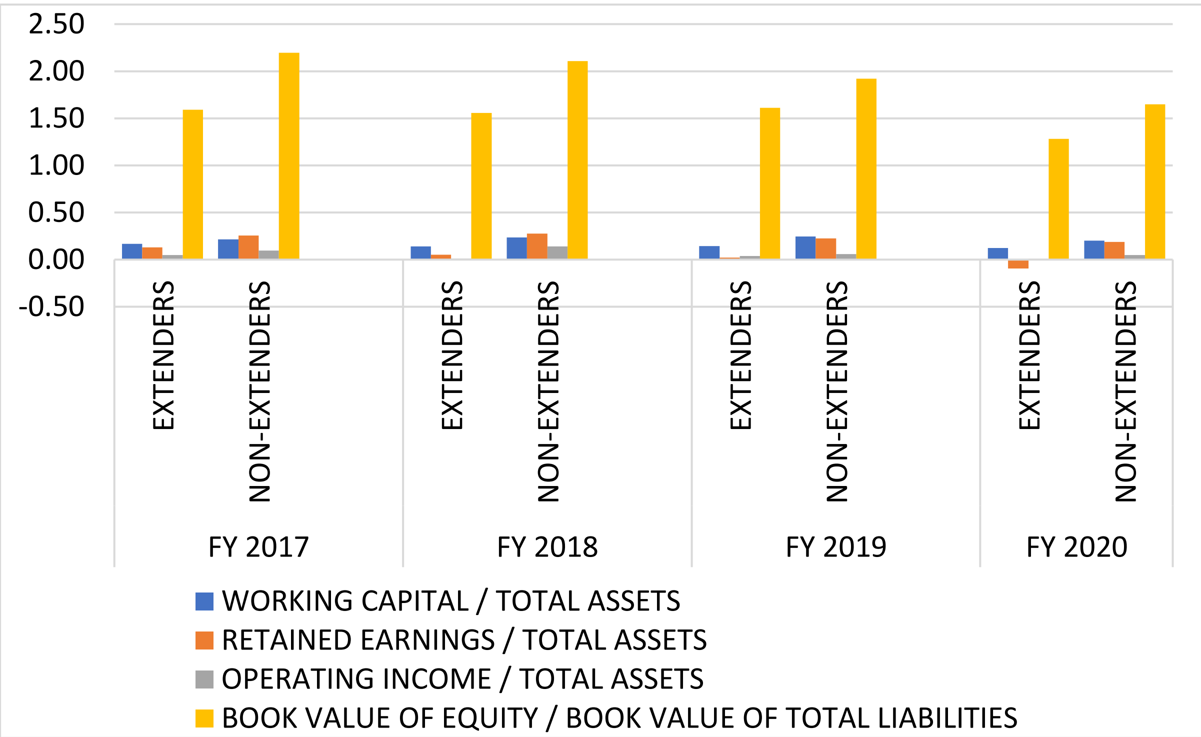
Simple observance of financial statement data to gauge their relationship to firms' EM scores shows no causal relationships. Individual financial statement data must be observed relative to each other to impart useful information on a firm's financial condition. For the EMS model, the financial statement data is observed relative to total assets and total liabilities (figure 5). Relativity is paramount, since a firm can have large total assets and still be financially unhealthy if the latter is outsized by its total liabilities, resulting in a lower book value of equity. Figure 5 displays the average ratios' aggregate contribution of the EMS model's four ratios (independent variables) to the EM scores (dependent variables) of the sample of firms. The book value of equity to book value of total liabilities ratio made the largest contribution to the EM scores of firms over the period, even though it has the lowest weighting in the EMS model's formula. Figure 6 displays the average ratio performance in each sample group over the study period. The scatter graphs in appendix 4 display a direct relation between the ratios and the EM score, that is - the higher the ratios of the EMS model, the better it is for a firm's EM score and therefore its financial health. Only the operating income over total assets ratio displayed an unconvincing scatter (see appendix 4). These are discussed in more detail below.

Figure 5: Aggregate average ratio contribution to EM scores: Extenders & non-extenders



Source: Prepared by the author

Figure 6: Annual ratios of extender and non-extender sample group



Source: Prepared by the author

- **Book Value of equity over total liabilities ratio**

The extender group had an average ratio of one-and-a-half times between equity and debt over the period, indicating their use of more leverage, which made them riskier and likelier to experience financial distress. The book value of equity over total liabilities ratio decreased from FY 2017 in both sample groups, corresponding to the average deterioration of firms' EM scores as detected by the EMS model. The non-extender group displayed a stronger ratio during the period. The non-extender firms had on average, two times more equity than liabilities, which significantly reduced their risk and exposure to market downturns.

- **Working capital over total assets ratio**

Both sample groups displayed a low working capital over total assets ratio, with both taking a slight dip by the end of FY 2020. The non-extender group did better than the extender group overall, although its own ratio is still small compared to the accepted standard of between one and two. The current assets over current liabilities ratio computed above indicated that the firms had adequate working capital, or net liquid assets. However, relative to total assets, the study observes a weaker liquidity and financial strength profile over the period.

- **Retained earnings over total assets ratio**

The extender group experienced a negative average retained earnings over total assets ratio in FY 2020. The non-extender group performed better than the extender group during the period. Both groups took a dip during FY 2020. The low ratios indicate that firms had been financing their capital expenditure through debt and not reinvested earnings since FY 2017, and that general profitability had been lacklustre since FY 2017.

- **Operating income over total assets ratio**

In line the latter, the operating income over total assets ratio show a lower figure for both groups, with the non-extenders slightly outperforming the extenders by a small margin. The low ratios indicate general lower income generation from both groups over the period. In FY 2020, the extenders show a very low operating income over total assets ratio, beaten by a small margin by the non-extenders.

4.3 Average EM score by industry group

Figure 7 shows the average EM scores per industry group for the 62-firm sample. Note that the 'industry group' classification of the Bloomberg Industry Classification Standard (BICS) convention groups firms into coherent peer groups based on their primary revenue source. Each total EM score *per year* of firms in the industry group category is summed and divided by the number of firms in that category. For example, the 'consumer discretionary services' industry group has two firms namely Arden Capital Ltd and City Lodge Hotel Ltd. Their combined yearly EM scores are divided by two to derive the average.

The 'software & tech service' industry's average EM score fared the best in the sample over the period. The firms in this industry operate in the IT services and application software sub-industries. The firms fall into the technology sector. The 'consumer staple products' average EM score fared the worst in the sample over the period. The firms in this industry operate in the agricultural producers and food sub-industries and fall into the consumer staples sector. Table

Table 4: Average EM scores by industry Group

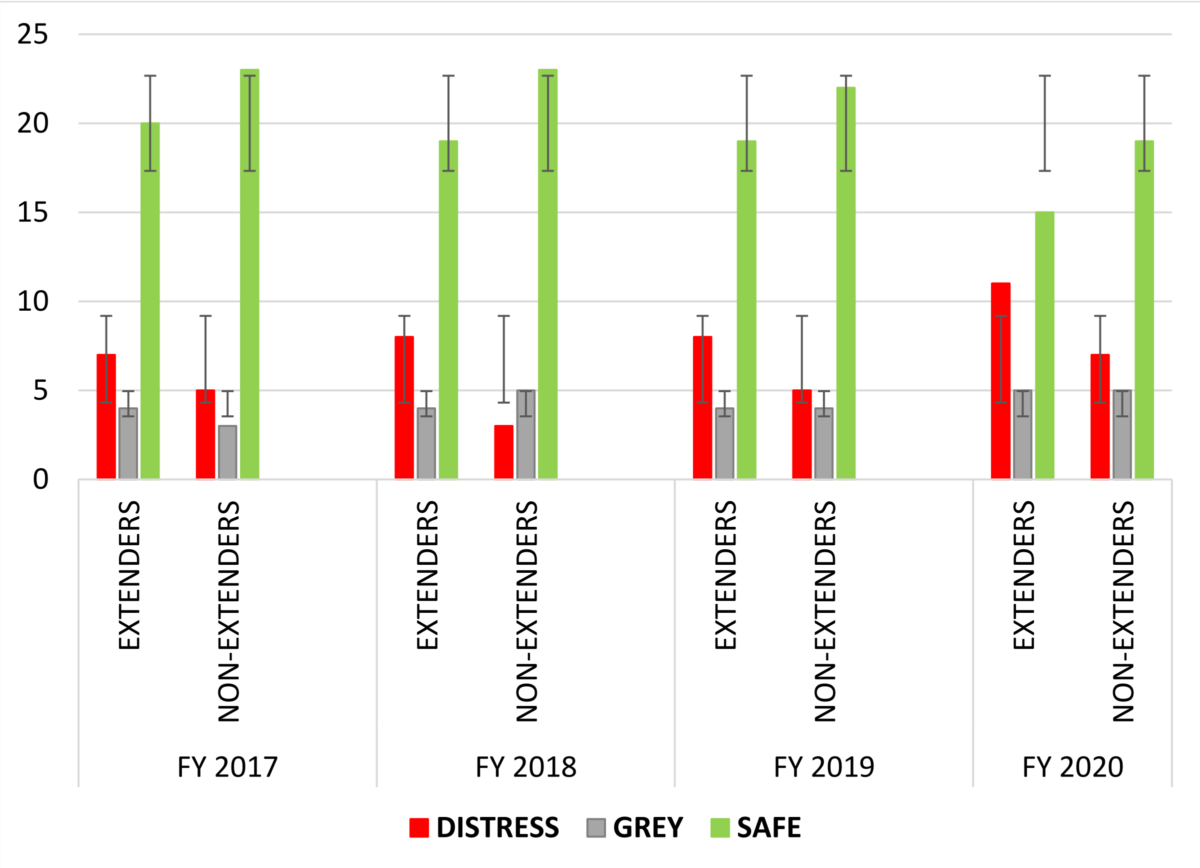
Industry Group Category (BICS)	FY 2017	FY 2018	FY 2019	FY 2020
Software & Tech Services	9.32	10.34	10.34	8.79
Materials	8.50	8.03	7.17	6.78
Retail & Wholesale - Discretionary	8.34	8.05	8.06	5.96
Industrial Products	7.44	7.39	7.16	7.23
Industrial Services	7.30	7.68	7.12	6.45
Transportation	7.05	7.33	7.81	5.91
Telecommunications	7.56	6.24	4.61	4.14
Consumer Discretionary Services	4.31	6.08	6.85	3.93
Tech Hardware & Semiconductors	5.16	6.23	5.21	2.33
Consumer Staple Products	5.32	3.32	3.43	4.47

Source: Prepared by the author

4.4 EMS model categorical outputs

The summary of the EMS model's results is displayed in appendix 3. For the entire 62-firm sample, 160 safe zone classifications, 53 distress zone classifications, and 35 grey zone classifications were observed over the study period from FY 2017 to FY 2020. Figure 8 displays the progression of the sample over the four-year period. The safe zone firms decrease slightly from FY 2017 to FY 2020, indicating that certain firms' financial health deteriorated. Likewise, the distressed zone firms increase from FY 2017 to FY 2020, indicating a deterioration in the financial health of several firms. The grey zone firms maintain an almost horizontal trend from FY 2017 to FY 2020. The grey zone firms are those believed to be in the 'zone of uncertainty' and are known to exhibit a moderate degree of financial distress. These must therefore be remedied or risk deteriorating further into financial distress. The following sections dive deeper into each category of the financial health categories and the performance of each sample group within each category.

Figure 7: EMS model categorical output



Source: Prepared by the author

- **Safe zone firms**

The extender group saw a steeper downward trend of its safe zone firms over the period compared to the non-extender group. The non-extender group had more safe zone firms over the period compared to the extender group. In both sample groups, the firms that were in the safe zone in FY 2020 had all been in the safe zone since FY 2017 with only a few exceptions (see appendix 3). In the non-extender group, 19 firms were in the safe zone as at FY 2020 and all 19 had an unbroken safe zone record since FY 2017. In the extender group, 15 firms were in the safe zone as at FY 2020, with 14 of these firms having safe zone statuses since FY 2017. One of the 15 had a prior grey zone status. The data indicates that the latter remedied its financial woes and increased its EM score to recover from the grey to the safe zone.

- **Distressed zone firms**

The extender group had more distressed zone firms during the period compared to the non-extender group. By FY end 2020, the extender group had 11 firms in the distressed zone compared to the non-extender group that had only six firms in the distressed zone. In addition, the extender group had an average of nine firms in the distressed zone over the period compared to the non-extender group that had an average of five. A similar trend is observed in firms that were financially distressed as those that were in the safe zone in FY 2020 (see appendix 3). In both the extender and non-extender groups, the firms that were in the distressed zone in FY 2020 had predominantly been in the distressed zone leading up to FY end 2020. A minority of them had been the grey zone prior to FY 2020. In other words, these distressed firms had been experiencing some degree of financial distress prior to FY end 2020, ranging from moderate (grey zone) to high (distressed zone).

- **Grey zone firms**

As mentioned in the literature, the grey zone denotes a peculiar state of uncertainty when categorising a firm's financial health. They are known to exhibit a moderate degree of financial distress and can go either way based on actions or inactions. For both sample groups, grey zone firms showed similar characteristics. Both groups had a small number of grey zone firms during the study period. While being in the grey zone is not ideal, it beats being in the distressed zone and being regarded as highly probable to experience financial distress.

The above highlights several takeaways. Firstly, the EM scores indicate that firms that maintained their financial health well throughout the period fared better than those that displayed moderate to high financial distress risk in the years prior to FY 2020. These firms were less likely to degenerate into a state of financial distress and were likewise less negatively affected by negative economic conditions.

Secondly, for some firms that had moderate to high financial distress, it was not impossible for them to remedy the cause of their distress and land in the safe zone. Thirdly, the latter highlights that the potential of the EMS model to predict several firms' financial distress, by measuring their financial condition prior to them degenerating into a state of distress. The EMS model also correctly predicted those firms who would experience favourable financial health by judging them healthy in the three years preceding FY ended 2020. The observational evidence indicated that the non-extender firms performed better than the extender firms in the study period, as measured and predicted by the EMS model. The discussion now turns to the performance of the EMS model.

4.5 Performance of the EMS model

For the FY ended 2020, the year of financial distress, the 31 firms constituting the extender group sample had extended the release of their financial results. As mentioned earlier, these 31 firms therefore acted as the study's proxy for financially distressed firms. The assumption was made that 100% of these firms experienced financially distress in FY 2020, and the accuracy with which the EMS model predicted the financial distress of these firms over the period was tested. The EMS model predicted financial distress for the sample with the following accuracy rates:

In FY 2019, one year prior to financial distress in FY 2020, 39% (12 out of 31) of extender group firms were classified as likely to experience financial distress in FY 2020. Eight of them were classified as highly distressed and four were classified as moderately distressed. The EMS model correctly identified 39% of these firms in FY 2019 as facing impending trouble that needed remedy, one year before they extended the release of their financial results in FY 2020.

In FY 2018, two years prior to financial distress in FY 2020, 39% (12 out of 31) of extender group firms were classified as likely to experience financial distress in FY 2020. Again, eight of them were classified as highly distressed and four were classified as moderately distressed. The EMS model correctly identified 39% of these firms in FY 2018 as facing impending trouble that needed remedy, two years before they extended the release of their financial results in FY 2020.

In FY 2017, three years prior to financial distress in FY 2020, 35% (11 out of 31) of extender group firms were classified as likely to experience financial distress in FY 2020. Seven were classified as highly distressed and four were classified as moderately distressed. The EMS model correctly predicted that 35% of these firms in FY 2017 as facing impending trouble that needed remedy, three years before they extended the release of their financial results in FY 2020.

Table 4: Performance of the EMS model – aggregate sample

Extender Group				
	FY 2017	**FY 2018**	**FY 2019**	**FY 2020**
Firms high to moderate default risk	11	12	12	16
% Firms high to moderate default risk	35%	39%	39%	52%
Non-extender Group				
	FY 2017	**FY 2018**	**FY 2019**	**FY 2020**
Firms high to moderate default risk	8	8	9	12
% Firms high to moderate default risk	26%	23%	26%	39%

Source: Prepared by the author

For comparison, note that in FY 2020, only 52% (16 out of 31) of extender group firms had varying degrees of financial distress as classified by the EMS model. 11 were classified as highly distressed and 5 were classified as moderately distressed. 15 extender group firms were classified as safe. Conversely, in the non-extender group only 39% (9 out of 31) were classified as highly or moderately financially distressed. The analysis shows that the non-extender group had better overall financial health than the extender group over the period. This answers the main research question.

4.5.1 T-test

The t-test was conducted to test whether a statistically significant difference existed between the mean EM scores of the two sample groups. The mean EM scores of the two sample groups were calculated from FY 2017 to FY 2020 and were used to compute an independent sample t-test, see table 5 below. A two-sample t-test assuming unequal variances was conducted at a significance level of 0.05. The degrees of freedom of 60 gives a critical value of 2.00. The computed t-value of 2.13 was greater than the t-critical two-tail value of 2.00. In other words, a statistically significant difference is found between the extender and non-extender group, and the statistical significance suggested that this finding cannot be attributed to chance. This answers sub-question a).

Table 5: T-test output

t-test: two-sample assuming unequal variances	
Hypothesized mean difference	0,00
df	60,00
t stat	2,13
P(T<=t) two-tail	0,04
t critical two-tail	2,00

Source: Prepared by the author

4.5.2 Fisher exact test

The Fisher's exact test was conducted to test for the existence of a statistically significant non-random relationship between the two sample groups (extender/non-extender) and the EMS model's categorical outputs related to the firms' financial health zone (distressed/safe). The answer to sub-question b) found that the relationship between the two sample groups and the EMS model's categorical outputs related to the firms' financial condition was not statistically significant. The Fisher's exact test's *p*-values were all above the significance level of 0.05 over the period. However, the EMS model did show that the occurrence of distressed firms was greater in the extender group than in the non-extender group. This answers sub-question b).

Table 6: Fisher's exact test contingency tables

EMS model EM score: the year of distress			
	Distressed	**Safe**	**Total**
Extender	16	15	31
Non-extender	12	19	31
Total	28	34	62
***p*-value: 0.1213**			

EMS model EM score: 1-year horizon			
	Distressed	**Safe**	**Total**
Extender	12	19	31
Non-extender	9	22	31
Total	21	41	62
***p*-value: 0.1545**			

EMS model EM score: 2-year horizon			
	Distressed	**Safe**	**Total**
Extender	12	19	31
Non-extender	8	23	31
Total	20	42	62
***p*-value: 0.1209**			

EMS model EM score: 3-year horizon			
	Distressed	**Safe**	**Total**
Extender	11	20	31
Non-extender	8	23	31
Total	19	43	62
***p*-value: 0.1559**			

Source: Prepared by the author

4.6 Summary of the results

The analysis indicates that the extender group underperformed the non-extender group over the period, observed by its lower average EM scores as measured and predicted by the EMS model. Statistically, the non-extenders displayed positive skewness indicating the presence of firms with large positive EM scores. The extenders displayed negative skewness indicating the presence of firms with large negative EM scores (appendix 6). The extender group's EM scores declined -24% over the period, versus a -14% decline in the non-extender group. The extender group had more distressed zone firms and less safe zone firms than the non-extender group over the period.

A trend was noticed in both groups, in that firms that were in the safe zone in FY 2020 had predominantly been in the safe zone leading up to FY end 2020. Similarly, firms that were in the distressed zone in FY 2020 had predominantly been in the distressed zone leading up to FY end 2020. The EMS model indicates that firms that well-maintained their financial health fared better than firms displaying financial distress in the years prior to FY 2020. In all four ratios, the non-extender group outperformed the extender group. In aggregate, the book value of equity to book value of total liabilities ratio made the largest contribution to the EM scores of firms over the period, even though it has the lowest weighting in the EMS model's formula.

The answer to the main research question 1) indicated that the EMS model's predictive accuracy was low over the study period. The study's proxy of 31 extender group firms, which were all expected to experience financial distress in FY 2020, were predicted by the EMS model with the following accuracy rates: In FY 2019, one year prior to financial distress in FY 2020, 39% (12 out of 31) of extender group firms were classified as likely to experience financial distress in FY 2020. In FY 2018, two years prior to financial distress in FY 2020, 39% (12 out of 31) of extender group firms were classified as likely to experience financial distress in FY 2020. In FY 2017, three years prior to financial distress in FY 2020, 35% (11 out of 31) of extender group firms were classified as likely to experience financial distress in FY 2020.

The answer to sub-question a) indicated that the t-test found a statistically significant difference existed between the mean EM scores of the two sample groups. and the statistical significance suggested that this finding cannot be attributed to chance. The answer to sub-question b) indicated that the Fisher's exact test did not find a statistically significant non-random relationship between the two sample groups (extender/non-extender) and the EMS model's categorical outputs related to the firms' financial health zone (distressed/safe). The Fisher's exact test's *p*-values were all above the significance level of 0.05 over the period. However, the EMS model did show that the occurrence of distressed firms was greater in the extender group than in the non-extender group.

The answer to the research questions provides inconclusive evidence that the EMS model is an accurate measure and predictor of financial distress for South African firms. Future studies are required, and a better proxy for financially distressed firms should be used to strengthen the thesis that the EMS model has utility as a measure and predictor of financial distress for South African firms.

5. Conclusion, Limitations and recommendations

The main objective of this study was to investigate the accuracy of the Emerging Market Scoring Model (EMS model) for measuring and predicting financial distress for South African firms. The EMS model was applied to a 62-firm sample composed of two independent groups for the period ranging from financial years (FY) ended 2017 to 2020. The study's proxy for financially distressed firms was 31 firms that extended the release of their financial results in FY 2020, named the extender group. The study made the assumption that all 31 firms experienced financial distress in FY 2020, and the accuracy with which the EMS model predicted their financial distress was tested, from FY 2017 to FY 2019. For comparison, the extender group was matched with 31 firms that did not extend the release of their financial results, named the non-extender group.

The analysis indicates that the extender group underperformed the non-extender group over the period, observed by its lower average EM scores as measured and predicted by the EMS model. A trend was noticed in both groups, in that firms that were in the safe zone in FY 2020 had predominantly been in the safe zone leading up to FY end 2020. Similarly, firms that were in the distressed zone in FY 2020 had predominantly been in the distressed zone leading up to FY end 2020. However, the EMS model's predictive accuracy was low over the study period, with the following accuracy rates: In FY 2019, one year prior to financial distress in FY 2020, 39% (12 out of 31) of extender group firms were classified as likely to experience financial distress in FY 2020. In FY 2018, two years prior to financial distress in FY 2020, 39% (12 out of 31) of extender group firms were classified as likely to experience financial distress in FY 2020. And in FY 2017, three years prior to financial distress in FY 2020, 35% (11 out of 31) of extender group firms were classified as likely to experience financial distress in FY 2020.

The t-test found that a statistically significant difference existed between the mean EM scores of the two sample groups, and the statistical significance suggested that the finding cannot be attributed to chance. The Fisher's exact test did not find a statistically significant non-random relationship between the two sample groups (extender/non-extender) and the EMS model's categorical outputs related to the firms' financial health zones (distressed/safe). The Fisher's exact test's *p*-values were all above the significance level of 0.05 over the period.

Therefore, the answers to the research questions provide inconclusive evidence that the EMS model is an accurate measure and predictor of financial distress for South African firms. this is largely attributed to the main limitation of the study which is the proxy chosen for firm financial distress. The literature states that firms extend the release of their financial results for several reasons, a major reason being financial distress. In other instances, firms extend the release of their financial results for different reasons unrelated to underlying financial distress. Of the 31 extender group firms, only 52% (16 out of 31) suffered moderate to high financial distress in FY 2020 as measured by the EMS model. The other 42% were classified as safe. Also, the proxy constituted firms that did not necessarily fail but experienced moderate to high financial distress leading up to FY 2020. For this reason, the extender group sample was not the best proxy to represent financially distressed firms, and a more robust sample of truly failed firms must be chosen to test the EMS model.

This again raises the debate of whether the extending of the release of financial results truly signal underlying financial distress. This is a viable avenue for future research since the literature is both mixed and simultaneously biased toward the thesis that financial reporting delays signal underlying financial distress. The study conducted by Agyei-Mensah (2018) on the impact of governance and financial reporting lags on the financial health of listed Ghanian firms is one of the few empirical inquiries done in sub-Saharan Africa. As indicated by Lukason & Camacho-Miñano (2019), the association between financial distress and information disclosure is a pivotal and evolving area for research, and this is especially true in the emerging markets.

Future studies are indeed required, and a better proxy for financially distressed firms should be used to investigate and strengthen the thesis that the EMS model is an accurate measure and predictor of financial distress for South African firms. Perhaps a sample of firms that truly reached the end-stage of financial distress, that is bankruptcy, will be better suited to conclusively answer the research questions. Future studies can also investigate whether firms delaying the release of their financial results signal underlying financial distress.

6. References

Agyei-Mensah, B.K. 2018. Impact of corporate governance attributes and financial reporting lag on corporate financial performance. *African Journal of Economic and Management Studies.* 9(3):349-366.

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

Altman, E.I. 2005. An emerging market credit scoring system for corporate bonds. *Emerging Markets Review*. 6(4):311-323.

Altman, E. I. 2018. Applications of distress prediction models: What have we learned after 50 years from the Z-score models? *International Journal of Financial Studies.* 6(3):70. http://dx.doi.org/10.3390/ijfs6030070

Altman, E.I. 2018. A fifty-year retrospective on credit risk models, the Altman Z-score family of models and their applications to financial markets and managerial strategies. *Journal of Credit Risk*. 14(4):1-35.

Beaver, W.H. 1966. Financial ratios as predictors of failure. *Journal of Accounting Research*. 4:71-111.
https://doi.org/10.2307/2490171

Bellovary, J.L., Giacomino, D.E. & Akers, M.D. 2007. A review of bankruptcy prediction studies: 1930 to present. *Journal of Financial education*. 33(1):1-42.

Bloomberg, L.P. 2014. *Bloomberg Industry Classification System (BICS) [Product Brochure]*. Brussels: Available: https://data.bloomberglp.com/professional/sites/10/Classification-Data-Fact-Sheet.pdf [2023, October 20].

Carmichael, D.R. 1972. *The Auditor's reporting obligation: The meaning and implementation of the fourth standard of reporting.* New York, United States: American Institute of Certified Public Accountants

Cassim, R.J. & Swanepoel, M.J. 2021. The bankruptcy prediction approach: An empirical study of comparison between the emerging market score model and bankruptcy prediction indicators approach in the Johannesburg Stock Exchange. *Journal of Economic and Financial Sciences.* 4(1):539.

Ciani, A., Hyland, M.C., Karalashvili, N., Keller, J.L. & Tran, T.T. 2020. *Making It Big: Why Developing Countries Need More Large Firms*. New York, United States: World Bank Publications.

Companies Act, No. 71 of 2008. 2009. Available: http://www.acts.co.za/companies-act-2008/companies_act__2008_act_no__71 [2023, October 20]

Elloumi, F. & Gueyié, J.P. 2001. Financial distress and corporate governance: an empirical analysis. *Corporate Governance: The International Journal of Business in Society*. 1(1):15-23.

Gredil, O.R., Kapadia, N. & Lee, J.H. 2022. On the information content of credit ratings and market-based measures of default risk. *Journal of Financial Economics*. 146(1):172-204.

Jung, S.H. 2014. Stratified Fisher's exact test and its sample size calculation. *Biometrical Journal.* 56(1):129-140.

Lukason, O. & Camacho-Miñano, M-d-M. 2019. Bankruptcy risk, its financial determinants and reporting extends: Do managers have anything to hide? *Risks.* 7(3):77.

Marais, A., Soni, S. & Chitakunye, P. 2014. The ability of the Altman Z-score to predict the relative success of industrial companies listed on the Johannesburg stock exchange. *Journal of Contemporary Management*. 11(1):451-469.

Ngwenya, S. 2018. Assessing the state of financial distress of listed gold and platinum mining companies in South Africa. *Acta Universitatis Danubius. Œconomica*. 14(4):655-677.

Nurquran, P.D. 2023. The Way Financial Distress Affects Financial Reporting Extend. *Jurnal Manajemen Teori dan Terapan*. 16(1).81–94.

Rama, K.D. 2012. An empirical evaluation of the Altman (1968) failure prediction model on South African JSE listed companies. Master's thesis. University of the Witwatersrand.

Sabela, S.W., Brummer, L.M., Hall, J.H. & Wolmarans, H.P. 2018. Using fundamental, market and macroeconomic variables to predict financial distress: A study of companies listed on the Johannesburg Stock Exchange. *Journal of Economic and Financial Sciences*. 11(1):1-11.

Venter, JC & Wolhuter, A. 2023. *The South African business cycle from 2013 to 2022.* Available: https://www.resbank.co.za/en/home/publications/publication-detail-pages/quarterly-bulletins/articles-and-notes/2023/the-south-african-business-cycle-from-2013-to-2022.pdf [2023, June 31].

Whittred, G. & Zimmer, I. 1984. Timeliness of financial reporting and financial distress. *Accounting Review*. 59(2):287-295.

Zopounidis, C. & Doumpos, M. 1999. Business failure prediction using the UTADIS multicriteria analysis method. *Journal of the Operational research Society*. 50:1138-1148.

7. Appendices

Appendix 1: Bloomberg Industry Classification Standard (BICS)

A Bloomberg Professional Services Offering

Content & Data Solutions

Classification data

More precise and accurate industry classification data.

Reference Data

While most industry classification data is based on broad strokes and stops at a company's description, Bloomberg classification data digs deeper to provide complete asset class coverage based on actual research, thereby delivering high-quality and consistent segmentation data across trading, risk management and operations. Bloomberg classification data can be accessed through both the Bloomberg Terminal® and via an enterprise data feed.

Security and entity level data

We offer three separate products to address the specific needs of risk managers, fund managers, compliance officers, investment bankers and more.

- BICS (Securities) provides data for individual securities. The product is broken down by asset class, just like Bloomberg's security master files, and it includes equities, corporates, governments, loans and preferred debt. Industry classification data is delivered for over 1.5 million securities.
- BICS (Legal Entities) provides coverage for over 2.6 million legal entities. The product includes both public and private companies.
- BCLASS also provides data for individual securities. It was designed to categorize securities within the Bloomberg Barclays fixed income benchmark indices but it has been expanded to cover non-index securities. BCLASS leverages both activity and government ownership to group securities with similar risk profiles. This global multi-asset class classification schema is widely accepted as the fixed-income standard.

Deconstructing risk exposure

Bloomberg classification data helps the buy side and sell side monitor concentration risk. If they observe they have become over-exposed to a certain industry, they can diversify investments to ensure the firm can withstand an unexpected industry event.

Accurate industry classification data is crucial for portfolio managers to construct a well-diversified portfolio and to manage systematic risk.

Industry specific limits could be imposed to manage the risk associated with collateral securities. Classification data can help clearing banks classify the collateral deposited by counterparties in repo agreements.

In-depth research for comprehensive classification

Bloomberg's research is more precise and allows the correct classification of issuers and securities; in addition, our classification data offers the following features:

- Seamless integration with a breadth of coverage and one provider for multiple asset classes.
- A classification system based on a company's main business line according to revenue.
- Multiple distribution channels across the firm, which ensures that everyone in the organization is looking at identical classifications for the same issuer or security.
- Multiple points of access to the data through the Terminal and enterprise data feed.
- A team dedicated to reviewing new data available, including corporate actions, to monitor and address any changes that could affect a company's classification.

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Appendix 2: EMS model Excel draft

FINANCIAL DISTRESS ANALYSIS; BANKRUPTCY RISK

PARAMETERS	2015	2016	2017	2018	2019	YEAR IN QUESTION 2020
INCOME STATEMENT						
NET SALES	10	150	150	150	150	
OPERATING INCOME (EBIT)	100	100	100	100	100	
BALANCE SHEET						
CURRENT ASSETS	50	200	200	50	200	
TOTAL ASSETS	400	400	400	200	400	
CURRENT LIABILITIES	500	400	400	500	400	
TOTAL LIABILITIES	500	500	500	100	500	
RETAINED EARNINGS	50	50	50	50	50	
BOOK VALUE OF EQUITY	1500	1500	1500	1500	1500	

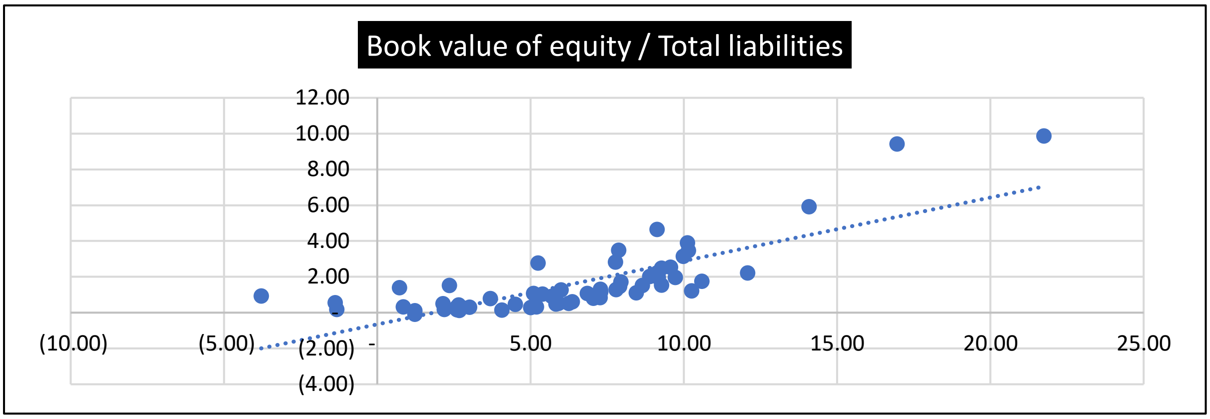
EMS MODEL = 6.56(X1) + 3.26(X2) + 6.72(X3) + 1.05(X4) + 3.25

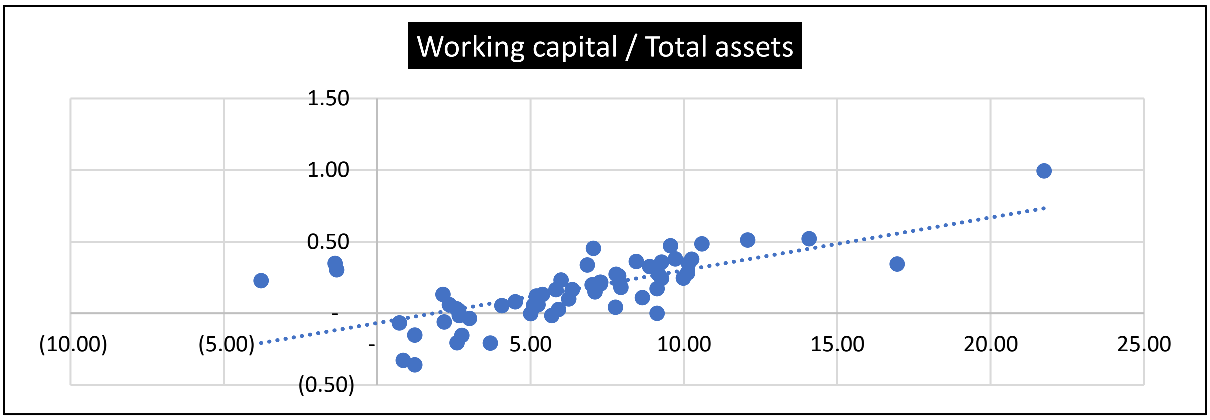
RATIOS AND CALCULATIONS	WEIGHTING	2015	2016	2017	2018	2019
X_1 WORKING CAPITAL i.e. CA-CL / TOTAL ASSETS	6.560	-1.13	-0.50	-0.50	-2.25	-0.50
X_2 RETAINED EARNINGS / TOTAL ASSETS	3.260	0.13	0.13	0.13	0.25	0.13
X_3 EBIT (or operating income)/ TOTAL ASSETS	6.720	0.25	0.25	0.25	0.50	0.25
X_4 BOOK VALUE OF EQUITY* / BOOK VALUE OF TOTAL LIABILITIES	1.050	3.00	3.00	3.00	15.00	3.00
	EM SCORE	1.11	5.21	5.21	8.42	5.21
	FINANCIAL HEALTH ZONE	DISTRESS ZONE	GREY ZONE	GREY ZONE	SAFE ZONE	GREY ZONE
	U.S. BOND RATING EQUIVALENT	D	BB	BB	AAA	BB

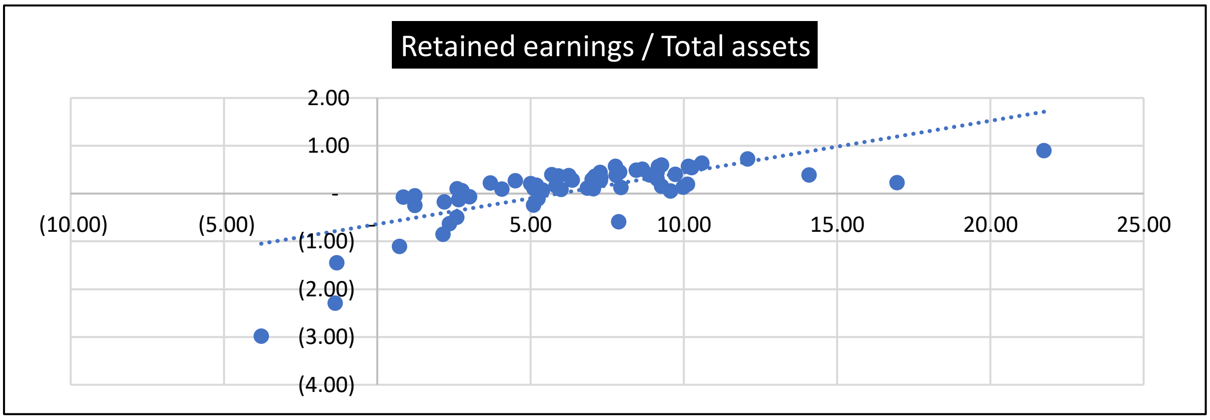
Appendix 3: EMS model's categorical outputs

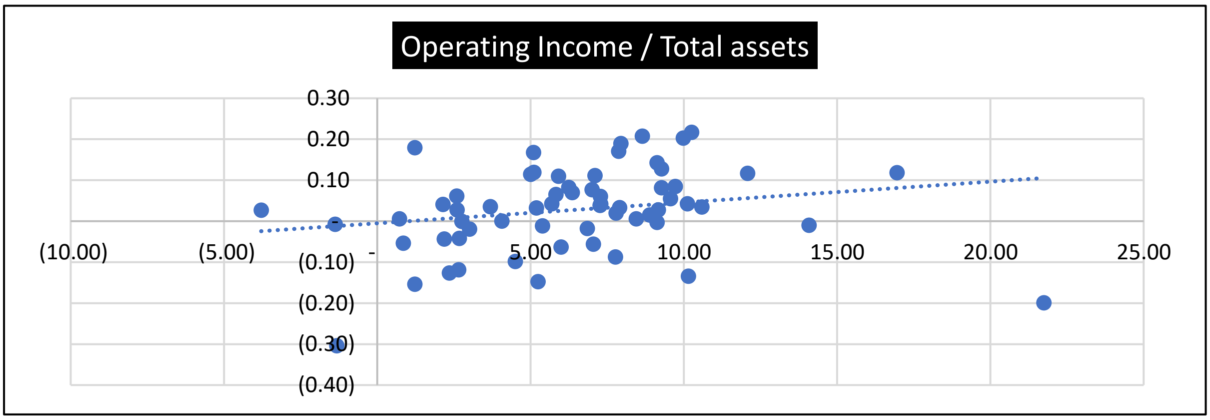
EXTENDING COHORT						NON-EXTENDING COHORT					
*Calendar Year	2016	2017	2018	2019	2020		2016	2017	2018	2019	2020
*Financial Year	FY 2017/18	FY 2018/19	FY 2019	FY2020-MAR19-FEB20	FY2021-MAR20-FEB21		FY 2017/18	FY 2018/19	FY 2019/20	FY2020-MAR19-FEB20	FY2021-MAR20-FEB21
ADCORP HOLDINGS LTD	GREY ZONE	GREY ZONE	SAFE ZONE	DISTRESS ZONE	GREY ZONE	WORKFORCE HOLDINGS LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE
AFRIMAT LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SALUNGANO GROUP LTD	GREY ZONE	GREY ZONE	GREY ZONE	DISTRESS ZONE	DISTRESS ZONE
ARDEN CAPITAL LTD (BRAINWORKS)	DISTRESS ZONE	GREY ZONE	SAFE ZONE	GREY ZONE	DELISTED	CITY LODGE HOTELS LTD	GREY ZONE	SAFE ZONE	SAFE ZONE	DISTRESS ZONE	DISTRESS ZONE
ARGENT INDUSTRIAL LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SOUTH OCEAN HOLDINGS LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE
BELL EQUIPMENT LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	ENX GROUP LTD	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	GREY ZONE
BRIKOR LTD	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	RANDGOLD & EXPLORATION CO	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE
CHROMETCO LTD	SAFE ZONE	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	THARISA PLC	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE
COMBINED MOTOR HOLDINGS LTD	DISTRESS ZONE	GREY ZONE	GREY ZONE	GREY ZONE	GREY ZONE	INVICTA HOLDINGS LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE
CROOKES BROTHERS LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	QUANTUM FOODS HOLDINGS LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE
CSG HOLDINGS LTD	SAFE ZONE	SAFE ZONE	GREY ZONE	GREY ZONE	SAFE ZONE	PRIMESERV GROUP LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE
ELLIES HOLDINGS LTD	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	DATATEC LTD	GREY ZONE	GREY ZONE	GREY ZONE	GREY ZONE	GREY ZONE
ETION LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	MIX TELEMATICS LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE
HULAMIN LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	RAUBEX GROUP LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE
IMBALIE BEAUTY LTD (BUKA INVESTMENTS)	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	GREY ZONE	MARSHALL MONTEAGLE PLC	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE
INSIMBI INDUSTRIAL HOLDINGS	SAFE ZONE	SAFE ZONE	SAFE ZONE	GREY ZONE	GREY ZONE	SANTOVA LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE
LEWIS GROUP LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	ITALTILE LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE
NICTUS LTD	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	CASHBUILD LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE
NOVUS HOLDINGS LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	COGNITION HOLDINGS LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE
NUTRITIONAL HOLDINGS LTD	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	DELISTED	AH-VEST LTD	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	GREY ZONE	SAFE ZONE
OMNIA HOLDINGS LTD	SAFE ZONE	SAFE ZONE	GREY ZONE	SAFE ZONE	SAFE ZONE	AECI LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE
PBT GROUP LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	CAPITAL APPRECIATION LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE
PPC LTD	GREY ZONE	GREY ZONE	GREY ZONE	DISTRESS ZONE	GREY ZONE	ARCELORMITTAL SOUTH AFRICA	DISTRESS ZONE	GREY ZONE	DISTRESS ZONE	DISTRESS ZONE	SAFE ZONE
SEBATA HOLDINGS LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	AFRICAN EQUITY EMPOWERMENT	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE
SEPHAKU HOLDINGS LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	TRANSPACO LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE
SPANJAARD LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	BAUBA RESOURCES LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	DISTRESS ZONE	DISTRESS ZONE
STEFANUTTI STOCKS HOLDINGS	GREY ZONE	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	AVENG LTD	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE
TASTE HOLDINGS LTD (LUXE)	GREY ZONE	SAFE ZONE	SAFE ZONE	DISTRESS ZONE	DISTRESS ZONE	REX TRUEFORM GROUP LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	GREY ZONE	SAFE ZONE
TELKOM SA SOC LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	GREY ZONE	SAFE ZONE	BLUE LABEL TELECOMS LTD	SAFE ZONE	GREY ZONE	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE
THE FOSCHINI GROUP LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	MR PRICE GROUP LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE
TONGAAT HULETT LTD	SAFE ZONE	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	DISTRESS ZONE	OCEANA GROUP LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE
VALUE GROUP LTD	SAFE ZONE	SAFE ZONE	SAFE ZONE	SAFE ZONE	DELISTED	FRONTIER TRANSPORT HOLDINGS	DISTRESS ZONE	SAFE ZONE	GREY ZONE	GREY ZONE	SAFE ZONE
DISTRESS ZONES	7	8	8	11	7	DISTRESS ZONES	5	3	5	7	5
GREY ZONES	4	4	4	5	5	GREY ZONES	3	4	3	4	2
SAFE ZONES	20	19	19	15	16	SAFE ZONES	23	24	23	20	24

Appendix 4: Trend of individual ratios and EM scores









Appendix 5: EMS model's Bond equivalent ratings

EXTENDER GROUP					NON-EXTENDER GROUP				
ADCORP HOLDINGS LTD	BB	BB	BBB+	CCC	WORKFORCE HOLDINGS LTD	AAA	AA+	AAA	AA+
AFRIMAT LTD	A	BBB+	AA	AAA	SALUNGANO GROUP LTD	BB+	BB-	B+	CCC
ARDEN CAPITAL LTD (brainworks)	CCC+	BB+	AA+	BB	CITY LODGE HOTELS LTD	BB	A-	BBB	CCC
ARGENT INDUSTRIAL LTD	AAA	AAA	AAA	AAA	SOUTH OCEAN HOLDINGS LTD	A-	AA+	AAA	AAA
BELL EQUIPMENT LTD	AAA	AAA	AA+	AAA	ENX GROUP LTD	B-	B	B	CCC
BRIKOR LTD	CCC-	CCC-	CCC-	CCC-	RANDGOLD & EXPLORATION CO	AAA	AAA	AAA	AAA
CHROMETCO LTD	BBB+	CCC-	D	D	THARISA PLC	AAA	AA+	A	AA+
COMBINED MOTOR HOLDINGS LTD	B	BB	BB	BB	INVICTA HOLDINGS LTD	BBB	AA+	AA+	AA-
CROOKES BROTHERS LTD	AAA	AA+	AA+	AA+	QUANTUM FOODS HOLDINGS LTD	AAA	AAA	AAA	AAA
CSG HOLDINGS LTD	AAA	AAA	BBB-	BB+	PRIMESERV GROUP LTD	AAA	AAA	AAA	AAA
ELLIES HOLDINGS LTD	CCC-	B-	B-	D	DATATEC LTD	B+	BB+	BB	BB
ETION LTD	AA+	AAA	A-	BBB	MIX TELEMATICS LTD	AAA	AAA	AAA	AAA
HULAMIN LTD	AAA	A+	BBB	A	RAUBEX GROUP LTD	AA	AA+	AA-	AA-
IMBALIE BEAUTY LTD (buka investments)	CCC-	D	D	D	MARSHALL MONTEAGLE PLC	AA-	A+	AA+	AAA
INSIMBI INDUSTRIAL HOLDINGS	BBB+	AA	BBB+	BBB-	SANTOVA LTD	A-	A+	AA	AA-
LEWIS GROUP LTD	AAA	AAA	AAA	AAA	ITALTILE LTD	AAA	AAA	AAA	AAA
NICTUS LTD	B	B	B	B-	CASHBUILD LTD	AA+	AA-	AAA	BBB
NOVUS HOLDINGS LTD	AAA	AAA	AAA	AAA	COGNITION HOLDINGS LTD	AAA	AAA	AAA	AAA
NUTRITIONAL HOLDINGS LTD	D	D	D	D	AH-VEST LTD	CCC+	CCC	B	BB
OMNIA HOLDINGS LTD	AAA	AA	BB+	AA-	AECI LTD	AAA	AA+	AA+	AA-
PBT GROUP LTD	AAA	AAA	AAA	AA+	METROFILE HOLDINGS LTD	AA	BBB-	BB+	BB
PPC LTD	BB	BBB-	BBB-	CCC+	ARCELORMITTAL SOUTH AFRICA	B-	BB+	CCC+	CCC
SEBATA HOLDINGS LTD	AAA	AAA	AAA	AA+	AFRICAN EQUITY EMPOWERMENT	AAA	AAA	AAA	AAA
SEPHAKU HOLDINGS LTD	AA+	AAA	AAA	AAA	TRANSPACO LTD	AAA	AAA	AAA	AAA
SPANJAARD LTD	AAA	AA	AAA	AAA	BAUBA RESOURCES LTD	AAA	AAA	A-	CCC-
STEFANUTTI STOCKS HOLDINGS	BB-	CCC+	CCC+	D	AVENG LTD	CCC	B-	CCC	CCC-
TASTE HOLDINGS LTD (luxe)	BB+	AA+	A+	D	REX TRUEFORM GROUP LTD	AAA	AAA	AAA	B+
TELKOM SA SOC LTD	AA-	A	A-	BBB-	BLUE LABEL TELECOMS LTD	AA+	BBB-	CCC	CCC
THE FOSCHINI GROUP LTD	AAA	BBB	A-	BBB+	MR PRICE GROUP LTD	AAA	AAA	AAA	AAA
TONGAAT HULETT LTD	AA-	D	D	D	OCEANA GROUP LTD	BBB	A+	AA-	AA-
VALUE GROUP LTD	AA-	AA	AA+	BBB	FRONTIER TRANSPORT HOLDINGS	CCC-	AAA	BB-	BB

Appendix 6: EM scores

	EXTENDING COHORT				NON-EXTENDING COHORT				
*Financial Year	FY 2017	FY 2018	FY 2019	FY2020		FY 2017	FY 2018	FY 2019	FY2020
ADCORP HOLDINGS LTD	5.20	5.17	6.28	2.65	WORKFORCE HOLDINGS LTD	8.41	8.09	8.23	7.79
AFRIMAT LTD	6.83	6.31	7.45	8.65	SALUNGANO GROUP LTD	5.50	4.80	4.58	2.76
ARDEN CAPITAL LTD (brainworks)	3.56	5.62	7.86	5.25	CITY LODGE HOTELS LTD	5.06	6.54	5.85	2.60
ARGENT INDUSTRIAL LTD	9.47	8.51	10.18	9.71	SOUTH OCEAN HOLDINGS LTD	6.63	8.05	8.22	9.56
BELL EQUIPMENT LTD	9.48	9.04	8.07	8.44	ENX GROUP LTD	3.97	4.35	4.23	3.01
BRIKOR LTD	1.75	1.90	1.93	2.14	RANDGOLD & EXPLORATION CO	23.36	25.26	21.91	21.75
CHROMETCO LTD	6.31	2.43	1.37	0.85	THARISA PLC	8.67	7.93	6.69	7.94
COMBINED MOTOR HOLDINGS LTD	4.35	5.18	5.15	5.00	INVICTA HOLDINGS LTD	6.14	7.68	7.73	7.04
CROOKES BROTHERS LTD	9.96	7.69	7.87	7.91	QUANTUM FOODS HOLDINGS LTD	10.01	11.44	9.63	9.27
CSG HOLDINGS LTD	10.20	8.45	5.65	5.39	PRIMESERV GROUP LTD	10.08	12.10	11.37	12.07
ELLIES HOLDINGS LTD	2.25	3.91	3.77	-1.32	DATATEC LTD	4.70	5.29	5.20	5.19
ETION LTD	8.08	8.54	6.65	5.99	MIX TELEMATICS LTD	9.16	9.44	9.56	9.12
HULAMIN LTD	8.75	6.98	5.95	6.84	RAUBEX GROUP LTD	7.55	7.62	7.13	7.28
IMBALIE BEAUTY LTD (buka investments)	2.32	-1.52	0.49	0.72	MARSHALL MONTEAGLE PLC	7.03	6.96	7.65	8.88
INSIMBI INDUSTRIAL HOLDINGS	6.32	7.39	6.31	5.83	SANTOVA LTD	6.62	6.94	7.33	7.01
LEWIS GROUP LTD	12.47	14.13	16.48	10.59	ITALTILE LTD	19.00	14.60	11.54	9.98
NICTUS LTD	4.39	4.40	4.25	4.06	CASHBUILD LTD	7.65	7.28	8.59	6.24
NOVUS HOLDINGS LTD	11.90	9.95	9.72	10.14	COGNITION HOLDINGS LTD	10.88	10.09	11.49	10.12
NUTRITIONAL HOLDINGS LTD	-4.96	-10.23	-7.69	-3.79	AH-VEST LTD	3.59	3.01	4.41	5.11
OMNIA HOLDINGS LTD	8.59	7.35	5.38	7.28	AECI LTD	8.74	7.69	8.09	7.27
PBT GROUP LTD	12.77	12.88	14.38	7.87	METROFILE HOLDINGS LTD	7.36	5.73	5.47	5.09
PPC LTD	5.21	5.75	5.74	3.68	ARCELORMITTAL SOUTH AFRICA	3.89	5.60	3.20	2.67
SEBATA HOLDINGS LTD	8.67	9.07	10.02	7.77	AFRICAN EQUITY EMPOWERMENT	8.63	14.58	12.25	14.08
SEPHAKU HOLDINGS LTD	8.00	8.67	9.24	9.12	TRANSPACO LTD	9.73	9.45	9.22	9.27
SPANJAARD LTD	8.43	7.38	9.00	9.17	BAUBA RESOURCES LTD	13.92	11.88	6.62	2.36
STEFANUTTI STOCKS HOLDINGS	4.81	3.51	3.54	1.22	AVENG LTD	2.78	3.82	2.60	2.19
TASTE HOLDINGS LTD (luxe)	5.31	7.96	6.85	-1.38	REX TRUEFORM GROUP LTD	11.98	12.18	8.99	4.50
TELKOM SA SOC LTD	7.06	6.68	6.53	5.69	BLUE LABEL TELECOMS LTD	8.07	5.80	2.68	2.59
THE FOSCHINI GROUP LTD	8.61	6.23	6.49	6.36	MR PRICE GROUP LTD	14.48	14.25	15.44	10.25
TONGAAT HULETT LTD	7.17	1.02	-0.86	1.23	OCEANA GROUP LTD	6.17	6.99	7.22	7.10
VALUE GROUP LTD	7.05	7.33	7.81	5.91	FRONTIER TRANSPORT HOLDINGS	1.87	8.76	4.93	5.10