An evaluation of financial distress prediction measures for listed companies in South Africa

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Abstract: The need for additional measures of financial distress for listed companies is tantamount and stems from the ever-increasing number of business failures in South Africa's current economic climate. This study investigates the prediction capabilities of using liquidity financial ratios, as a method of predicting financial distress and investigates the effect of combining that analysis with a secondary measure, in an attempt to increase the ability of predicting financial distress. This is done by calculating and contrasting the liquidity financial ratios and Ohlson O-scores of forty companies with each other, in order to determine any relevant patterns or differences. These forty companies were divided into two groups of twenty companies, in one group the top 20 listed companies on the JSE and in group two, twenty companies that have been delisted or liquidated within the years of 2015-2017.

The financial statements of each company for the three years under scrutiny (top 20 companies) or the three years prior to delisting or liquidation (delisted companies) were used as basis for the calculations of the five primary liquidity ratios and the Ohlson O-score for each company and group.

This study found that the ratios under scrutiny behaved unexpectedly in some cases which can easily confuse the researcher when due care is not given to investigating the problem further. While liquidity ratios do have a strong correlation with showing financial distress, they don't provide a comprehensive prediction model when used in a silo. The addition of Ohlson's O-score as a secondary measure, improved the predictive capabilities of the analysis.

Therefore, this study has found that liquidity financial ratios and Ohlson's O-score analyses provide more accurate financial distress predictions when combined. Further study with a focus on smaller or private businesses should be conducted, in order to refine the process for non-listed companies.

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Background and Research design

South Africa has seen a rising number of businesses fail under the ever-increasing economic pressure that the country is currently facing (Statistics South Africa, 2018). This has placed the average South African business under extreme strain and has caused the ultimate failure of many organisations. The failure of these organisations has also been paired with multiple, extreme cases of bad corporate governance and fraud (Mangena & Chamisa, 2008) by major players in the South African markets. Many economic factors may be considered as contributing to the rate of business failures. However, situations such as the Value Added Tax hike and rises in fuel prices in 2018, has damaged the average investor's ability to invest in businesses, which has led to the fall in share prices of multiple large organisations such as Shoprite, Mr. Price and Woolworths (Gernetzky, 2019). This situation has led to renewed interest in financial distress and how it can be dealt with.

In the South African context, financial distress is defined by the South African Companies Act (71 of 2008). According to Chapter 6, Section 128(f) of this act, *"financial distress"* can be defined as follows –

- *It would seem unlikely that the company will be able to pay all of its debt as needed or within the six months that follow.*

  Or
- *It is quite likely that the company will become insolvent within the next six months*.

The financial distress that many firms have faced in the past have been linked to either weak compositions of boards of directors, and little to no practise of accepted corporate governance practices (Elloumi & Gueyié, 2001). Investors and shareholders are forced to be ever more vigilant in their search for prospective investments in the stock market and in private enterprise. Controls are put in place by stock exchanges, such as the JSE, to try to provide a safer option to prospective shareholders and investors in the form of audited financial statements and corporate governance requirements (JSE, 2007).

It can then logically be deduced that a firm that is subject to a comprehensive list of requirements and controls, is not expected to fail. By requiring firms to adhere to these terms, stock exchanges subconsciously lull investors into complacency as, to them, this is proof of the organisation's financial position and its current performance.

The use of audited financial statements can easily provide a false indication of a company's wellbeing (Tassadaq & Malik, 2015), as it is subjected to many accounting policies that can easily be manipulated by the organisation (Ball, 2006). The manipulation of accounting policies includes, but is not limited to, hiding liquidity problems behind the fact that larger amounts of fixed assets belong to the organisation and thus creating the illusion that the current financial position is much better than it truly is (Cagle *et al*., 2013).

The problem arising from financial statements, and by extension, financial ratios not being completely reliable (Perols & Lougee, 2011), leave investors with little information as to whether or not an investment in a company can be viewed as a sound investment. While taking all of this into consideration, various authors stress that the use of financial ratios remains a key indicator of financial distress (Aziz & Dar, 2006) and that it still shows the possible problems that an organisation faces (Beaver, 1966), even if the statements are adjusted. This is especially true for liquidity ratios in the South African context (Jooste, 2006).

Financial ratios are generally used within the accounting profession and by investors as a way of making financial statements and information more understandable and giving unique information such as comparable parameters and metrics that are easily understandable to most investors, other than simply amounts (O'Connor, 1973). It also gives potential shareholders something against which to measure a company's current performance.

Liquidity ratios remain key among financial ratios. Liquidity is often overlooked, as the lack thereof is easily justified through the ownership of a large amount of assets. It is, however, regarded as one of the cornerstones of a company by Jones (1975). Organisations tend to focus on their accounting profits and operations, and then ignore liquidity as a vital part of an organisation's wellbeing. Yu-Thompson *et al.* (2016) show that adequate control over liquidity ensures greater confidence in the abilities of the management of a company, and less shareholder concern over the misuse of liquidity reserves.

Therefore, it is shown that liquidity plays a crucial role in an organisation's ability to perform (Dharmasena, 2015). Therefore, the question of how to predict the financial distress of companies more reliably in the South African context, must be considered with some urgency. The usefulness of using liquidity as a determinant for financial distress has been established, specifically focusing on liquidity financial ratios. By considering liquidity in a financial distress context, it can be assumed that there is a pattern between so-called successful firms, and a different pattern between unsuccessful firms.

Aziz and Lawson (1989) proposed the concept of combing financial ratios, which has to do with liquidity and other financial distress models, in order to get a more accurate prediction of financial distress by widening the horizon. These included models that have generally been used in the prediction or measurement of financial distress. By combining a model with liquidity ratios, Aziz and Lawson (1989) postulated that more conclusive results can be found than by simply looking at traditional cash flow analyses.

1.1. Problem Statement

As can be deduced from the background provided, financial distress is occurring due to the current economic environment, and this creates unease among shareholders. Organisations tend to fail without much warning, and it appears that the existing measures of predicting or indicating this financial distress leaves stakeholders with a lack of information. If one considers the theoretical functioning of an organisation only, these organisations should not be able to fail, if placed under the amount of controls that they are.

The problem from the current situation is that companies cannot accurately predict when financial distress is unfolding. The unease under shareholders has provided an environment where organisations are under ever-increasing pressure by the public to prove their financial position and provide reasonable assurance as to their longevity. This has led to the need for a measure, or the combination of measures, that will provide some sort of clarity for listed companies in South Africa.

The consideration of whether or not financial distress can be predicted with more reliable measures, through the combination of certain measures, so that the attainment of a more conclusive method becomes possible, needs to be examined.

This leads to the question of whether or not financial distress prediction can be improved by using a combination of both liquidity financial ratios and an existing model.

The use of other models in conjunction with financial ratios has been tested in the past, although no consensus as to the specific model to be used, has been achieved (Dimitras *et al*., 1996). The model that will provide the best combination with liquidity ratios will have to be determined, for the purpose of predicting financial distress in South African businesses.

1.2. Objectives

1.2.1. Primary objective

As deduced from the problem statement, this study aims to evaluate the prediction properties of liquidity financial ratios, an existing prediction model and whether a combination of measures can be included to improve these properties.

1.2.2. Secondary objectives

In support of the aforementioned objective, secondary objectives have been identified.

The utility of the proposed models will be examined in the literature study (Chapter 2) in order to determine the most relevant model. In the data and results chapter, the aim of the study is to test the utility of each measure with regard to liquidity (3.1) and the measure selected in the literature study (3.2). This will be concluded in the discussion of the results chapter (Chapter 4) where the combination will be attempted in partial address of the primary objective.

1.3. Methodology

1.3.1. Research theory and assumptions

Companies exist because of the need to maximise shareholder wealth therefore ensuring the going concern of the entity (Bainbridge, 1993). Maximising shareholder wealth can be achieved through effective management of the entity and its liquid assets (Karns, 2011). This is the prevalent theory pertaining to all companies but has been expanded upon and challenged in the past by the stakeholder and agency theories.

Stakeholder theory states that the executives of an organisation should consider all parties that have a stake in the organisation when making decisions as this is integral to the organisation's survival (Freeman *et al.*, 2018). Agency theory states that an organisation's executives operate as the agents of the principals (shareholders) and so provide the relevant financial information to the shareholders concerning the organisation's current financial position (Shapiro, 2005).

Investors then examine the financial information and keep the agents accountable for the position the organisation is in, in order to determine whether or not their share value increases (Ross, 1973). This study accepts the agency theory as being most prevalent with regard to the scope of this study, as this study focuses on the acceptability of financial information given by the agents to the principals, and the interpretation thereof to understand financial distress.

The idea of executives being the agents of the shareholders, firstly defines the need for accountability, and secondly, that insight into the possible financial distress of the organisation needs to be provided (van Puyvelde *et al.*, 2012). This can be done by providing the proposed combination of liquidity ratios and an existing model, as it provides investors with a means of measuring the security of their investment in the organisation by being able to assess whether the organisation is experiencing financial distress or not. This will allow the investors (principals) to keep their agents liable and provides insight into whether the agency relationship is functioning effectively or not.

In the case of organisations, as described by agency theory, the most relevant financial information is created in the form of financial statements using accounting rules. These rules are applied to financial ratios and are used for financial analysis. This information needs to be accurate to allow the organisation to pick up any relevant problems (Lennox, 2003). Therefore, the need arises to expand financial analysis beyond simply ratio analysis to provide useful tools for multiple parties, such as analysts, brokers, etc. It can therefore be assumed that since all listed companies have these basic needs and adhere to the same rules, a pattern will exist regardless of industry barriers.

This study is focused on an objective and deductive view of research, this is coupled with a positivistic paradigm, as the data is of a quantitative nature. It will focus on the identification of the best alternative to be selected to solve the problem of the unpredictability of financial distress and aim to combine previous views in the effort of creating a combination of approaches. The data to be gathered is of a strictly objective and impersonal value, as no opinions of any parties will be gathered, indicating a clear focus on pragmatism and stated facts.

The study has been deemed a low risk for ethical considerations because of these approached to the gathering of the needed data and therefore in-depth analysis of these implications is not included.

This study makes use of an analysis of trends to establish whether or not any patterns between the relevant population and groups, of listed and de-listed companies, can be identified and analysed. Furthermore, this study accepts the limitations of the availability of financial statements of de-listed companies and will take this into consideration for the selection of the population.

1.3.2. Literature review

This study builds on multiple, similar studies, undertaken in many different areas in the world concerned with predicting financial distress, in which financial ratios, and combining them with other models, are specifically used. There are three components to the current study: liquidity financial ratios; the existing models used to predict financial distress; and the combination of these elements to find a conclusive answer. The literature to be studied will start with the utility of liquidity and its predictive capabilities.

This study then looks at the relevant theories of different predictive models, ending off with studies that support the combination of models with liquidity ratios.

1.3.2.1. Liquidity ratio studies

There are two studies that are most relevant to this study, and will serve as the basis for the arguments in favour of including liquidity as an important measure in financial distress.

Lieu *et al.* (2008) stated that, "financial ratios remain the principle variables for predicting corporate financial distress". Lieu *et al.* (2008) attempted to create a prediction model for financial distress in all companies by utilising financial ratio analysis and combining it with factors pertaining to non-financial information. This study also affirms the use of the three years prior to financial distress as the base-line period for predicting financial distress. While their study focused on many different ratios, such as solvency, profitability, financial structure, and liquidity as their primary ratios, this study takes a narrower approach by only utilising liquidity ratios to assess financial position and performance. This study also accepts the time restraints of three years, as set out in Lieu *et al*.'s study.

Yu-Thompson *et al.* (2016) measured the liquidity practices of family-run firms against that of listed companies and found that these firms exhibit a higher level of liquidity and lower levels of risks towards their liquid position. The study also emphasised the importance of liquid companies, as opposed to simply profitable ones, by the use of a mix of financial ratios and best practise norms.

Furthermore, Yu-Thompson *et al*.'s study takes its focus on liquidity as a determinant for financial distress. It increases the scope to which liquidity should be emphasised in the understanding of financial information.

These studies will be discussed and examined in greater detail in the literature study chapter, where a comprehensive analysis of previous studies will be offered.

1.3.2.2. Studies for possible models

Almamy *et al.* (2016) investigated the use of combining cash flow ratios and Altman's Z-score in an effort to predict corporate failure in the UK context. By using the Z-score as discriminant analysis and the ratios as a performance test, a new model was created that shows an 82.9% more conclusive answer than the base Z-score. The purpose of their study was to expand the Z-score for UK businesses, in an attempt to more accurately predict corporate failure. The study also specifically affirms the utility of using cash flow/liquidity financial ratios when investigating financial distress. It does, however, focus on a statistical view where this study assumes an accounting view.

In his study, Ohlson (1980) analysed the existing models of financial distress prediction and theoretically tested the utility of three different models, Altman's Z-score being one of them. Ohlson found that while the existing models bare some fruit, none of these models examined probability as part of their models. In the study he proposes a model, the O-score, which is based on combining nine different financial ratios with probability indexes. As stated above, this study takes on an accounting view of the model and does thereby not adjust the formula or probability indexes.

These studies show the two most prevalent models to be used in financial distress prediction and that fall within the parameters set by the scope of the study. Each will be analysed in greater detail in the literature study and the best model to be used in combination with the liquidity ratios will be selected.

1.3.3. Empirical research

Before commencing with the empirical study, the relevancy of liquidity will be determined through the use of a literature study. This study also includes the consideration between the relevant models to be used and will determine which of the proposed models will be applied to the data under scrutiny.

The study utilises a stratified population sampling technique, where the population is divided into two sub-populations as discussed below and the sampling method differs slightly for both.

The population will consist of the following – twenty companies that have been de-listed from the JSE between 2015 and 2017, and whose financial statements are still freely available. These will then be followed by twenty companies that are still listed and make up the top twenty organisations on the JSE by market capitalisation.

The use of the twenty listed companies will serve as a benchmark for what are considered healthy companies, compared to the twenty de-listed companies, who have all experienced financial distress of liquidation, in a pattern analysis to find useful patterns as to the financial state of these companies in the three years before their de-listing.

The data of de-listed companies will be directly obtained from the JSE and this list of companies will be used together with each year's financial statements in the three years prior to de-listing. The second group's financial statements from 2015-2017 will be used in the analysis, as all of these companies' financial statements are freely available for comparison purposes. A pattern analysis will be applied to the data in order to establish the underlying relations between the data in an attempt to address the primary objective.

In the first part, the data will be applied against five key liquidity financial ratios in a normal analysis of the cash position of the organisation in the three-year period under scrutiny, to reaffirm the usefulness of liquidity. Each of these ratios' results will be analysed, and an overall result about the liquidity position of each organisation will be drafted. The usefulness of these ratios will be analysed through the comparison of the de-listed companies' results with those of the listed companies.

Next, the model selected from the literature study will be applied to the same population on a per-company and -group basis. Each of the models' accepted formulae will be directly used in the application of the study, if the model is selected. This study does not seek to adjust the formulae, but simply test the utility.

The results from applying the model to each organisation will be analysed and compared with the results of the rest of the organisations in the group. The two groups' results will then be compared to establish the individual usefulness of the selected model.

In both cases described above, the financial ratios and the model, the study will apply the following statistical analysis tools in order to showcase the relations and variances of each ratio and the model to each organisation and the population groups as a whole and will serve as the basis for the pattern analysis.

Mean average – The mean averages are the main tools to be utilised in establishing the underlying pattern in the findings of each sub-population group and the driver to used for establishing the accuracy of each method before combining the two. These averages will be calculated by removing the outlier data that may render a group's results inaccurate and then establishing the mean by taking the average results for each group in a certain result by taking the standard deviation in the data group into consideration.

Standard deviation – The standard deviation will be utilised to establish the mean average by acting as a determinant for inclusion into its calculation.

Outliers – The outliers in each result group will be established using standard statistical techniques and will act as a first line determinant for inclusion or exclusion of data items from the calculation of the mean averages.

After establishing the results of both methods when applied to the data sets, the study will determine the accuracy of each method by assuming that each company in group B is/was in financial distress and the companies in group A were not. This will then be taken into account when the methods are combined.

Lastly, the end result will consist of the results of each of the measures that will be combined and compared again, in order to establish whether or not the selected model and the liquidity combination has indeed improved the results of prediction from those attained by looking at the liquidity ratios and the selected model in isolation.

1.4. Layout of chapters

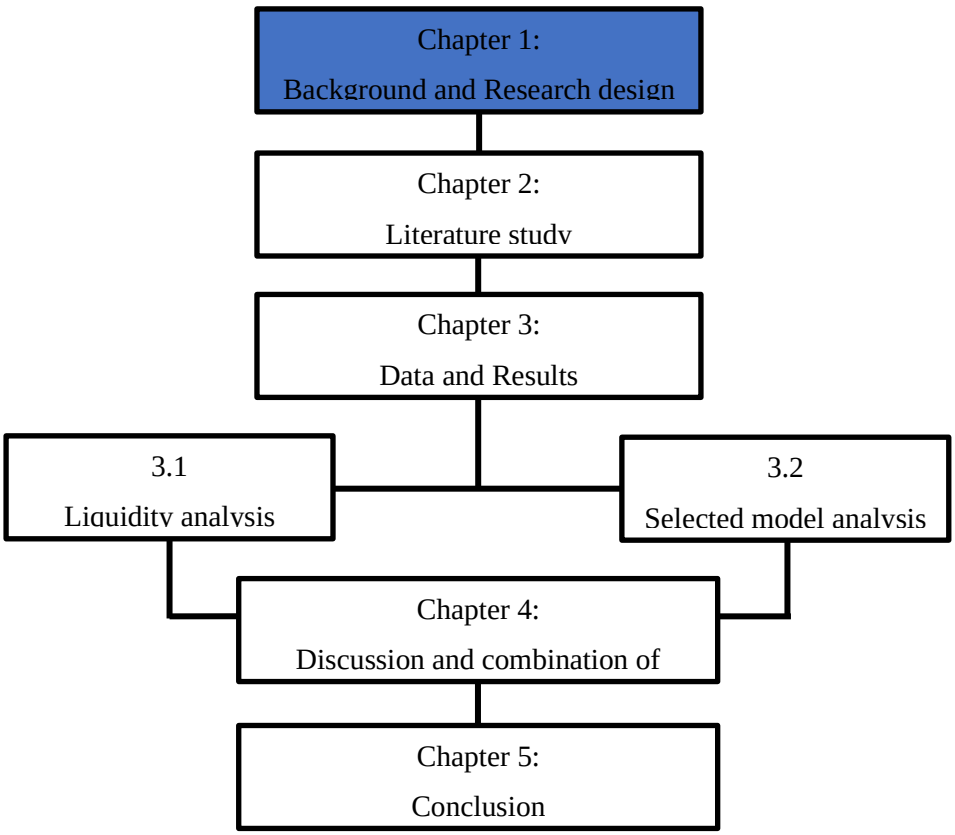

Figure 1 – Chapter layout (Ch. 1)

Chapter 1: Background and research design

The background describes the setting in which this study takes place and the problem from which this study's research goal originates. A clear indication as to the need for the study and the actuality thereof in the current South African context is given, which allows the reader to understand the real-world implications of the current economic pressures, and the crisis for shareholders in listed or de-listed companies. A comprehensive discussion of the research design of the study is given in order to establish the necessary boundaries and explain the route taken in the application of the study on the data. A short literature review gives background as to the origin of the study and the relevant studies previously associated with the research topic.

Chapter 2: Literature review

A literature review will be conducted at the start of the study, in order to establish the usefulness of liquidity as a component in financial distress prediction. This will be done by examining previous studies that assert the need for including liquidity as a measure in any financial distress analysis.

The second part of the literature review will examine the two proposed existing models for predicting financial distress and discuss the arguments for and against the use of either model in the proposed combination with liquidity ratios. The study aims to examine the base literature for each model and studies that support or oppose the use of each in financial distress prediction.

Chapter 3: Data and results

In Chapter 3, the data will be analysed in two sub-sections, liquidity and the selected model.

3.1 Liquidity analysis

In this sub-section, the key liquidity ratios, as stated in the research design, will be applied to the population and a pattern analysis will be carried out that compares each company in each group with each other and the groups as a whole to test the predictive capabilities of these ratios.

3.2 Selected model analysis

In the second sub-section, the model selected in the literature study will be applied to the same aforementioned population. The same pattern analysis that compares the companies in each group with those in the same group and then the results of both groups as a whole with one another, will be carried out to test the predictive capabilities of the model.

Chapter 4: Discussion and combination of results

The discussion of the results will entail the examination of each of the previous two sub-sections' results and how each fared in isolation. This will then be followed by combining the results of the sub-sections and discussing the change or lack of change in the overall results. The establishment of which combination is the best will then be possible.

Chapter 5: Conclusion

In the conclusion, the combined results will be reflected on and a recommendation, as to whether or not the combination needs to be further improved on, will be made. This will give reference to whether the research objectives have been achieved or not. Lastly, recommendations for future studies will be made.

Chapter 2 - Literature Study

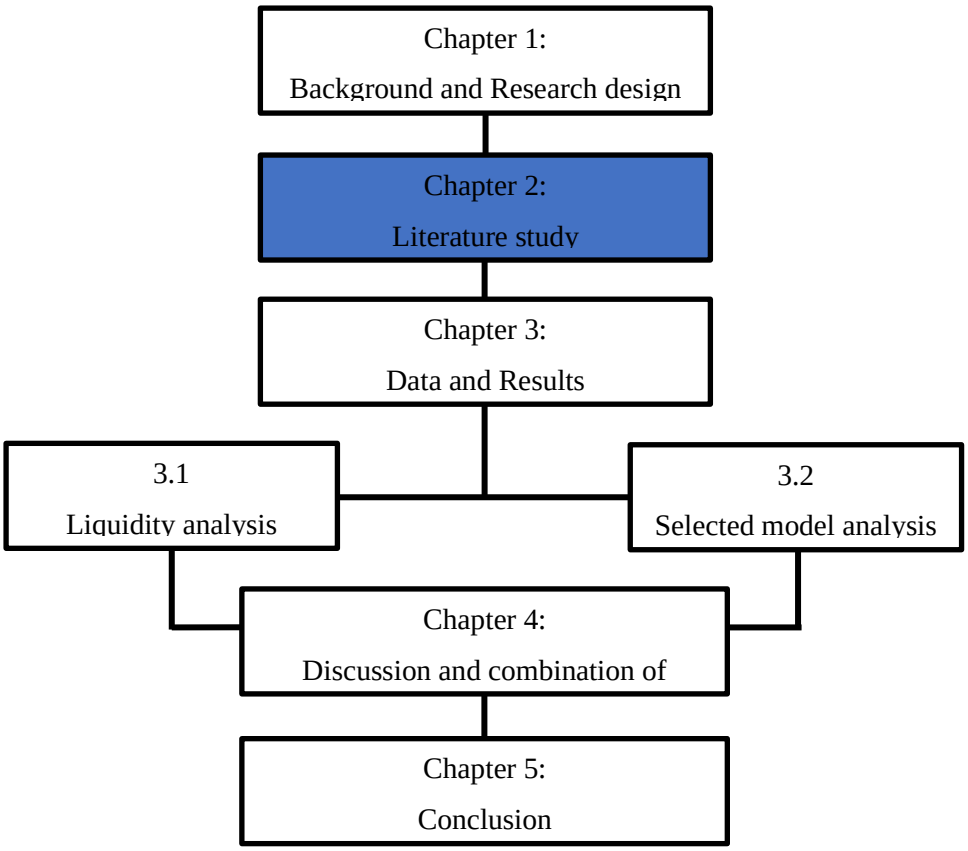

Figure 2 – Chapter layout (Ch. 2)

The literature study serves as a discussion of the relevant theory pertaining to this study, and which underpins the research question and objectives set out in Chapter 1. Furthermore, the chapter also sets out a theoretical framework for the study, around which the methodology can be further refined.

This chapter, firstly, attempts to establish the utility of liquidity financial ratios in the prediction of financial distress as stated in the background information, and secondly, examine both of the proposed models for financial distress that were named in the research design, in detail. This will be done in order to establish the model that will be applied to the data as discussed in chapters 3 and 4, respectively.

2.1. The liquidity and financial ratios in financial distress prediction

As previously stated, liquidity is seen as a cornerstone of any company and thus, a crucial part of financial well-being (Dharmasena, 2015). Dharmasena's study is related to the need for companies to remain liquid, so as to be able to honour short- and long-term liabilities (Rodrik & Velasco, 1999).

Companies that have not been able to remain liquid in the past, have often not survived and serve as an example to the dangers of overlooking the importance of liquidity, as so many managers and companies tend to do (Jones, 1975).

As discussed above, liquidity is of extreme importance and therefore needs to be analysed and interpreted. Interpretation of liquidity is mostly done in practice using liquidity financial ratios, which is analysed and re-affirmed in Goldmann's (2017) study on liquidity and profitability in practice, and the utility of analysing and managing these two aspects in business. This study aims to combine liquidity financial ratios with one of two excepted models for financial distress prediction in order to re-establish the utility of liquidity financial ratios in the process.

There are three main studies that provide insight into the utility of financial ratios, which this study accepts as the most salient underpinning studies for the use of liquidity ratios in this context, i.e.:

- Lieu *et al.* (2008) - Financial early-warning models on cross-holding groups.
- Yu-Thompson *et al.* (2016) - Liquidity and corporate governance: evidence from family firms.
- Aziz & Lawson (1989) - Cash Flow Reporting and Financial Distress models.

Lieu *et al.* (2008:1060) stated that financial ratios remain some of the primary factors of financial distress prediction, especially in the three years prior to financial distress being most prevalent, or the date of liquidation or downsizing. Lieu *et al.* (2008) used different financial ratios in their analysis and combined ratios with non-financial measures. This study, however, has a narrower application and simply focuses on liquidity and its prediction capabilities, as underpinned by Dharmasena (2015) and Jones (1975:218) in the above-mentioned discussion.

While Lieu *et al.* (2008:1065) used financial ratios, this study focuses on a traditional ratio analysis as described by Chen & Shimerda (1981:54), where ratios are applied to a data set and a pattern analysis over multiple periods is carried out.

Yu-Thompson *et al.* (2016:144) showed that family firms in the US proved to have higher levels of liquidity than their non-family counterparts. These levels of liquidity were combined with these firms showing a healthier long-term prospect than the non-liquid firms as an increased trust in management ability provided easier access to liquid assets.

Yu-Thompson *et al.'s* (2016) study shows the utility of liquidity in the prediction of financial distress and thereby gives credence to a focused study on the predictive capabilities of liquidity financial ratios, such as this study aims to do.

This study supports both Lieu *et al.* (2008:1079) and Yu-Thompson *et al.'s* (2016:172) views of using financial ratios and specifically focussing on liquidity financial ratios, as the arguments clearly show that financial ratios are still useful in the prediction of financial distress. The afore-mentioned studies also accept the use of three years prior to financial distress as the appropriate time frame for a study to be performed, as it has been shown to give more conclusive results.

Yu-Thompson *et al.'s* (2016:152) study is viewed as the most relevant study in regard to liquidity and financial distress prediction as Lieu *et al.'s* (2008:2080) focus is broader as a result of the use of other ratios. This study focuses on listed firms in the South African context and not family-owned or private firms in the USA, therefore the existence of possible discrepancies and changes are anticipated.

Aziz and Lawson (1989:56) investigated the utility of using a secondary model in conjunction with liquidity financial ratios as a possible predictor for financial distress. This showed that the implementation of a second model provides a more conclusive prediction. This study accepts the need for a secondary measure and will, therefore, apply one of the two proposed models to be discussed and chosen later in this chapter.

The liquidity ratios that this study applies to the dataset, is decided on by taking the traditional liquidity ratios as set out by Kirkham (2012) in his analysis of the telecommunication sector in Australia, by applying a liquidity ratio analysis. This is combined with the views set by Richards & Laughlin (1980), where traditional ratios are combined with the cash conversion cycle and the ratios that sprout out of it.

These ratios thus include:

- Current ratio = $\frac{Total\ Current\ Assets}{Total\ Current\ Liabilities}$
- Quick ratio = $\frac{(Total\ Current\ Assets - Inventory)}{Total\ Current\ Liabilities}$
- Receivables turnover = $\left(\frac{Trade\ Receivables}{Revenue}\right) 365$
- Payables turnover = $\left(\frac{Trade\ Payables}{Purchases}\right) 365$
- Inventory turnover = $\left(\frac{Inventory}{Cost\ of\ Sales}\right) 365$

The current and quick ratios are seen as the base liquidity ratios and examine the direct ability of the organisation to meet its short-term debt, using its short-term assets (Finstanon, 2006). The quick ratio is expanded by removing the inventory of the organisation from the equation and establishing whether or not the organisation can survive while not taking its stock into consideration, as this tends to be a problem that most retail, and other organisations face. This is stated most prevalently by Singh (2008), where his study examined the liquidity problems faced by firms when weak inventory and working capital management is applied.

Singh's (2008) study also stressed the importance of working capital and thereby affirms the use of the three working capital ratios. Receivables and payables turnovers show the organisations ability to meet its shot-term debts and collect from its short-term debtors in comparison to the rate at which its inventory is being sold and bought in the inventory turnover ratio.

2.2.Selection of an appropriate prediction model

As discussed in detail in the first chapter, this study aims to combine the above-mentioned liquidity ratios with one of two models in an attempt to arrive at more conclusive results for the prediction of financial distress. In this sub-section, both models will be examined in order to establish the model that is most suited to this study's focus. The section that follows will focus on the formula of each model and discuss each model's background, as well as the arguments for and against the respective models by previous research. The two models proposed in the research design are Altman's Z-score and Ohlson's O-score.

2.2.1. Altman's Z-score

The Z-score, as created by Prof. E Altman in 1967 and then updated in 2012 to include the application of the model to more types of organisations, is a model that is generally used in isolation to predict corporate bankruptcy (Altman, 1968). The model includes the use of the products of standard deviations and five key financial ratios. This model has been in use since its initial publication in 1967 and continues to be a popular measure of turnaround management, financial distress, credit risk analysis, etc. (Calandro, 2007). The Z-score formula and ratios include five ratios that are not focussed on a specific category of financial analysis, as discussed in depth by Eidleman (1995).

The Z-score's formula is stated as:

$$Z = 1.2(A) + 1.4(B) + 3.3(C) + 0.6(D) + 1.0(E)$$

Table 1 - Explanation of Z-score formula

Ratio/Component	Formula
A = Working capital	$\frac{\text{Current Assets}}{\text{Current Liabilities}}$
B = Earnings to assets	$\frac{\text{Retained Earnings}}{\text{Total Assets}}$
C = Return on capital employed	$\frac{\text{EBIT}}{\text{Total Assets}}$
D = Equity to debt	$\frac{\text{Market value of Equity}}{\text{Total Liabilities}}$
E = Sales efficiency	$\frac{\text{Sales}}{\text{Total Assets}}$

The table above briefly sets out the components of the formula; the values shown in front of each component in the formula are the standard deviations set out in Altman's 2012 adaptation of the formula and must be multiplied with the specified ration for that component. Working capital is the exact same ratio as the current ratio discussed under liquidity, measuring the liquidity of the organisation. Earnings to assets and Return on Capital Employed (ROCE) both measure the amount of earnings generated by the assets that the organisation owns.

Equity to debt measures the value of the equity of the organisation as opposed to the amount of debt and thereby the level of investment by shareholders in the organisation. Lastly, sales efficiency measures the level of sales generated by the assets owned by the organisation (Bragg, 2018).

This model functions on the basis of interpreting the values given by the model in relation to four rules (Altman, 1968).

These rules can my interpreted as – "when the Z-score is":

- >= 3.0 – the firm is most likely safe based on the financial data.
- 2.7 < Z < 3.0 – the company is probably safe from bankruptcy, but this is in the grey area and caution should be taken.
- 1.8 < Z < 2.7 – the company is likely to be bankrupt within 2 years.
- <= 1.8 – the company is highly likely to be bankrupt.

There are three main studies that advocate the use of this model for financial distress prediction above all others, i.e.:

- Altman (1968) - Financial ratios, Discriminant analysis and the prediction of Corporate Bankruptcy
- Clandro (2007) - Considering the utility of Altman's z-score as a strategic assessment and performance management tool
- Almamy *et al.* (2016) - An evaluation of Altman's Z-score using cash flow ratios to predict corporate failure amid the recent financial crisis: Evidence from the UK

Altman (1968) stated that the trust practitioners traditionally placed in financial ratio analysis was being questioned and he asked the question as to whether or not financial ratio analysis can still be of use in the assessment of financial distress.

According to Altman (1968) combining certain traditional financial ratios with the popular but rigorous statistics analysis, a more conclusive model for predicting financial distress in organisations, can be created. Furthermore, it was proposed that the creation of the Z-score, where certain key financial ratios are combined with industry or general standard deviations, so as to give a clearer answer about the organisation's current state and whether or not business rescue plans, should be drawn up (Altman, 1968).

This study accepts the model used by Altman and the standard deviations used for all types of businesses in the updated version of the model in 2012, as the scope of this study does not include adjusting the accepted formula of the model.

Calandro (2007) reaffirmed the usefulness of the Z-score in assessing and predicting financial distress. His study inspected the utility of the Z-score for the purposes of being used by corporate managers as a strategic assessment and performance management tool. Calandro (2007)'s study found that the Z-score has been underutilised in most companies, even though the findings were clear that the utility of the model cannot be understated.

Almamy *et al.* (2016) examined the combination of a liquidity/cash flow ratio with the Z-score and determined that the addition of an extra variable increased the predictive capabilities of the model and thereby establishing a more conclusive prediction. This study is, therefore, used as the underpinning study in favour of the use of the Z-score model as a combination effect has already been tested using one liquidity ratio.

On the other side of the spectrum, there are a few reports produced in practise that challenge the usefulness of the Z-score. Since these reports vary depending on industry and most voice the same concerns, the most relevant and extensive report, that of David Kirk (2008) for the GTI group, will be analysed.

In his report, for the then struggling GTI group, Kirk (2008) concluded that the use of the Altman Z-score is outdated and has not been sufficiently updated in to keep up with the dynamics of the business world. He stated that the model in itself should not be used as a turnaround model as a clear indication of financial distress, because the clear areas/rules provided by the model often lead organisations to accept these rules as targets, rather than parameters within which they should function.

The problem of the model not being industry specific and the standard deviations having to be adjusted for every industry, to increase the accuracy, is stated and decreases the model's usefulness.

2.2.2. Ohlson's O-score

James Ohlson researched and tested many previous models for financial distress in 1980 and came to the conclusion that many of these previous models missed, what he describes as "a crucial component of financial distress prediction" (Ohlson, 1980). In answer to this, he created the O-score. This model is also generally used, albeit not as much as the Z-score, to predict financial distress by combining nine financial ratios with a probability factor, based on the Gross National Product (GNP) price level index.

The O-score formula includes one financial ratio and nine variables that create a model which does not solely focus on financial ratios; in strong contrast to the Z-score above. This gives the model the ability to cross industries, which the Z-score struggles with.

The O-score's formula is stated as:

$$O = -1.32 - 0.407\,log\frac{TA_t}{GNP} + 6.03\frac{TL_t}{TA_t} - 1.43\frac{WC_T}{TA_T} + 0.0757\frac{CL}{CA} - 1.72X - 2.37\frac{NI_t}{TA_t} - 1.83\frac{FFO_t}{TL_t} + 0.285Y - 0.521\frac{NI_t - NI_{t-1}}{(NI_t)+(NI_{t-1})}$$

Table 2 - Explanation of O-score formula

Ratio/Component	Formula
TA	Total Assets
GNP	Gross National Product price index level
TL	Total Liabilities
WC	Working Capital: Current Assets / Current Liabilities
CL	Current Liabilities
CA	Current Assets
X	X=1 (if TL>TA) X=0 (if TL<TA)
NI	Net Income
FFO	Funds from operations
Y	Y=1 (if Net loss for 2 years) Y=0 (If no Net loss for 2 years)

Most of the components of the formula can be acquired directly from the financial statements of an organisation and will therefore not be described in detail in this chapter. These variables are total assets and liabilities; current assets and liabilities; net income and funds from operations (CIMA, 2016). The only ratio to be included in this model is also the working capital liquidity ratio, which links the model to liquidity as with the previous model.

There is only one variable that is completely independent from the organisations under scrutiny and that is the GNP price level index. This component is shortly defined as the average price over the entire current spectrum of goods in a certain economy (Kenton, 2019) and thereby the variable that makes the model more applicable over many industries (Church, 2016), other than the Z-score, as this is one of the biggest arguments against financial distress models.

The X and Y factors are determined by the state of the ratio between total liabilities and assets, and the time period for a net loss respectively, as stated in the table above. These factors effectively cancel one-another out and are seen as the regulatory factors of the formula (Ohlson, 1980). The O-score has no specific rules as the answer/score is expressed as a percentage of probability for financial distress occurring.

The following formula is used on the O-score answer to convert it into a probability of distress:

$$\text{p(failure)} = \frac{e^{O-score}}{1+e^{O-score}}$$

There are two main studies that advocate the use of this model for financial distress prediction above all others:

- Ohlson (1980) - Financial Ratios and the Probabilistic Prediction of Bankruptcy
- Griffin & Lemmon (2002) - Book-to-Market Equity, Distress Risk, and Stock Returns

Ohlson (1980), examined previously accepted models at the time and decided that by simply using standard deviations and statistics, the true prediction of financial distress is not possible. This led to Ohlson creating the O-score that combines financial ratios and amounts with a probability index, in order to arrive at a more conclusive answer for the prediction of financial distress and not only relying on the companies' financial information.

This study accepts the original formula for the O-score as the model has not been updated and agrees with the application of the model for all firms.

Griffin & Lemmon (2002) examined the relationship between book-to-market equity, distress, risk, and stock returns and used the O-score as the predictive determinant of each firm's distress risk. The study showed the O-score to be highly effective and affirmed the utility thereof for financial distress prediction, when used as a secondary measure, and the use of percentages increased the comprehensibility of the data to non-financial parties.

As this is a lesser known and used model, no substantial argument has been raised against it. The accuracy of the model has, however, been challenged by the following study:

- Jouzbarkand *et al.* - Bankruptcy Prediction Model by Ohlson and Shirata Models in Tehran Stock Exchange

Jouzbarkand *et al.* (2013) applied the model against Iranian firms in much the same way as described in this study's methodology, where healthy and failing firms' O-scores and another model were calculated and compared, in order to test the predictive capabilities of each.

The study found that the O-score was the more comprehensive model of the two and had a 10% inaccuracy level. Jouzbarkand thus places the O-score at a higher accuracy than the Z-score, at 90%. This study accepts the aforementioned argument, even though the model still lacks industry specific coefficients.

2.3. Choice of the relevant model

In the points above, both the Z- and O-scores were theoretically tested, through the opinions stated by previous studies, where both models seem promising. This will be weighed up directly in this last sub-section, and the most appropriate model will be chosen.

There is one relevant study that weighed both models against each other that will also be taken into consideration. Pongsatat *et al.* (2004) examined the comparative predictive capabilities of both models by applying both to the same set of 60 bankrupt and 60 non-bankrupt firms in Thailand. Their study concluded that each model has predictive capabilities and that there are no significant differences in their respective capabilities.

However, since the aforementioned study does not provide a clearly defined guide as to the criteria used, the models will be weighed against the following criteria as could be deduced, in order to choose the relevant model:

1. Accuracy determined by previous studies
2. Availability of variables
3. Appropriateness over all industries
4. Complexity of the model
5. Arguments for and against the model

2.3.1 Altman's Z-score

2.3.1.1 Accuracy determined by previous studies

According to Clandro (2007) the Z-score has an accepted accuracy level of 95% for 1 year before financial distress, and 72% for 2 years before financial distress. This second-year accuracy is said to be increased to 80% by adding cash-flow measures, as stated by Almamy *et al*. (2016).

2.3.1.2 Availability of variables

As the standard deviations of the Z-score will not be adjusted in this study, the only variables will be the ratios. Each ratio as stated above is easily calculated from the available financial information.

2.3.1.3 Appropriateness over all industries

The Z-score is generally criticised as its standard deviations need to be adjusted for each industry, this is however outside of this study's scope and will therefore remain a limitation.

2.3.1.4 Complexity of the model

While the Z-score calculation is simplistic, the result produced by the formula can only be understood by using the four rules as stated above, which therefore, makes the use of the model more complex.

2.3.1.5 Arguments for and against the model

The Z-score mainly has three previous studies that support its use in financial distress prediction, albeit for different reasons. The first of these is Altman (1968) himself that proposed the model and did extensive research towards financial distress prediction and the root causes thereof. Secondly, is the study of Calandro (2007) who reaffirmed the use of the Z-score as a strategic management tool and its predictive capabilities. Lastly, the study of Almamy *et al.* (2016) stated the utility of combining the Z-score with cash-flow ratios in an attempt to provide more conclusive results.

There is only one main study that provides an argument against the Z-score and that is the study/report of Kirk (2008) which states that the model is outdated and has not been able to keep up with the dynamics of the business environment and should, therefore, not be used as a turnaround tool.

2.3.2 Ohlson's O-score

2.3.2.1 Accuracy determined by previous studies

Jouzbarkand *et al.* (2013) used the O-score over a period of eight years (2003-2011) where the model was shown to have a test statistic of error, less than 10%. Setting the confidence level in the model at 90%.

2.3.2.2 Availability of variables

The only variable in the Ohlson O-score that is not found in the firm's financial information is the GNP price level index. This is easily found, though not as many sources freely provide this information.

2.3.2.3 Appropriateness over all industries

The use of the GNP price level index rather than standard deviations, places the focus of the O-score on probability and not on statistics and makes the model more appropriate for use over multiple industries.

2.3.2.4 Complexity of the model

The O-score is the inverse of the Z-score, as the formula is complex and takes work to calculate, whereas, the result is expressed as a percentage, making it more understandable to non-financial personnel.

2.3.2.5 Arguments for and against the model

There are mainly two previous studies that support the use of the O-score for financial distress prediction. The first of these studies is the study carried out by Ohlson (1980) himself. Ohlson proposed the model in this study after researching and testing many previous models, including the Z-score, and finding that the existing models were unsatisfactory. The O-score was thus proposed as a model that encompasses all industries and is an improvement on previous models.

The second study, and most prevalent, is that of Griffin & Lemmon (2002) which affirmed the use of the O-score in distress risk prediction when used as a secondary measure, as well as the comprehensibility of the model to non-financial parties, because of the percentage score. There are no relevant arguments against this model, possibly since the model is not as widely used or known.

2.4 Selection

When taking the above-mentioned arguments and criteria into consideration, both models seem to be quite evenly substantiated as predictors of financial distress, although the O-score seems to be the more applicable model. This decision was based on the O-score's higher accuracy in previous studies and that it can be applied over multiple industries with more ease. A summary of the decision process and arguments can be found in the matrix attached at the end of the chapter.

2.5 Summary and result of chapter

After taking all the above-mentioned arguments into consideration, it has been re-established that the use of the liquidity ratios is substantiated in financial distress prediction in order to assess the liquid position of each organisation, and make the relevant conclusions concerning the financial distress level solely based on these ratios.

As discussed in section 2.3.2, the O-score is seen as a more suitable model as it is more easily applied to varying industries and has been proven to be more accurate. The O-score will also help to determine the financial distress of each company and group as well as an increase the likelihood of showcasing financial distress as being more predictable, thus building on the previous research examined above.

Table 3 - Empirical decision matrix for choice of model

Comparison of Predictive models			
Criterion	**Z-score**	**O-score**	**Most relevant**
Accuracy determined by previous studies	According to Clandro (2007) the Z-score has an accepted accuracy level of 95% for 1 year before financial distress, and 72% for 2 years before financial distress. This second-year accuracy is said to be increased to 80% by adding cash-flow measures, as stated by *Almamy et al*. (2016)**.**	Jouzbarkand *et al*. (2013) used the O-score over a period of eight years (2003-2011) where the model was shown to have a test statistic of error less than 10%. Setting the confidence level in the model at 90%.	O-score
Availability of variables	As the standard deviations of the Z-score will not be adjusted in this study, the only variables will be the ratios. Each ratio is easily calculated from the available financial information.	The only variable in the Ohlson O-score that is not found in the firm's financial information is the GNP price level index. This is easily found, though not as many sources freely provide this information.	Z-score

Appropriateness over all industries	The Z-score is generally criticised as its standard deviations need to be adjusted for each industry, this is however outside of this study's scope and will therefore remain a limitation.	The use of the GNP price level index rather than standard deviations, places the focus of the O-score on probability and not statistics and makes the model more appropriate for use over multiple industries	O-score
Complexity of the model	While the Z-score calculation is simplistic, the result of the formula can only be understood by using the four rules as stated above, which therefore makes the use of the model more complex.	The O-score is the inverse of the Z-score, as the formula is complex and takes work to calculate, whereas the result is expressed as a percentage, making it more understandable to non-financial personnel.	No clear advantage
Arguments for and against the model	Arguments for:	Arguments for:	No clear advantage
	Almamy *et al.* (2016)	Griffin & Lemmon (2002)	
	Calandro (2007)	Ohlson (1980)	
	Altman (1968)	-	

	Arguments against:	Arguments against:	
	Kirk (2008)	-	
Chosen model			O-score
	Z-score	1	20%
	O-score	2	40%
	No clear advantage	2	40%
	Total	5	100%

Chapter 3 - Data and Results

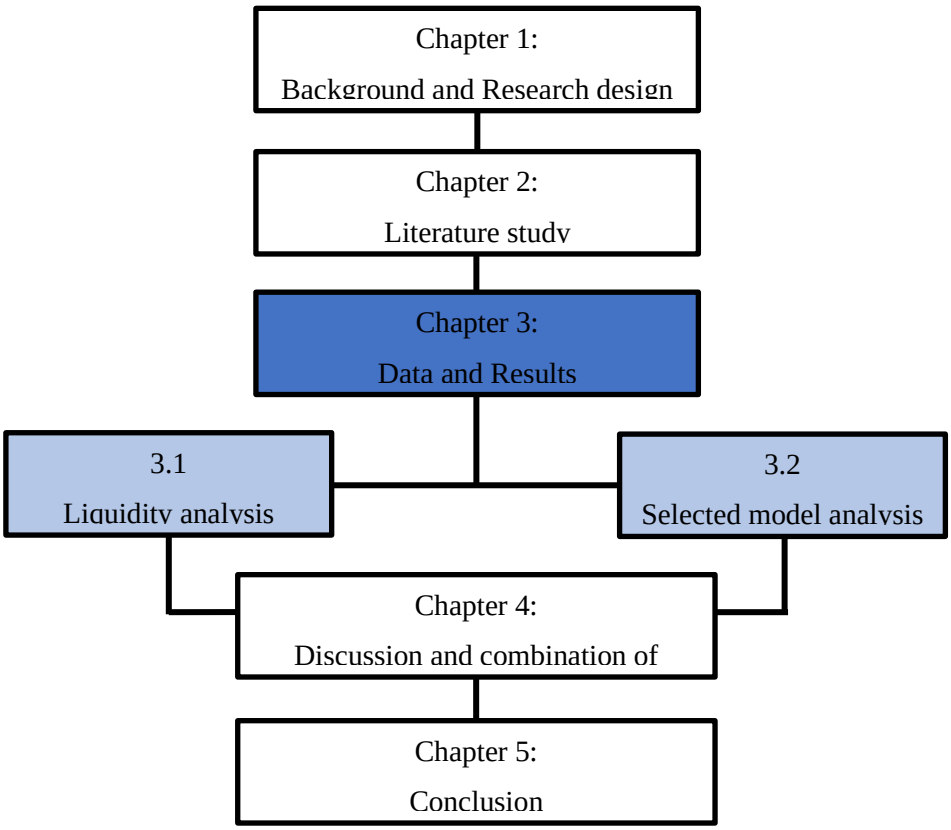

Figure 3 – Chapter layout (Ch. 3)

In this chapter, the aim of the study is to apply both the liquidity ratios and the O-score to the dataset and aim to address the secondary objectives set out in Chapter 1. The chapter will be split into two sub-chapters, as each will contain the separate application of the two focal points of this study.

The population of the study consists of companies that were still listed on the JSE at the time of this study, and companies that have been delisted. They are split between the top 20 companies listed on the JSE, measured by market capitalisation, and 20 companies that have delisted or have been liquidated within the three years under scrutiny (2015-2017). Table 11 contains the top 20 companies by market capitalisation as at 31 August 2018. Table 12 contains the companies in distress and was sourced from the JSE in August 2018 (see appendix for tables). Both of these groups of companies are those whose financial statements are still readily available. The first group of companies are used as a benchmark of what is perceived as healthy companies, to be measured against which the second group that contain companies under financial distress, will be measured. These groups are hereafter referred to as Group A and B respectively.

The chapter is structured to include two sub-chapters, for the analysis and discussion of the two measures used in this study. In section 3.1, the analysis using the liquidity financial ratios is set out. This sub-chapter splits the liquidity analysis into the main liquidity ratios, current and quick ratios, and the secondary ratios. Each ratio is separately discussed and analysed against the dataset, and the averages of the two groups are compared standard deviations and any relevant outliers have been identified and eliminated. The combination of the two measures, in an attempt to provide a more conclusive prediction of financial distress, is only applied and discussed in Chapter 4.

In section 3.2, the model selected in the literature study (Ohlson's O-score) is applied to the dataset and discussed at length, which is followed by a discussion of the default probability component, in order to provide a comprehensive overview of how the model functions. Thereafter, the model is applied to the dataset and the results are analysed and discussed.

All tables used for calculations of the different ratios and values and referred to in this chapter, are included in Appendix A. These exclude the tables explaining the formulae and statistical information.

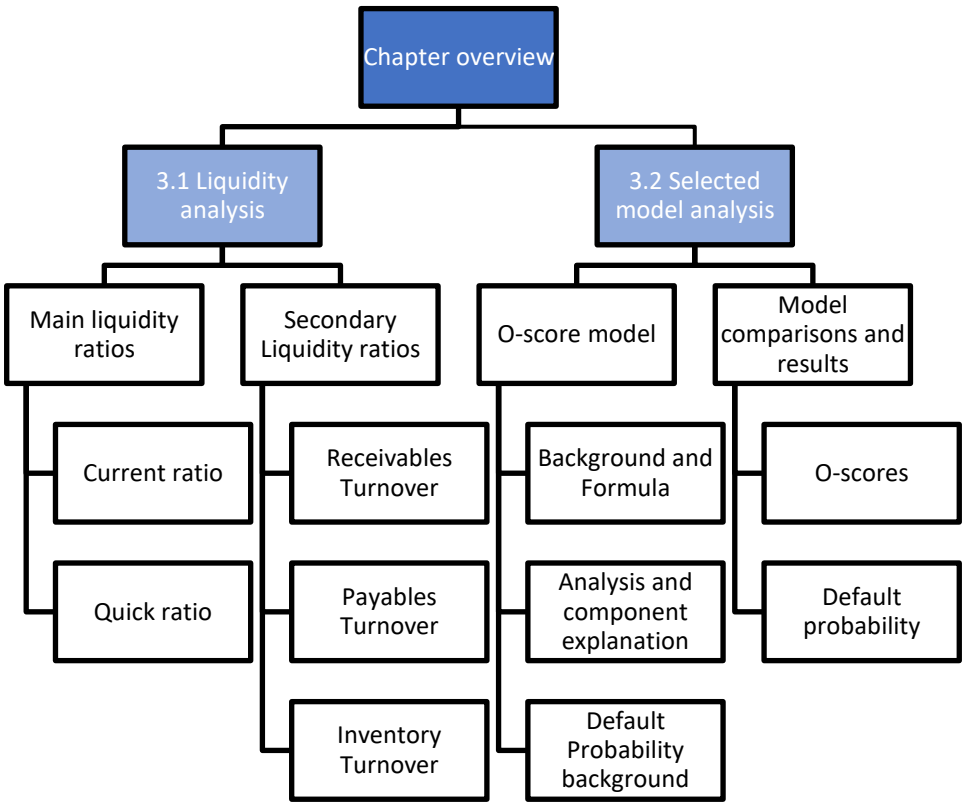

Figure 4 – Chapter 3 breakdown

3.1 Liquidity analysis

The use of a liquidity ratio analysis is one of conventional accounting knowledge and is used in general practise. However, when looking at the utility of such an analysis in the context of this study, the study performed by Kordestani *et al.* (2011) clearly shows the ability of a liquidity ratio analysis to predict financial distress. Their study used a similar model as in the current study of analysing two groups of healthy versus unhealthy companies as a dataset to which the ratios were applied. Their study clearly shows the link between cash flow problems and financial distress of any company, as the study states cash flow as its direct precursor.

Their findings can be further substantiated by that of Almamy *et al.* (2016), where their study found that while using a liquidity analysis is useful in the prediction of financial distress, the combination thereof with a secondary measure, as attempted in the current study, will provide more conclusive predictions. It also showed the effectiveness of using liquidity and their chosen model in isolation, finding a clear increase in accuracy.

This section will focus on identifying any differences in the liquidity financial ratios of the two groups and analysing the results for any underlying patterns. The analysis of these companies was done by using the below-mentioned financial ratios in order to establish and compare the results for each group. As this study does not focus on any specific industry, there will not be a focus on of rules-of-thumb, though generalised focus is used as a base. This is because the rule-of-thumb differs between all industries and it would not be possible to take all of these into account (Slaubaugh, 2004).

Table 4 - Liquidity ratios used

Ratio	**Formula**
Current ratio	Total Current Assets / Total Current Liabilities
Quick ratio	(Total Current Assets – Inventory) / Total Current Liabilities
Receivables turnover	(Trade receivables/Revenue) x 365 days
Payables turnover	(Trade accounts payable/Purchases) x 365 days
Inventory turnover	(Inventory/Cost of Sales) x 365 days

Current and Quick ratios (Main liquidity ratios)

The current ratio is generally used to assess whether a company will be able to cover its short-term debt by utilising current/liquid assets. These assets and liabilities are generally made up of the following (Peavler, 2018).

- Cash and cash equivalents
- Inventory
- Trade and other receivables
- Trade and other payables
- Short term debt

While this is far from an exhaustive list, it can rather be seen as, in general terms, umbrella line-items for limitless amounts of short-term/current assets. This is because each industry differs widely in their general type of current assets, and the study gives an overall view over multiple industries (Filbeck & Krueger, 2005).

The quick ratio, in essence, analyses the same ability of the company but takes into consideration that inventory is not always liquid enough, as the demand for the product may either be low or there exists other problems as to why the inventory is not selling. This then causes the problem of the organisation not being able to rely on the sale of their inventory for liquid funds (Gulsan *et al.*, 2016).

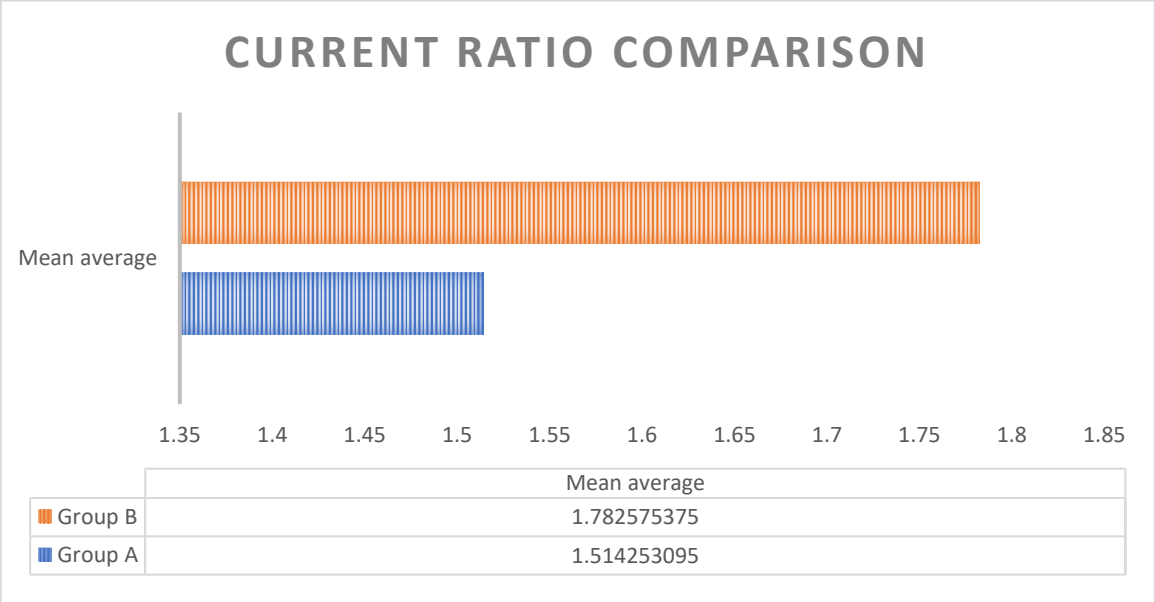

Chart 1 – Current ratio comparison

Statistical instrument	Current ratio	
X	Group A	Group B
Median	1.249	1.353
Standard deviation	0.662	8.236

Tables 13 and 14 (see appendix) are used to calculate both the current and quick ratios and show the averages of all the companies in both groups. As stated, the make-up of both the assets and liabilities differ between industries, thus only the net amount was selected from each company's financial statements. Tables 13 and 14 also shows the ratios and amounts for each company for three years. The years are labelled Y1-3 as the years in question differ, based on the assumptions made earlier in the study that the last three years before delisting or liquidation is used to assess financial distress, regardless of the specific year, in comparison with the other companies (Lieu *et al*., 2008).

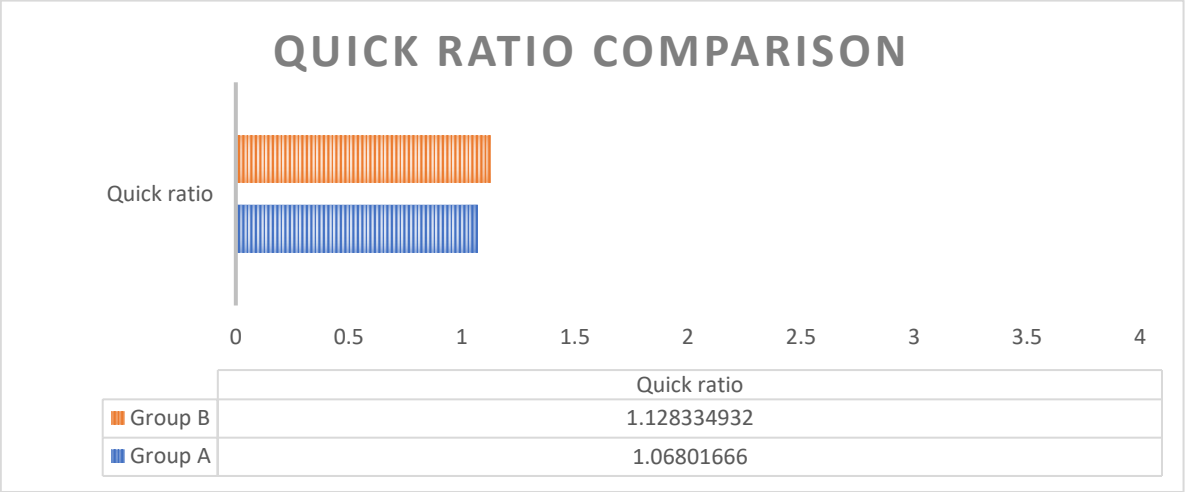

Chart 2 – Quick ratio comparison

Statistical instrument	**Quick ratio**	
X	Group A	Group B
Median	0.821	0.912
Standard deviation	0.599	8.293

As can be seen, both the current and quick ratios are higher, in the case of Group B compared to those of Group A. In general terms, this should indicate that the organisations in Group B have a better short-term solvency than those in Group A, i.e., they are better able to pay their short-term liabilities utilising their short-term assets. This is because the companies in Group B have much larger debtors than creditors in many cases, and that they are less inventory intensive than the companies in Group A (Kirkham, 2012).

However, when looking at the statistical information, it can be seen that Group A contains no outliers, making its average a better representation of each individual organisation. In Group B, there are two outliers to the general group-dataset, throwing out the average, therefore, these outliers are excluded from the graph above, in order to provide a better representation of the group. The two outliers are Moneyweb (6.03) and M-Fitec (39.0) in the case of the current ratio and Cadiz Holdings (3.31) and M-Fitec (39.0) again for the quick ratio (see table 14). All three companies experienced extreme financial distress that was focused around their inventory and receivables.

It can also be deducted that the companies in Group B vary much more in their current and quick ratios as the standard deviation is high in both cases, also indicating possible financial instability in the group (Alexander, 2001).

In many of these cases, the Group B companies tend to gravitate to larger, long-term debt, and as a result, will not be able to afford large amounts of short-term debt or extra interest. The Group A companies, however, tend to have greater diversity in the spread of their capital structure.

The current and quick ratios are umbrella ratios for liquidity (Kirkham, 2012) and can be seen in the above-mentioned data to not have many companies fall outside of the mean. Therefore, these two ratios, as the main liquidity ratios, do not provide an accurate view of the actual situation between the two groups and it was decided to extend the study to the next three ratios that make up the second level of liquidity analysis.

Receivables and Payables turnovers

The receivables turnover ratio analyses the ability of an organisation to ensure that debtors pay their relevant debts on a timely basis, by showing how many days the organisation takes in collecting the debts owed to it by its debtors. This, in conjunction with the payables turnover ratio, measures whether or not the organisation will be able to pay its operational costs and short-term debt, based on the amount and rate of funds flowing into, and out of, the organisation (Attari & Raza, 2012).

As already stated, the payables turnover ratio[1], works in conjunction with the receivables turnover. This ratio shows the efficiency with which an organisation pays its debt to its creditors, as shown in the amount of days before a creditor is paid.

The payables turnover should preferably constitute a longer period than the receivables as that would mean that funds flow into the organisation faster than it flows out (Attari & Raza, 2012). Tables 15 and 16 (see appendix), show the calculation of both the receivables and payables turnover ratios, respectively. As the amount of credit sales are not always available, the revenue was used instead for the receivables ratio. The trade receivables showed in the tables are the trade receivables that are included in the notes to the financial statements of each organisation as a separate line item.

In general terms, organisations tend to keep the receivables ratio rather low, as this will mean that the money owed by debtors is collected more efficiently (Hutchison *et al.*, 2007). The rate at which cash flows into the business is also higher, thus between 30-60 days would be preferable to ensure that enough cash is on hand to pay short term liabilities (ACCA, 2015).

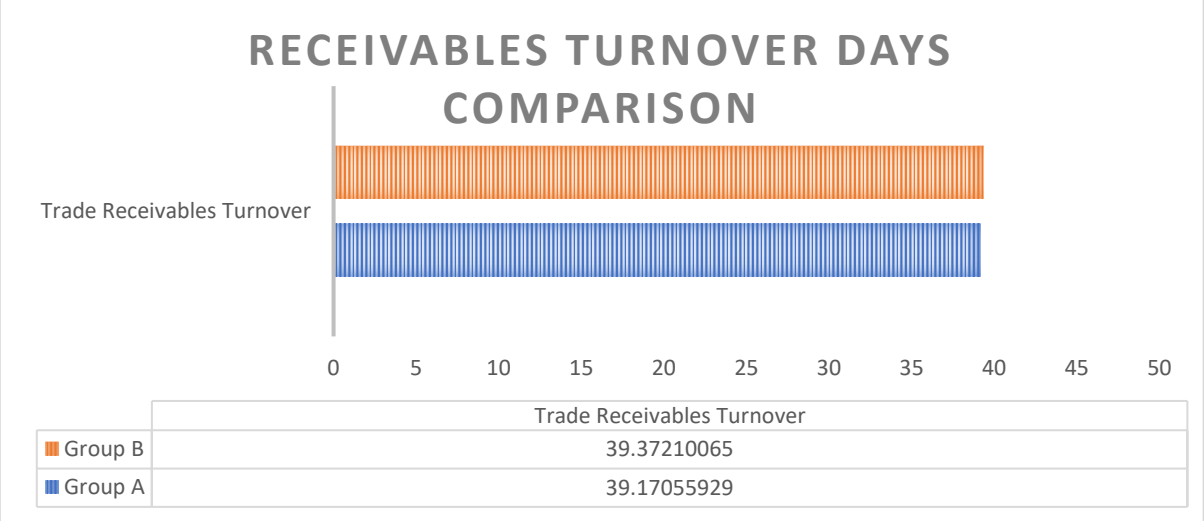

Chart 3 – Receivables turnover comparison

Statistical instrument	Receivables turnover	
X	Group A	Group B
Median	36.075	35.705
Standard deviation	20.434	29.803

[1] With regard to the payables turnover ratio, as the amounts purchased were unavailable in most financial statements, the ratio allows for the use of the cost of sales figure to be used in its place.

Both groups' receivables turnover is well within normally acceptable terms and does not signal any specific problem areas. Thus, the organisations on both ends of the spectrum have efficient working capital management to enable the organisations to service their short-term debt.

This also justifies the excessive Current and Quick ratios of the Group B companies and lessens the impact of possible outliers in both groups, as the standard deviations in each group is not excessive. There was only one outlier in either group, with the outlier in Group B being Rockcastle Global with 117 days. This is very high, even though the company's inventory of real-estate properties does tend to increase this ratio as payments on real-estate tend to lag behind often. The unforeseen outlier for Group A was Aspen with a turnover of 91 days, thereby also greatly exceeding the acceptable credit arrangements.

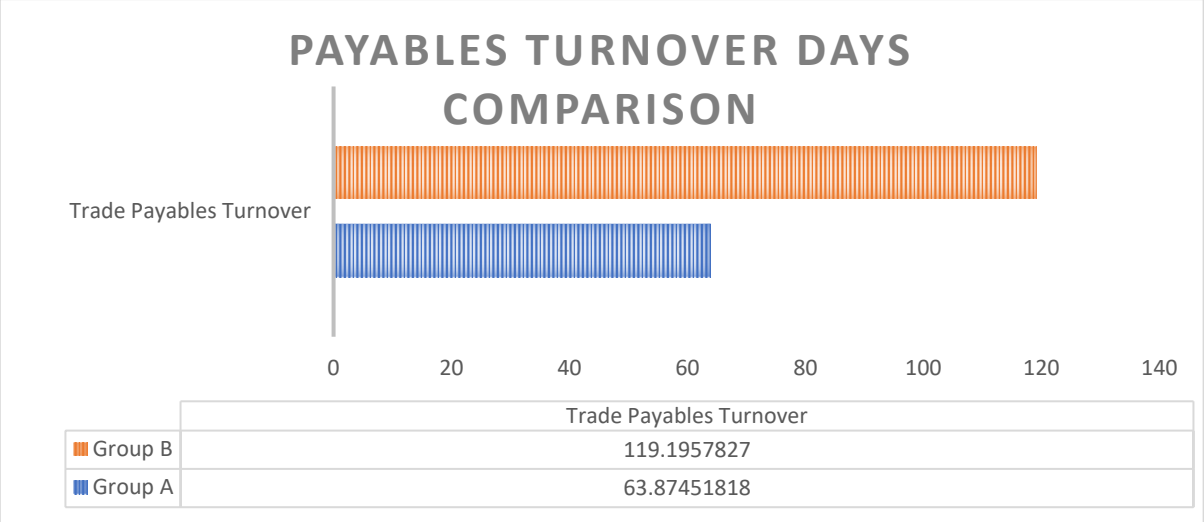

Chart 4 – Payables turnover comparison

Statistical instrument	Payables turnover	
X	Group A	Group B
Median	53.142	66.673
Standard deviation	62.068	260.120

On the other hand, organisations try to keep their payables ratio higher, as this will mean that there is more time for cash to flow into the organisation before any creditors have to be paid. This is normally lengthened by negotiating longer credit periods with creditors. While this is advantageous, the higher the ratio, the higher the risk of creditors demanding their money or involving the organisation in legal action to extract their funds.

Therefore, there needs to be a balance between comfortable credit terms and negligence of payments, between 60-90 days, as this will prevent damage to the organisation's reputation with each creditor (Tauringana & Afrifa, 2013).

This ratio indicates that these companies have little to no funds that they can use to pay off their creditors and that creditors are not likely to receive their funds as many companies will start to take legal action long before this time (Clark, 1977). Therefore, the true problem for the Group B companies lies with their payables turnover. While some of the Group A companies do have higher than expected turnovers, such as Anheuser-Bush InBev and FirstRand who are the outliers in this group, the Group B mean average of 120 days is much higher than the mean average of Group A (64 days).

Many of the Group B companies tend to have large amounts of fixed debt that incur high levels of interest and takes up most of the excess cash that is available, as can be seen in the current, quick, and receivables ratios. The inability to service their short-term debt was in many cases also one of the main factors contributing to the liquidation of some of the Group B companies.

In the case of the two outliers, Rockcastle Global and Giyani Gold, both have excessive payables turnovers of 1179 and 508 days respectively (see appendix, table 16). These are extremely high rates even though Rockcastle Global is a real-estate company, which generally exceeds basic payables turnover ratios as their inventory is less liquid and require high input costs.

Inventory turnover

Inventory turnover refers to the amount of days the organisation takes to completely sell their inventory and then have to replace it. This is an indication of the efficiency of the organisation's ability to turn their inventory from assets into cash to be used in the servicing of their short-term debt. This further expands upon the current and quick ratios as the ratio shows whether or not the amount of current assets of the organisation truly reflect its liquidity.

Tables 17 and 18 (see appendix) show the calculations relating to the inventory turnover ratio. As previously stated, the organisations that make up both groups are from varying industries that include differing definitions of inventory. Therefore, only items that were specifically expressed as inventory were included in these calculations.

In the graph below it can clearly be seen that the inventory turnover of Group A is considerably lower than that of the Group B companies. The Group A companies are still well within the acceptable parameters of 45 days; this will not significantly damage the organisations' liquidity and is still at a comfortable ratio in comparison with the general amount of days for the payables to be paid.

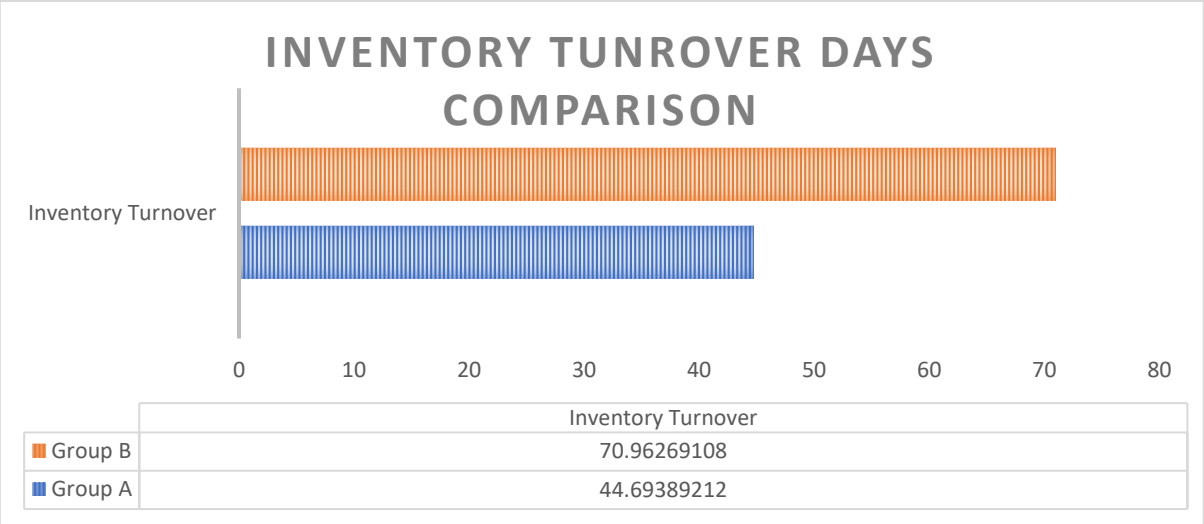

Chart 5 – Inventory turnover comparison

Statistical instrument	Inventory turnover	
X	Group A	Group B
Median	45.473	40.317
Standard deviation	20.778	322.336

Group B shows a mean average ratio of 71 days for turnover. This is high and shows that the companies in this group suffer great difficulties with the sale of their inventories and can also be an indicator of financial distress as there is not enough cash flowing into the organisations, through the sale of inventories, to service debt. This also excludes the outlier companies, such as Moneyweb (1491 days) and Oakbay Resources (360 days), that both show extremely high turnovers (see table 18).

The differences in industry, however, do contribute to the high turnover rate, as certain industries have very high turnovers because of the nature of their inventories, contributing to the high third quartiles and upper bounds for this ratio. This difference is not enough to ensure that this observation is void however (Lazaridis & Tryfonidis, 2006), as the influence of inventory remains high in all of the companies in the dataset. This can be attributed to the fact that the liquidity analysis is made up of all five ratios, as is discussed further in Chapter 4.

After analysing the companies in Group B and determining the liquid position of the group as a whole, a breakdown of the probable main causes for financial distress or liquidation can be achieved. Chart 6 illustrates that only 20% of the companies in Group B suffered from receivables as their main indicator of financial distress, including the outlier of Rockcastle Global.

The main causes of financial distress for the dataset were split between the companies' payables and inventory turnovers, where multiple companies struggled with both their short-term debts and inventory sales, but had a larger concern on one of the two problems. Even though it only makes up 40% of the companies that experienced their only or main problems with inventory, the inventory turnover was a problem factor for 12 of the 20 companies, and therefore, remains the key issue.

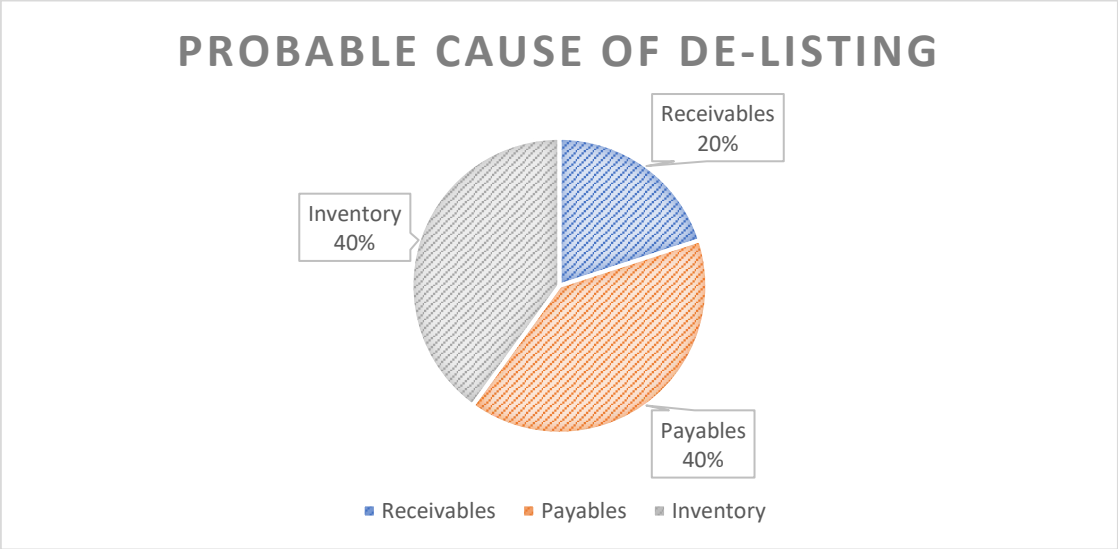

Chart 6 – Probable cause of de-listing

When taking all of the above-mentioned information into consideration, the utility of a liquidity analysis for financial distress is evident. There is however a clear indication, through the necessity of further analysis for many of the ratios, that a secondary measure of financial distress would provide a more conclusive prediction. This secondary measure will be applied and analysed in the form of Ohlson's O-score for business failure in section 3.2 of this chapter.

3.2 Selected model analysis

As discussed in Chapter 2, the model selected to be applied to the dataset is Ohlson's O-score. This section will focus on applying this model to the two groups and analyse the results for any underlying patterns. The analysis was performed by using the formula shown in the literature study, applied to each group separately and then analysed by comparing the results and averages from each group, after eliminating any outliers. The O-score will be discussed in more detail in the first part of this section as well as how the model should be analysed, according to Ohlson.

The O-score model

Background and Formula

The model uses a combination of financial information that is retrievable from the financial statements of each organisation and coefficients that are constants in the formula to produce a value of lower or higher than 0, to show the probability of business failure for each organisation. The model includes the Gross National Price-level index (GNP index), which allows for the model to be applied over industry barriers (Church, 2016).

The formula used is described in Chapter 2, and therefore will not be broken into each variable again. However, the variables for each value will be shown with a short description of the calculation thereof. The formula is stated below.

$$O = -1.32 - 0.407\, log\, \frac{TA_t}{GNP} + 6.03\frac{TL_t}{TA_t} - 1.43\frac{WC_T}{TA_T} + 0.0757\frac{CL}{CA} - 1.72X - 2.37\frac{NI_t}{TA_t} - 1.83\frac{FFO_t}{TL_t} + 0.285Y - 0.521\frac{NI_t - NI_{t-1}}{(NI_t)+(NI_{t-1})}$$

Analysis and component explanation

This study calculates each of the nine values that make up the formula separately and then combines the values in the formula to calculate the O-score for each organisation. These values are calculated using the different financial information line items and ratios, as discussed, and then combined with the coefficients. Tables 19 and 20 show the input values for the Group A and B companies respectively and Tables 21 and 22 (see appendix for tables) show the nine calculated values for Group A and B respectively. These nine values were then used in the calculation of the O-scores for each company, after which the averages, after taking outliers into consideration, for the three financial years and a total average for the group were calculated.

As explained above, the nine values all use the variables in different smaller calculations. These are discussed below (Ohlson, 1980). See Table 2 included in the literature study of Chapter 2 for a breakdown of the below-mentioned abbreviations and variables.

Table 5 - O-score coefficients

Score Value	Formula	Coefficients
0	-	-1.32
1	$log \frac{TA_t}{GNP}$	-0.407
2	$\frac{TL_t}{TA_t}$	6.03
3	$\frac{WC_T}{TA_T}$	-1.43
4	$\frac{CL}{CA}$	0.0757
5	X	-1.72
6	$\frac{NI_t}{TA_t}$	-2.37
7	$\frac{FFO_t}{TL_t}$	-1.83
8	Y	0.285
9	$\frac{NI_t - NI_{t-1}}{(NI_t) + (NI_{t-1})}$	-0.521

Value 0 – There is no value included as the coefficient of -1.32 is not directly linked with a value that needs to be calculated, as is the case with the other nine values.

Value 1 – This value is the logarithm of the total assets of each organisation, divided by the GNP index. The total assets include all assets listed on the balance sheet of each organisation and does not exclude any line items. The GNP indexes are the indexes of 2015 – 2017 and were retrieved from Trading Economics (2017) for each period. As previously stated, the GNP price level index can shortly be defined as the average price over the entire current spectrum of goods in an economy (Kenton, 2019). This is combined with a coefficient of -0.407.

Value 2 – This represents the total liabilities of each organisation, divided by the total assets. The total liability amounts also do not exclude any line items and constitute the entire amount listed on the balance sheets. The formula the combines this value with a coefficient of 6.03.

Value 3 – The calculation of this value is the division of the working capital ratio, by the total assets of the organisation. The working capital ratio is calculated by subtracting the total current liabilities from the total current assets of the organisations. Current assets and liabilities were discussed in more detail in section 3.1 under the current and quick ratios. This is then combined with the coefficient of -1.43.

Value 4 – This value is calculated by dividing the total current liabilities by the total current assets. This is combined with the coefficient of 0.0757.

Value 5 – This value is shown as an "X" in the formula and is not calculated. The X = 1 if the total liabilities exceeds the total assets, used in the calculation of the previous value, and X = 0 if not, combined with a coefficient of -1.72.

Value 6 – This value is calculated by dividing the net income before taxation, as listed on the income statement of each organisation, by the total assets amount. This net income amount is not adjusted for cash-flow items, as is done in a liquidity analysis. This value is then combined with a coefficient of -2.37 in the formula.

Value 7 – The calculation of this value is the division of the funds from operations; in most organisations' cases, this was the profit from operations line-item on the income statement, by the total liabilities amount. The coefficient combined with this value is -1.83.

Value 8 – This value is shown as a "Y" in the formula and is also not calculated. The Y = 1 if the organisation experienced a net loss for the preceding two years and Y = 0 if not. This is combined with a coefficient of 0.285.

Value 9 – This is the most complex value and is calculated by subtracting the net income after tax from the net income before tax, divided by the sum of the absolute amount of the net income before tax and absolute amount of the net income after tax. Lastly, it is combined with its coefficient of -0.521.

As stated in Chapter 2, this study does not seek to adjust the formula proposed by Ohlson, and simply seeks to establish the utility thereof in the South African context. Therefore, the study accepts the formula and coefficients as stated above and will apply the calculation of each value to the information gathered from each organisation's financial statements directly, without any alterations to the suggested formula of coefficients.

Default probability

The default probability is used in order to state the result of an O-score calculation as a percentage of the probability that an organisation will be liquidated. This does, however, alienate the organisations that are simply in financial distress but will not be liquidated. The use of percentages increases the understandability of the score for non-financial clients or personnel (Gruszczynski, 2015).

$$\text{p(failure)} = \frac{e^{O-score}}{1+e^{O-score}}$$

The default probability was applied to the dataset, both on the individual companies and years and the mean average thereof was then calculated for each company and group.

O-score analysis and comparison

As previously stated, tables 19 and 20 show the inputs from each company in each group for all three years that were used to calculate the O-scores for each company. Table 21 and 22 (see Appendix A) shows the O-score values, as discussed above, calculated separately for each company, per year. As in the previous section, the years are shown as Y1-3 before liquidation/delisting in the case of Group B and 2015-2017 in the case of Group A.

Tables 23 and 24 (see appendix) show the calculated O-scores and default probabilities of groups A and B, respectively. The model states that any score calculated below 0 can be seen as a low risk company for financial distress. The inverse is then also true, as any company with a score of 0 or more can be seen as a company facing potential business failure (Imelda & Alodia, 2017). Firstly, the comparison of the change in the O-score is shown in charts 7 and 8, showing the average O-scores for Y1-3 for both groups. This clearly shows that the O-scores decrease as the company falls into further financial distress.

In the case of the Group A companies, the score starts as a negative and further falls from the line of default (0) in the years leading up to Y1. This is a clear indication that the organisations continue to grow as time progresses (Karamzadeh, 2012).

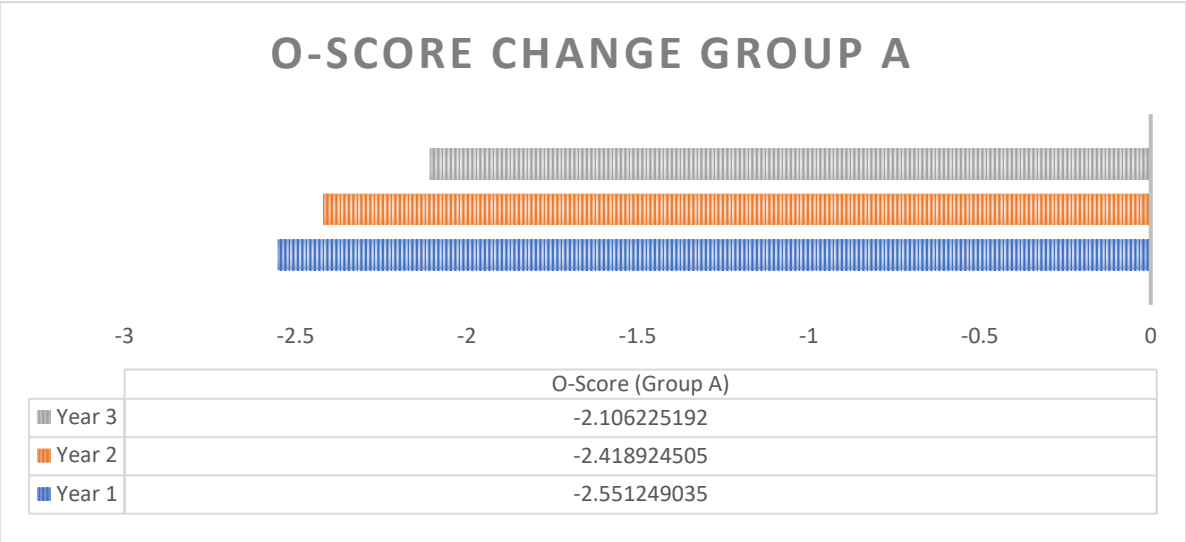

Chart 7 – O-score results (Group A)

This is however, also reflected in the scores calculated for the Group B companies, as can be seen from chart 8 below. Where the initial score is far above 0 and thus shows a high tendency for financial distress, Y2 and 1 show a clear fall in the score to better than the accepted, non-financial risk, levels.

The reason for this unexpected shift lies in the restructuring that takes place prior to scaling down or liquidation of a company. This is stated in the study of Denis and Rodgers (2007), where they proved that the drastic reduction of assets and liabilities, as well as limitation of operations, gives a company the best chance of remaining a going concern while under a restructuring process. Many of the companies in Group B, such as Holdsport and Oakbay Resources, survived their period of financial distress but dramatically reduced their operations, thereby cutting expenses and servicing their short-term liabilities.

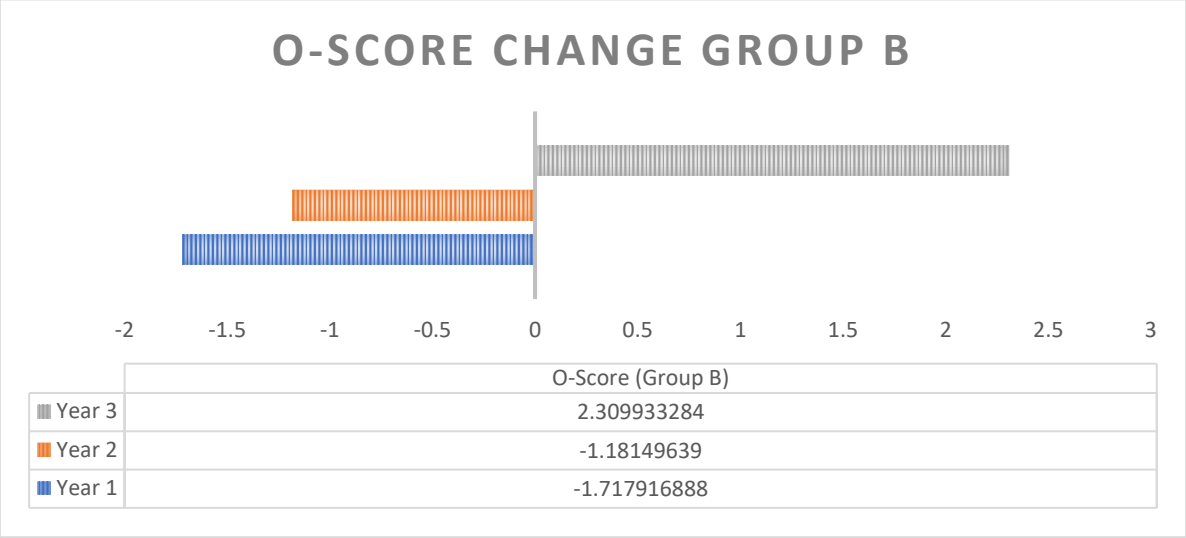

Chart 8 – O-score results (Group B)

However, this was not enough to stop the delisting of the companies from the JSE and in many cases was a requirement, in order to effectively restructure.

The effects of restructuring can be seen when looking at the improvements in the net income before and after taxation of the companies in Group B, listed in Table 20 (see appendix). The average between the companies in the group shows an upward curve of both the net income before taxation and after. This can mostly be interpreted as being the work of the drastic increases in the Funds from Operations (FFO) amounts of most companies in Group B. This is shared with Group A, as the same pattern can be seen taking place in the FFO amounts of that group.

According to Kim (2013), the O-score's success lies in the use of the FFO variable, as this variable is shown as being linked to return and possessing return-predictive properties. This explains the seeming anomaly, that the scores for Group B cannot be interpreted as accurate.

In most cases, an increase in the profitability or returns of an organisation would constitute the improvement of an organisation's financial health and refute the existence of financial distress. In this context, however, this fact is refuted as an organisation significantly increases its profits in the two years after financial distress is first recognised since corrective action is taken too late and not upheld (Whitaker, 1999). The loss in financial wellbeing can still be seen in the Working Capital (WC) variable/value as these values continued to decrease, even though the net income of the Group B companies increased for the two years before delisting.

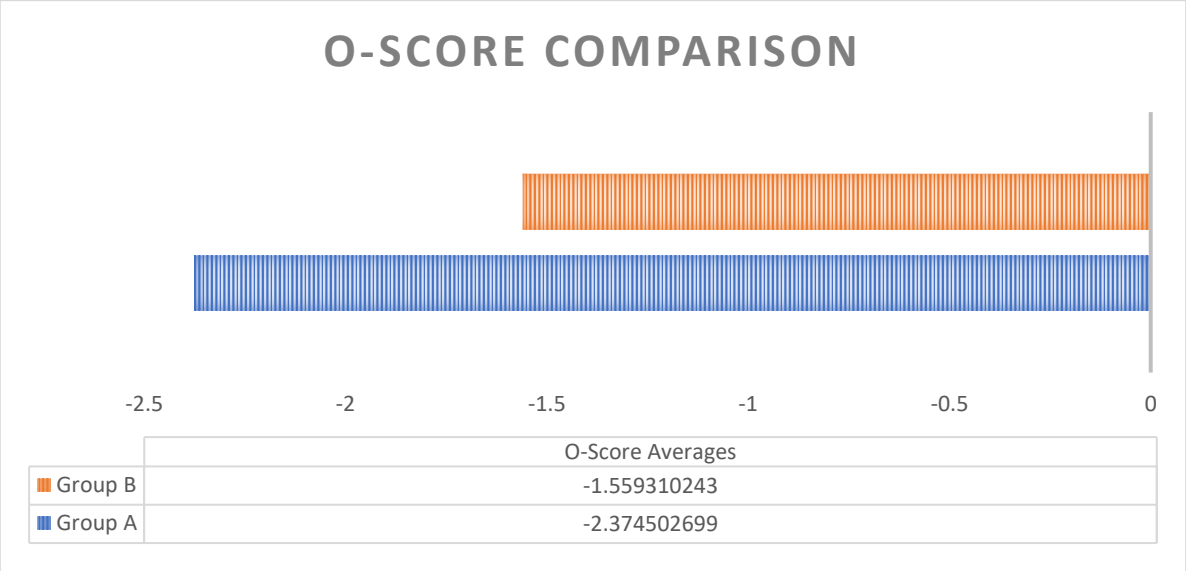

Chart 9 – O-score comparison

Statistical instrument	O-score	
X	Group A	Group B
Median	-2.34241	-1.90313
Standard deviation	1.636352	7.199525

While the average O-score of the Group B companies still fall below the 0 mark, the distinction between the two groups is undeniable. The reason for this can be attributed to the fact that not all the companies in Group B experienced high levels of financial distress and only delisted, where many were liquidated. These companies, such as Illovo Sugar (-2.814) and Holdsport (-5.727), drive down the average as both companies' scores are very far below 0 and therefore show that their de-listing is not attributed solely to financial distress and that they were not liquidated after de-listing.

The high standard deviation of the Group B companies shows the high differentiation as well, as the difference between liquidated companies like M-Fitec and those that scaled down but survived, is very high and thereby decreases the overall statistics of the group and model. This shows that the O-score can be very volatile in its predictions as it focuses on pure business failures, instead of financial distress.

Default probability comparison

The applicability of the O-score can more clearly be seen when applying the Default

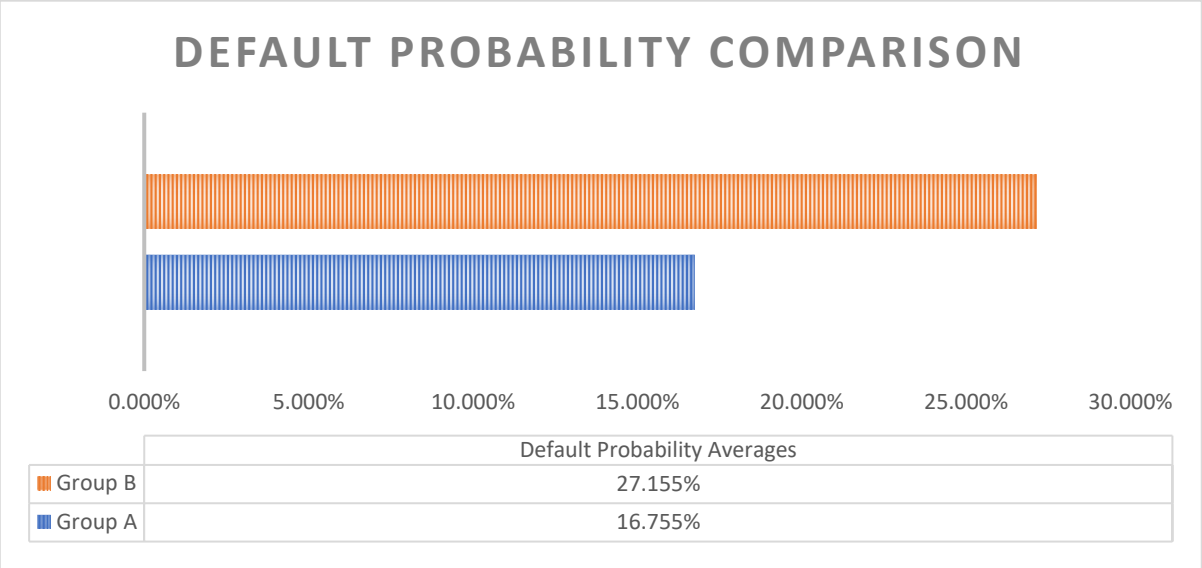

Chart 10 – Default probability comparison

Statistical instrument	Default probability	
X	Group A	Group B
Median	11.587%	18.892%
Standard deviation	13.757%	24.904%

Probability (DP) formula, as stated above, to the scores calculated in the previous step. By applying this formula, the O-scores are converted into percentages that show the probability of financial distress or bankruptcy more clearly.

While the probability of the Group B companies does exceed that of the Group A companies by 12%, it is not a high probability. This can be explained by the DP only showing the companies most likely to default on their short-term liabilities and not those in financial distress. This shows a lack of conclusive information provided by the O-score and that the model's utility as a business failure model, is more prevalent than its ability to simply predict financial distress.

When taking the difference in results obtained from the raw O-scores of each group and their respective default probabilities into account, the conclusion can be drawn that the O-scores in their raw form provide conclusive information to a degree. However, the use of the DP decreases the model's predictive capabilities and contribute to the sentiment of allocating the model to business failure rather than financial distress.

3.3 Chapter summary

In this chapter, the two measures decided on in Chapter 2 were separately applied to the dataset and the results were analysed in order to establish the predictive capabilities of each measure in isolation. The liquidity financial ratios have shown to have high predictive capabilities, although neither of the five ratios can be analysed separately form the other four. The O-score's results were analysed inspecting both the raw O-scores and applying the DP to the dataset. The difference in the results obtained from the DP and raw O-scores were also reflected upon.

The results obtained will be analysed and discussed further in Chapter 4 and the combination of both measures will applied in an attempt to address the main research question of this study.

Chapter 4 - Discussion of results

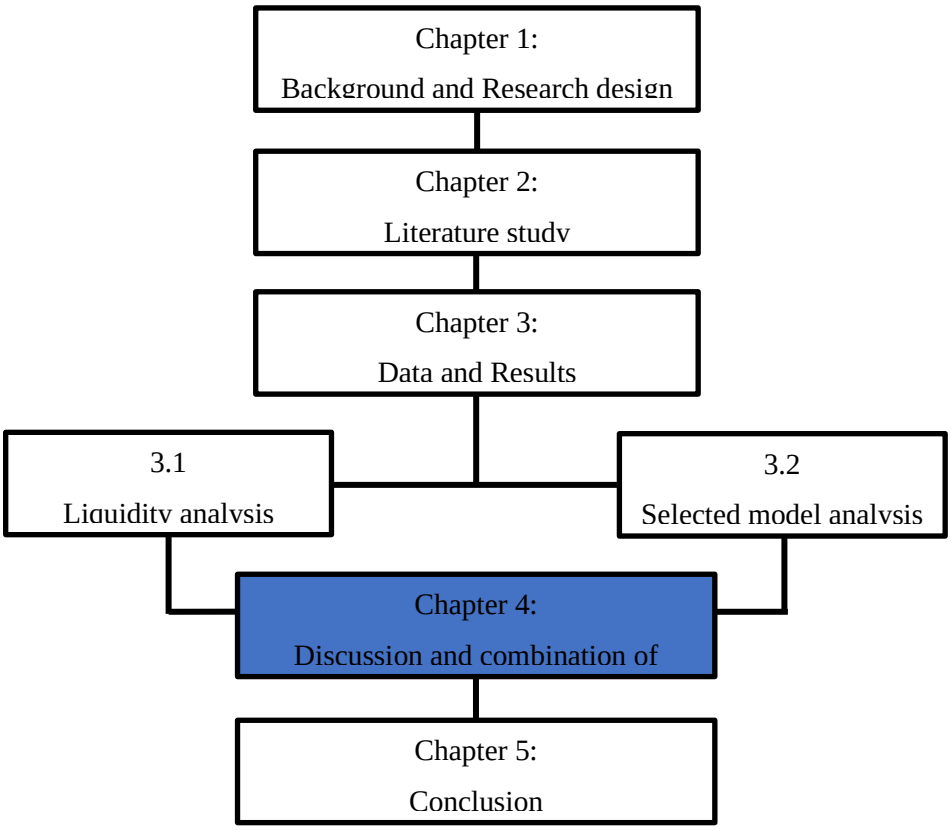

Figure 5 – Chapter layout (Ch. 4)

In this chapter, the results obtained in Chapter 3 will be analysed and reflected on, in order to determine the predictive capabilities of both the liquidity and O-score analyses in isolation. This is done in order to benchmark the difference in each measure's effectiveness without combining the two. The three-year period used as the optimal period of financial distress prediction, as established in Chapter 2, will also be reflected upon in the secondary findings.

After the conclusions about the separate capabilities of both measures have been made, the chapter will focus on answering this study's main research question. This will be done through the combination analysis.

The combination of analyses assesses the accuracy of both measures and compares the two, after which the accuracy statistics are drafted using the results of Chapter 3. The results of the combination measure are then compared between the two groups and a final result is discussed as to the capabilities concerning the measures.

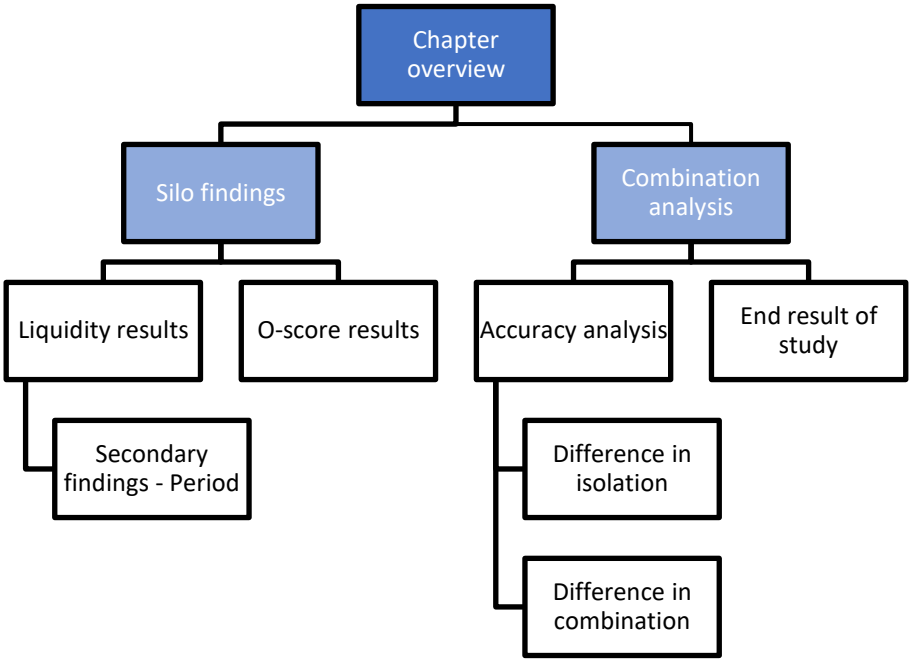

Figure 6 – Chapter 4 breakdown

4.1 Liquidity analysis as a silo prediction model for financial distress

Using the five main liquidity ratios, this study has determined that there is indeed a correlation between the results obtained from the ratios and whether or not a company can be defined as being in financial distress. This correlation in the cases of the current, quick and payables ratios was unexpected as the companies in Group B's ratios appeared favourable at first glance, when using conventional logic towards financial analysis. It was only on closer inspection that the reason for the unexpected results was discovered and the contrary was proven.

The current and quick ratios increased for the Group B companies as a backlog of debtors was created and the companies in distress' efficiency with which they collected their debt was compromised (Cagle *et al*., 2013). It was however, found that these two, as the two main liquidity ratios, cannot be analysed alone when analysing liquidity. The main problem was found to be working capital and the companies in Group B's ineffective management thereof (Filbeck & Krueger, 2005).

Group B's ineffective management of working capital can be seen in the results when analysing the three other liquidity ratios. In the case of the receivables turnover, the ratio rose for Group A in consistency with the current and quick ratios, indicating that the assumption of a backlog of debtors do play a role in the higher ratios (Lazaridis & Tryfonidis, 2006). Group B fluctuates with a general fall in Y2 and a rise to almost the same levels as Y3 in Y1.

Year 1 is the year prior to delisting and this year generally sees companies in this group tightening their debt collection in order to salvage the fall in share prices and facilitate the process of delisting (Wang & Campbell, 2010).

The payables turnover consistently fell as the date of delisting approached for Group B companies. This is because many of these companies were liquidated in Y1 and some of the short-term liabilities were covered. The Group A companies' ratios also fell, although not by any considerable margin, therefore, this can simply be seen as efficient working capital management, rather than any sign of distress.

Lastly, in the case of the inventory turnover ratio, inventory levels fell dramatically for the Group B companies, with many not holding any inventory by Y1, before liquidation or delisting. This can be attributed to the companies not producing or buying any new inventory or just enough to remain in business for these years. The Group A companies' ratios fluctuated through the three years, but not substantially, remaining within the 40-50 days margin. Therefore, this is no prelude to financial distress either.

This study has found that the use of the two main liquidity ratios, current and quick ratios, do not provide enough substantive information to warrant use in any financial distress analysis, except as umbrella ratios for the more focused working capital ratios.

Therefore, these three liquidity ratios do show a correlation with financial distress, but all three ratios need to be analysed together and they do not provide a comprehensive prediction model with which financial distress can be predicted. This is because many of the companies in Group B were already in financial distress by Y3. The use of more sophisticated methods, in conjunction with these ratios would be advisable (Smith & Begemann, 1997).

4.2 O-score analysis as a silo prediction model for financial distress

Ohlson's O-score has been found an unlikely model to be used in financial distress prediction, as opposed to the more famous Altman Z-score, as discussed in Chapter 2. However, this study came to the conclusion that using the less known O-score gives more credence to the results found as the scope of the study includes companies over multiple industries. Ohlson's O-score provides a broader analysis of each company and includes measures such as the GNP price level indexes for the period under scrutiny and therefore, provides a more conclusive analysis.

When analysing the results obtained from applying the O-score to the dataset, it can be accepted that a correlation does exist between a score of 0 or higher, 0 being the model's rule-of-thumb, and financial distress. The results were also unexpected, however, as the Group A and B companies' scores did not vary to the degree anticipated. The most conclusive results, when looking at the separate components of the model, was found to be the fall in or lack of control and performance of the Group B companies in the management of their FFO. This can also be tied in with the effective management of these companies' working capital as seen with the liquidity ratios.

When looking at the results of Group B, it can be seen that while the model shows a very clear tendency for financial distress in these companies in year three before de-listing (Y3), this changed drastically in Y2 and Y1, as the restructuring of many companies improved their financial position (Denis & Rodgers, 2007). This was temporary, however, as the restructuring process shows a false climb in financial position for the first two years thereafter (Whitaker, 1999). This can be seen with all of the companies in Group B still de-listing, whether they were liquidated or not, as a result of the down-scaling process or down scaling of their operations.

The results after using the default probability was also unexpected as it lessened the overall gap, when compared to the raw O-scores. It does, however, mostly serve as a method of increasing the understandability of the O-score for non-financial users, therefore, it is not given too much credence in comparison to the raw O-scores.

These factors lead to the conclusion that the use of the O-score does correlate with the occurrence of financial distress in listed companies and, therefore, does possess predictive capabilities. The model does require a longer period before financial distress or de-listing to be more accurate as the restructuring part of the financial distress process negatively influences the utility of the model.

4.3 Secondary findings – three-year period

According to Lieu *et al.* (2008), the optimal time period to apply financial ratios as a form of analysis is three years before any financial distress. In this way, Lieu *et al.* (2008) shows that financial distress can be predicted using this time period, as accepted by this study in Chapter 1.

In this study, it is seen that each financial ratio reacted differently in the three years under scrutiny. Therefore, the utility of the period assumption will be reflected upon separately for each ratio.

For the current and quick ratios, the ratios consistently rose throughout the three years for both groups. As can be seen by the findings and discussion above, this is not necessarily a clear indication of financial distress as the amount of current assets does not necessarily indicate a sound liquidity position. The amount by which the ratios increased annually are substantial and may indicate a backlog of debtors as previously discussed.

The three-year period has mixed results when applied to the three working capital ratios in the event of financial distress. The receivables turnover started very high in Y3 and continued negative performance for Group B companies up to Y1, however the Y3 results are much higher than those of the next two years and therefore an expansion of the period might decrease the high difference and show an earlier problem in these companies' debtor management. The same conclusion can be drawn for both the payables and inventory turnovers as many companies cease inventory production and, therefore, decrease their creditors two- and one year before de-listing.

When examining the O-score's application to the dataset, it can be seen when looking at the change over the period in the scores of both groups, that the third year prior to de-listing or financial distress provides an outlier to the other two years. This is accepted to be the cause of the restructuring of many of the Group B companies in the first and second years prior to de-listing (Denis & Rodgers, 2007). However, this does indicate that the O-score is not completely compatible with the three-year period as additional years before Y3 could provide extra insights into the correct period to apply the model to, when predicting financial distress.

Therefore, this study concludes that while the three years prior to de-listing provide insights into the financial distress of Group B companies and can coincide with prediction methods, an increase of the period by two additional years would increase the accuracy and utility of financial distress prediction.

4.4 Combination analysis

After analysing the two methods of financial distress prediction discussed above, the need for more conclusive analysis cannot be disregarded. This study now seeks to combine the results obtained from Chapter 3 and attempt to provide a more holistic prediction of financial distress for the Group B companies. This will be done by combining the mean averages of each company in both groups' O-score for Y3-1 and analysing these in conjunction with the mean averages from all five liquidity ratios for each company in each group over the same period.

Both parts' results will be converted into a safe/distress factor, in comparison to the general rules-of-thumb accepted in section 3.1 and the >0 in section 3.2, in order to make the results compatible and enable the combination of the two. These factors will then be analysed for each company and group, and then be compared against the other group. Thereafter, the utility of a combination model can be determined and discussed in Chapter 5.

As can be seen below, the results from either method varies, as all the companies in the dataset are not liquidated companies and did experience financial distress, but some only briefly. There exists a clear difference in the accuracy of the two methods for both groups. The O-score was not very successful in a definite prediction on its own in the case of Group B, where it only identified 25% as definite business failures. It should be considered that the model is used to identify business failure and not simply financial distress (Ohlson, 1980). The liquidity analysis of Group B was more successful and achieved a 57% accuracy rate, when taking the mean average of all five ratios into consideration.

In the case of Group A, the O-score has a 100% success rate in disproving all companies in the group of experiencing true financial distress or business failure. The liquidity ratios' averages also showed a high accuracy rate of 70%, though the liquidity ratios can be interpreted differently if observed from different perspectives (Lev & Sunder, 2012), as discussed in section 3.1. These accuracies are calculated in tables 25-28 (see appendix).

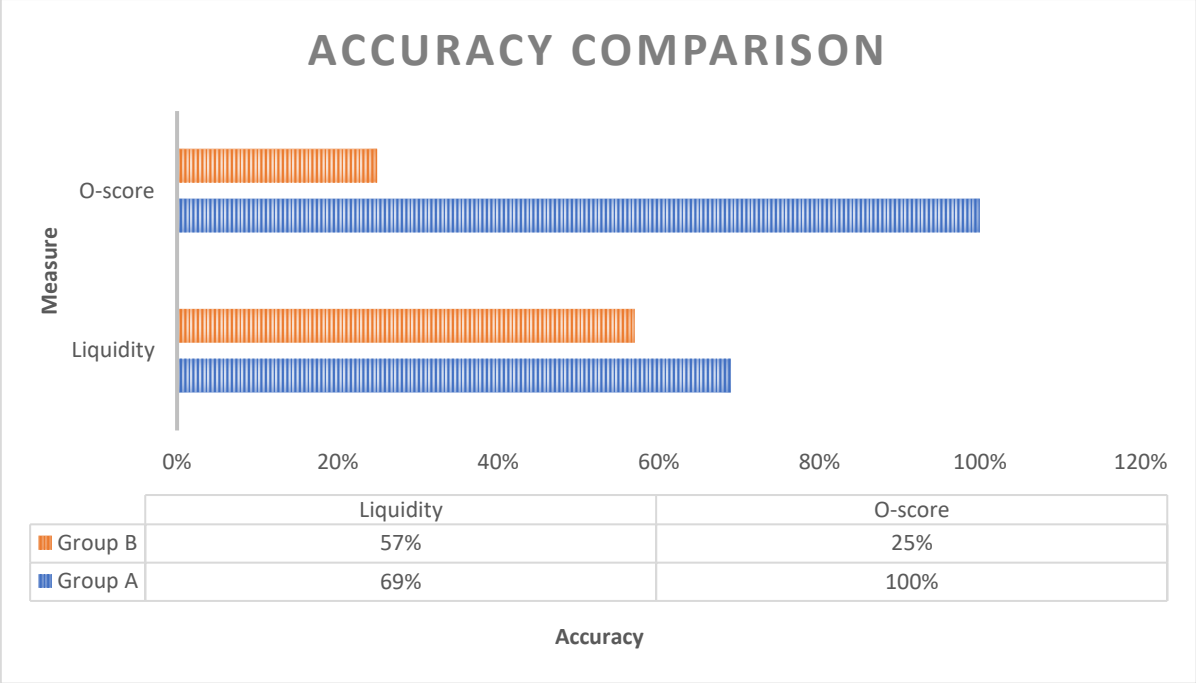

Chart 11 – Accuracy comparison

Combination - A							
Measure	**Liquidity ratios**					**Selected model**	**Averages**
	CR	**QR**	**RT**	**PT**	**IT**	**O-score**	
Total Safe	18	11	16	13	12	20	14
Accuracy	90%	50%	80%	65%	60%	100%	74%

Combination - B							
Measure	**Liquidity ratios**					**Selected model**	**Averages**
	CR	**QR**	**RT**	**PT**	**IT**	**O-score**	
Total Safe	12	12	7	12	14	5	11
Accuracy	60%	60%	35%	60%	70%	25%	52%

Taking this information into consideration, the need for a more conclusive method or model is evident. Therefore, the two methods have been combined, as discussed above, in an attempt to address the primary objective of this study and provide a more conclusive view of financial distress prediction. In Table 10 below, the accuracy of each liquidity ratio for each group, as well as the accuracy of the O-score for each group is summarised and this was used to create the combination analysis for the combined method.

The overall accuracy was determined by using the Safe/Distressed factors as stand-in variables. The companies' results from both methods were converted into these variables by using the rules-of-thumb in the legends of tables 26 and 27 (Attari & Raza, 2012), as well as the <0> rule of the O-score analysis.

A Safe (S) variable was attributed to results that positively exceed or fell short of the rules-of-thumb or <0> rule. The inverse being true when attributing a Distressed (D) variable. The assumption, as stated in Chapter 1, being that all companies in Group A are "Safe" companies and all companies in Group B are "Distressed" companies. The total "Safe" companies for Group A and "Distressed" companies for Group B were then weighed up against the total of 20 companies in each group to arrive at the accuracy measure for each group by taking any company with a D in Group A as reducing the accuracy and the inverse with S for Group B.

As seen in the chart below, the combination of the two methods, increase the accuracy for financial distress prediction in both of the groups' cases. The overall accuracy for Group A increased to 74%, whereas the average accuracy thereof for only the liquidity ratios amounted to 71%. The Group B companies also saw a rise in accuracy of 3% from 49% to 52% when combining the measures, the O-score bringing the accuracy down considerably.

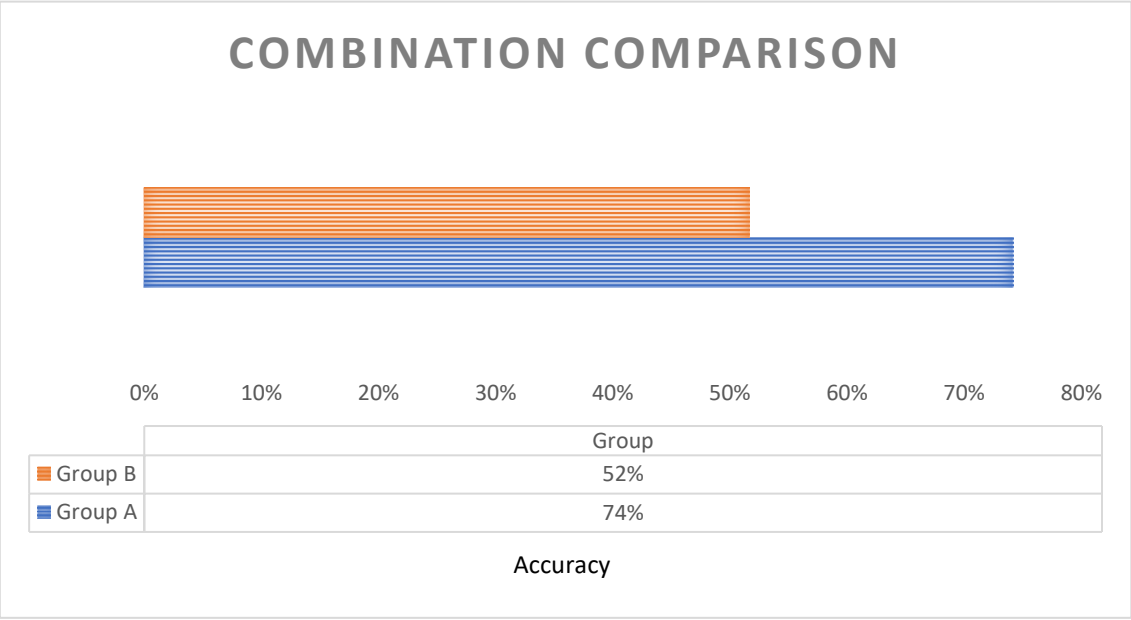

Chart 12 – Combination accuracy comparison

4.5 Chapter summary

This chapter reflected on the results of Chapter 3 in regard to the two measures applied in isolation and their predictive capabilities, as well as the period that this study used in applying the measures to the datasets. It was determined that both measures do correlate to financial distress in the three years prior to financial distress and its prediction, although a longer period is proposed to increase accuracy. It was also found that these measures do not provide conclusive enough predictions in isolation.

This established the outcomes of the secondary objective to test the predictive capabilities of both measures for financial distress in isolation. These outcomes lead to the primary objective and research question posed in chapter one – whether financial distress prediction through liquidity ratios can be improved by combining a liquidity analysis with a secondary measure.

Therefore, the measures were combined, and the charts showed above clearly show that the combination of these two measures increase the effectiveness of financial distress prediction and that more conclusive results can be found by combining more than one measure, when predicting financial distress in listed companies in the South African context.

Chapter 5 - Conclusion

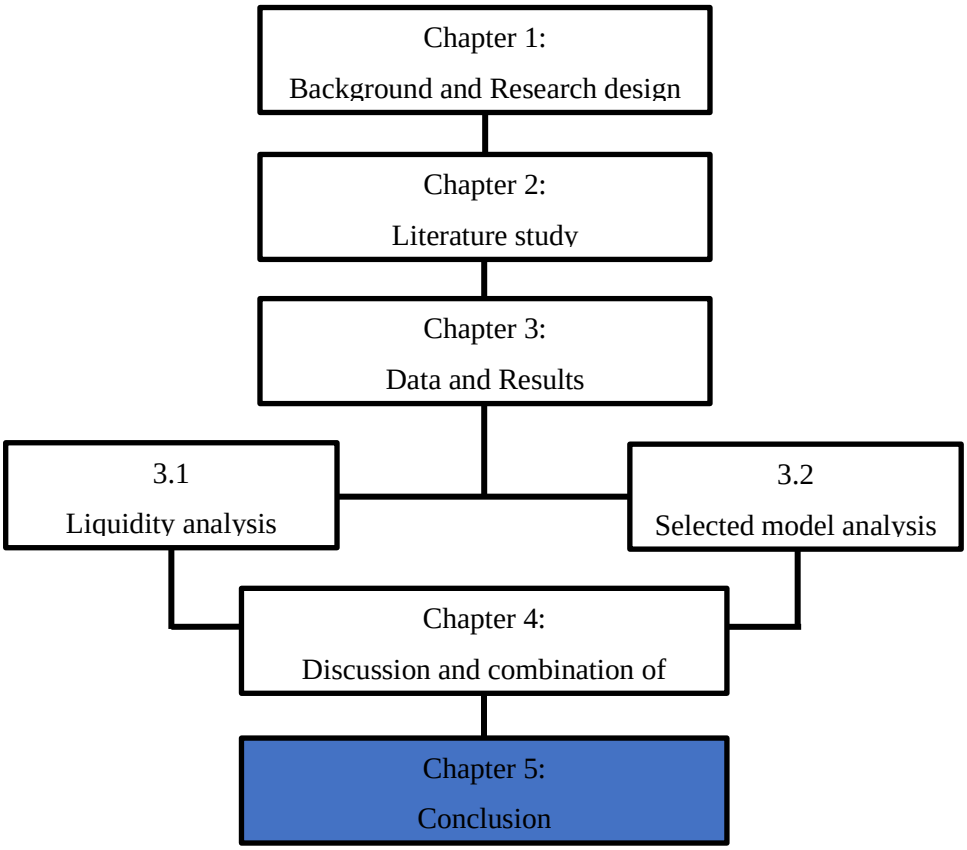

Figure 7 – Chapter layout (Ch.5)

In this chapter, the study will reflect on the previous chapters and the results or statements gained form each. These will be discussed in short and a summative conclusion reached on the success of each. This will be followed by revisiting the study's objectives in order to determine if all have been met. Lastly the chapter will close with a restatement of the problem statement, as stated in chapter one and a brief synopsis of the limitations of the study, followed by a final overall conclusion, the contribution thereof and any recommendations.

5.1 Summary of previous chapters

In chapter two, the utility of a liquidity analysis and the two proposed existing models for financial distress prediction was analysed through the literature study of all three topics. In the chapter, it was determined that liquidity is seen as a key area for financial distress, as well as business success by many previous studies. It was determined that the liquidity analysis should include five key liquidity ratios, as performed by previous studies and that the use of these in financial distress prediction has often been overlooked in practise.

The chapter continued in an analysis of both Altman's Z-score and Ohlson's O-score, where the basic structure of both models were investigated and the applicability thereof to the current study determined. It was found that while the Z-score is more widely used in practise, the O-score provided better chances of accuracy in its prediction, as it includes factors that remain constant over many industries, as opposed to the Z-score, whose standard deviations need to be recalculated per industry. This study has therefore accepted the O-score as the more appropriate model to be combined with liquidity ratios in the predictions of financial distress.

Chapter three applied both the liquidity ratios and the O-score to the dataset in isolation in an attempt to determine each measure's separate predictive capabilities. These were applied to each company in each group over the three years included in the period. Each company's results were averaged per ratio and for the model. The outliers in each group and each ratio were determined and a mean average that better represents the entire group was calculated, in order to be compared with the other group. Here it was determined that both measures do correlate with financial distress prediction and the main causes for liquidity problems faced by Group B companies were indicated.

In chapter four the results of chapter three were discussed and the accuracy of each ratio and the model was determined through the use of "safe/distressed" factors as to the correct prediction of the measure or ratio in the case of each company in both designated groups. These results were then combined in an attempt to address the primary objective of the study, where the results showed a positive inclination to the combined method, as opposed to the use of both measures as silo prediction measures.

5.2 Objectives

The objectives of this study were stated in chapter one and have been addressed in separate chapters and sub-chapters throughout the study. The objectives have been stated as the following:

I. Primary objective

- To evaluate the prediction properties of liquidity financial ratios, and whether a combination of measures can be included to improve these properties (Ch. 4).

II. Secondary objectives

- Determining the utility of liquidity analysis and the proposed financial distress models, in order to determine the most relevant model (Ch. 2).
- Test the predictive capabilities of each measure with regard to liquidity and the selected model in isolation (Ch. 3).

5.3 Problem statement

In the current South African economic climate, businesses are under increasing pressure, creating unease under shareholders. The failure of many listed companies has occurred without much warning and the existing measures for predicting financial distress do not provide conclusive enough indications. The need to expand on existing knowledge by combining two or more measures are therefore needed. This study has found that the South African context does not change the effectiveness of such a combination method and that through the use of liquidity ratios and Ohlson's O-score, more conclusive predictions can be achieved, if the necessary information is available.

5.4 Conclusions

5.4.1 Prediction of financial distress through a combination of measures in the South African context

The primary objective of this study was to affirm if the criticism against a liquidity ratio analysis can be addressed by combining it with a secondary measure. The primary objective was achieved in chapter four with the combination of the isolated results of the liquidity ratios and those of Ohlson's O-score.

The combination shows a sharp increase in the conclusive results for Group A companies as the benchmark, as well as a marginal increase in accuracy for the Group B companies. This can be attributed to many Group B companies undergoing restructuring in the two years prior to de-listing and therefore shows the possible utility in an analysis over a longer period than initially proposed. This study shows a 75% accuracy for Group A companies and 52% for Group B companies, over the period of three years before de-listing, i.e. a total accuracy average of 63%. South African companies do react in correlation with those of equivalent studies in other countries, however the current economic climate increases pressure on businesses as a whole.

Therefore, this study has found that there does indeed exist an increase in the overall financial distress prediction capabilities for the companies in the dataset if the two measures are combined.

5.4.2 Liquidity financial ratios as a silo predictor of financial distress

As stated in chapter 4, the use of liquidity financial ratios remains central to financial analysis in all companies (Jooste, 2006) and this study has concluded that the use thereof provides conclusive information regarding the liquidity and solvency positions of a listed company. The five key liquidity ratios, as applied by this study, can however not be analysed in isolation from one another as all five are necessary in order for the analyser to be provided with a conclusive result of a company's liquid position.

The current and quick ratios do not provide conclusive insights without any further investigation as the normal rule-of-thumbs are not always applicable to every industry. Both the receivables and payables turnovers require deeper analysis and provide the expected results after this analysis (Dharmasena, 2015). The inventory turnover provided expected results and can be seen as a key problem area for companies in distress, when applicable to the company industry.

This analysis has also shown that focus can be placed on the management of a company's working capital when financial distress is first identified as this was found to be a key problem experienced by most companies in the de-listed group.

5.4.3 Ohlson's O-score as a silo prediction of financial distress

After weighing up the O-score to the more popular Altman Z-score, this study found the O-score to be more applicable and accurate and therefore chose it as the combination model and in doing so met the secondary objective of determining the utility of these two models. The O-score incorporates the GNP price level index, giving it a cross-industry advantage and takes many different areas of the financial position of a company into consideration. While the use of the model in insolation proved less conclusive than the liquidity ratios, the correlation between financial distress and the model still exists and the use of the FFO factor in the formula increases its utility (Kim, 2013).

This also ties the model with the liquidity ratios and the above-mentioned problems faced with working capital management. This study affirms the use of the model as a predictor for financial distress however, the model is more suited to predicting business failure and not simply financial distress, as can be seen in section 3.2 and four of this study.

The model does show the potential for more accurate readings when taking a larger time period into consideration than the three-year period in this study, as can be seen in the large change in the Group B companies' O-scores between Y3 and 2. These two points do however, show that each measure does have predictive capabilities in isolation and therefore meets the last secondary objective of this study.

5.5 Limitations of the study

The study encountered many small limitations however, none of these have influenced the overall findings of the study to any great degree. The first limitation encountered was the collection of financial information from the de-listed (Group B) companies, as many of these companies have liquidated and therefore do not have information generally available in the exact same years as those in Group A. This did not pose a problem however, as the mismatch of years between the companies in Group B and to those in Group A don't affect the results gained. This assumption is made on the grounds of previous studies that state that the exact years are not as relevant as the concept of the period before financial distress, regardless of year number. Therefore, the financial information available for each company was sourced for the three years before delisting, with some causing a slight mismatch of years.

Another limitation was found in the companies grouped in Group B, as the list sourced from the JSE included 80 companies that have de-listed between 2015 and 2017, but not all of these companies have experienced high levels of financial distress which affects the overall averages obtained from the group. This was solved by eliminating the outliers in each group per ratio and for the O-score, so as to make the results obtained comparable. This is coupled with all the companies in both groups ranging over different industries however, this was solved by using the O-score model as the inclusion of the GNP price level-indexes increased the model's effectiveness cross-industry barriers.

Lastly it was found that the ideal period for financial distress prediction proposed by Lieu *et al.* (2008), limits the analyses to some degree. While this did not refute the objectives and findings of this study, lengthening the period might showcase an earlier indication of financial distress, if longer periods' information can be obtained.

5.6 Contributions of the study

The findings obtained from this study has shown that the combination of liquidity financial ratios with the Ohlson O-score as a secondary measure, increase the ratios' financial distress prediction capabilities if applied to the financial information available to each company in the periods leading up to de-listing or liquidation. This is in agreement with previous studies, such as performed by Jouzbarkand et al. (2013) in Tehran and affirms the utility thereof for listed companies in the South African context.

5.7 Recommendations

As the South African economy has been very unstable in the past few years, the study's focus on listed companies stems from the availability of information and the large-scale failure of large corporate entities in the country up to the date of this submission. The usefulness of the results obtained shows the utility of this method however, the focus on small and medium enterprises (SME's) has not been attempted and might provide further insight into smaller business failures.

This study focuses on financial information, but the influence of non-financial aspects is present and can be seen as a possible point for further study, in order to provide insights into the governance factors leading to the adverse financial figures showcased in this study.

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Appendix A – Tables

Y = Year prior to delisting/liquidation (Group B) Y= Year prior to 2018 (Group A)

Table 6 - Group A companies list

JSE Top 20 listed companies - As at 05/09/2018				
Num.	**Company Name**	**Country of Origin**	**Sector/Industry**	**Market Cap (ZARm)**
1	Anheuser-Bush InBev Ltd.	Belgium	Beverages	1,975,691
2	Barclays Africa Group Ltd.	South Africa	Banking	1,561,873
3	Anglo American plc.	United Kingdom	Mining	1,354,662
4	Aspen Pharmacare Holdings Ltd.	South Africa	Pharmaceutical	908,282
5	BHP Billiton Ltd.	Australia	Mining and Oil	604,528
6	British American Tobacco plc.	United Kingdom	Tobacco	592,034
7	FirstRand Ltd.	South Africa	Financial Services	414,613
8	Glencore plc.	Switzerland	Mining	336,569
9	Mondi plc.	Austria	Packaging/Paper	328,366
10	MTN Group Ltd.	South Africa	Telecommunication	294,031
11	Naspers Ltd.	South Africa	Internet and Media	255,716
12	Nedbank Ltd.	South Africa	Banking	212,545
13	Old Mutual Ltd.	South Africa	Financial Services	199,516
14	Richemont Group plc.	Switzerland	Luxury Goods Holdings	176,305
15	Sanlam Ltd.	South Africa	Financial Services	168,046
16	Sasol Ltd.	South Africa	Chemicals	138,268
17	Shoprite Holdings Ltd.	South Africa	Retail	136,630
18	South32 Ltd.	Australia	Mining	133,193
19	Standard Bank Ltd.	South Africa	Banking	126,977
20	Vodacom Group Ltd.	South Africa	Telecommunication	115,025

Table 7 - Group B companies list

JSE 20 Delisted companies - Group B				
Num.	**Company Name**	**Country of Origin**	**Sector/Industry**	**Year of delisting**
1	Holdsport Ltd.	South Africa	Retail	2017
2	International Hotel Properties Ltd.	United Kingdom	Hospitality	2017
3	Evraz Highveld Steel & Vanadium Ltd.	Russia	Steel and Engineering	2014
4	Moneyweb Holdings Ltd.	South Africa	Media	2016
5	M-Fitec International Ltd.	South Africa	Technical services	2016
6	Metmar Trading Ltd.	South Africa	Commodities trading	2015
7	Rockcastle Global Real Estate Ltd.	Mauritius	Real estate	2017
8	Oakbay Resources and Energy Ltd.	South Africa	Mining	2017
9	The Pivotal Fund Ltd.	South Africa	Property development	2016
10	Lodestone Reit Ltd.	South Africa	Real estate	2016
11	Gooderson Leisure Corporation Ltd.	South Africa	Hospitality	2016
12	Giyani Gold Corporation	Canada	Mining	2016
13	Datacentrix Holdings Ltd.	South Africa	Information technology	2017
14	Ascension Properties Ltd.	South Africa	Real estate	2016
15	Masonite Africa Ltd.	South Africa	Manufacturing	2017
16	Astrapak Ltd.	South Africa	Packaging	2017
17	Keaton Energy Holdings Ltd.	South Africa	Mining	2016
18	Cadiz Holdings Ltd.	South Africa	Financial services	2016
19	Illovo Sugar Ltd.	South Africa	Agriculture/Manufacturing	2016
20	Infrasors Holdings Ltd.	South Africa	Mining	2015

Table 8 - Current and quick ratios (A)

Current and Quick Ratios - A																	
	Y1	Y2	Y3	Y1	Y2	Y3	Y1	Y2	Y3	Y1	Y2	Y3	X	Y1	Y2	Y3	X
Company	Current Assets			Current Liabilities			Inventory			Current Ratio			Average	Quick Ratio			Average
Anheuser-Bush InBev	23960000	43061000	18294000	36211000	40116000	28456000	41190000	39130000	28620000	0.661677	1.073412	0.642887	0.792659	0.547927	0.975870	0.542311	0.688703
Barclays Africa Group	37163 4000	33852 7000	39889 4000	16740 2000	13363 0000	18637 8000	56853 000	45153 000	78277 000	2.22 0009	2.53 3316	2.14 0242	2.29 7856	1.88 039	2.19 542	1.72 0251	1.93 202
Anglo American	14604000	12449000	13770000	73510 00	65250 00	58390 00	44410 00	37270 00	40510 00	1.98 6668	1.90 7893	2.35 8281	2.08 4281	1.38 2533	1.33 6705	1.66 4497	1.46 1245
Aspen	38100 0000	37200 0000	32700 0000	34800 0000	40700 0000	21800 0000	13600 0000	11800 0000	10800 0000	1.09 4828	0.91 4005	1.5	1.16 9611	0.70 4023	0.62 4079	1.00 4587	0.77 7563
BHP Billiton	21056000	12699000	16369000	11366000	67510 00	12853000	10950 00	76400 0	46600 0	1.85 2543	1.88 1055	1.27 3555	1.66 9051	1.75 6203	1.76 7886	1.23 7299	1.58 7129
British American Tobacco	13966000	72940 00	98140 00	15544000	37110 00	90060 00	58640 00	57930 00	42470 00	0.89 8482	1.96 5508	1.08 9718	1.31 7903	0.52 123	0.40 4473	0.61 8143	0.51 4616
FirstRand	12734 7000	12794 8000	11554 5000	76970 000	82456 000	64484 000	14380 000	12514 000	73540 00	1.65 4502	1.55 1712	1.79 184	1.66 6018	1.46 7676	1.39 9947	1.67 7796	1.51 5139
Glencore	49726000	43412000	42198000	44255000	43367000	40872000	24084000	18347000	18303000	1.12 3624	1.00 1038	1.03 2443	1.05 2368	0.57 9415	0.57 7974	0.58 463	0.58 0673
Mondi	20550 0000	23440 0000	19430 0000	15250 0000	19180 0000	14530 0000	86700 000	85000 000	83800 000	1.34 7541	1.22 2106	1.33 7233	1.30 2294	0.77 9016	0.77 8936	0.76 0496	0.77 2816
MTN	59900000	79611000	95432000	65116000	77726000	89519000	11493000	13853000	56350 00	0.91 9897	1.02 4252	1.06 6053	1.00 3401	0.74 3396	0.84 6023	1.00 3105	0.86 4175
Naspers	56390 00	32370 00	27000 00	29280 00	20460 00	21810 00	15400 0	19400 0	26200 0	1.92 5888	1.58 2111	1.23 7964	1.58 1988	1.87 3292	1.48 7292	1.11 7836	1.49 2807
Nedbank	85878 6000	85771 9000	82354 6000	77455 1000	77655 8000	75203 0000	68963 7000	69192 5000	66680 7000	1.10 8753	1.10 4514	1.09 5097	1.10 2788	0.21 8383	0.21 3499	0.20 8421	0.21 3434
Old Mutual	13405 1000	17247 000	96450 00	12560 9000	58772 000	39592 000	24500 0	13400 00	30760 00	1.06 7209	0.29 3456	0.24 361	0.53 4758	1.06 5258	0.27 0656	0.16 5917	0.50 0611

Richemont	14433000	14358000	13982000	3900000	6700000	6730000	5302000	5345000	5163000	3.703769	2.142985	2.077563	2.640439	2.341282	1.345224	1.310401	1.665636
Sanlam	43497000	48699000	51250000	34642000	48753000	51417000	20813000	18106000	18915000	1.255615	0.998892	0.996752	1.083753	0.654812	0.62751	0.628878	0.637067
Sasol	25021000	10813000	10667800	12999000	41602000	41342000	9316000	23798000	23141000	1.92484	2.599226	2.580378	2.368148	1.20817	2.027186	2.020633	1.751996
Shoprite	31032000	27351000	25053000	26482000	25370000	19100000	17794000	15055000	13321000	1.171815	1.078084	1.311675	1.187192	0.499887	0.484667	0.614241	0.532931
South32	4332000	2701000	2868000	1744000	6760000	9210000	8100000	7470000	9530000	2.483945	3.995562	3.114007	3.197838	2.4375	2.890533	2.079262	2.469098
Standard Bank	15447 4700	14908 9500	18722 0600	13955 9300	13451 3900	13637 7600	10480 2700	10656 2800	10771 6700	1.106875	1.108358	1.37281	1.196014	0.35592	0.316151	0.582969	0.418347
Vodacom	29011000	27618000	25353000	26719000	25770000	26614000	12680000	16750000	11890000	1.085782	1.071711	0.952619	1.036704	1.038325	1.006713	0.907943	0.984327
										1.529563	**1.552246**	**1.460736**	**1.514253**	**1.102732**	**1.078837**	**1.022481**	**1.068017**

Table 9 - Current and quick ratios (B)

Current and Quick Ratios - B																	
	Y1	Y2	Y3	Y1	Y2	Y3	Y1	Y2	Y3	Y1	Y2	Y3	X	Y1	Y2	Y3	X
Company	**Current Assets**			**Current Liabilities**			**Inventory**			**Current Ratio**			**Average**	**Quick Ratio**			**Average**
Holdsport Ltd.	658762	578274	521866	141432	276944	121229	511845	459191	365396	4.6578	2.0880544795	4.30355	3.68	1.038782	0.429989	1.290698	0.919823
International Hotel Properties Ltd.	6037100	5952927	1160916	5848305	5610907	6905425	9515	9422	9131	1.032282	1.060956	0.168117	0.753785	1.030655	1.059277	0.166794	0.752242
Evraz Highveld Steel & Vanadium Ltd.	2072	1865	1866	1796	1370	1169	984	899	1372	1.153675	1.361314	1.596236	1.370408	0.605791	0.705109	0.422583	0.577828
Moneyweb Holdings Ltd.	20335	25410	28050	4537	4926	3318	13075	18587	18679	4.482037	5.158343	8.453888	6.031423	1.600176	1.385099	2.824292	1.936523
M-Fitec International Ltd.	754055	787255	753152	1242	4149	2017	0	0	0	60.71256	18.97445	37.33862	39.00854	60.71256	18.97445	37.33862	39.00854
Metmar Trading Ltd.	776741	114398	110024	844062	109625	917107	429662	547832	423539	0.920242	1.047384	1.199687	1.055771	0.411201	0.545993	0.737866	0.56502
Rockcastle Global Real Estate Ltd.	860366	107538	31366	145800	150692	106763	326565	18979	7589	5.901001	0.713628	0.029348	2.214659	3.661187	0.587682	0.022247	1.423705
Oakbay Resources and Energy Ltd.	264488	504150	444518	280460	487415	431116	188499	183516	208513	0.943051	1.034334	1.031087	1.002824	0.270944	0.657825	0.547428	0.492066
The Pivotal Fund Ltd.	593053	497667	330863	1076149	429611	51382	0	0	0	0.551088	1.158413	0	0.569834	0.551088	1.158413	0	0.569834
Lodestone Reit Ltd.	302833	11605	148449	20947	46345	60532	0	0	0	1.445696	0.250405	2.452405	1.382835	1.445696	0.250405	2.452405	1.382835
Gooderson Leisure Corporation Ltd.	2334084	2290982	2070888	4902227	3747903	2919996	2054350	2023338	2020617	0.476127	0.61127	0.709209	0.598869	0.434221	0.557311	0.64001	0.543847
Giyani Gold Corporation	453867	225619	86189	510314	123323	245034	0	0	0	0.889388	0.182862	0.035174	0.369141	0.889388	0.182862	0.035174	0.369141
Datacentrix Holdings Ltd.	933775	780739	756190	464919	348604	385321	154766	31122	44408	2.008468	2.239616	1.962494	2.070192	1.67558	2.15034	1.847244	1.891055

Ascension Properties Ltd.	261960	167333	100954	619109	175267	170044	159200	0	0	0.423124	0.954732	0.593693	0.657183	0.16598	0.954732	0.593693	0.571469
Masonite Africa Ltd.	587737	558946	240398	231178	232518	92485	225940	208393	92049	2.542357	2.403883	2.599319	2.515186	1.565015	1.507638	1.604033	1.558895
Astrapak Ltd.	521555	472038	819191	349087	398168	617284	174614	130378	289491	1.494054	1.185525	1.327089	1.335556	0.993853	0.85808	0.858114	0.903349
Keaton Energy Holdings Ltd.	274075	308014	259426	394390	350946	280094	36650	54110	35081	0.694934	0.877668	0.92621	0.832937	0.602006	0.723485	0.800963	0.708818
Cadiz Holdings Ltd.	954211	190765	248212	54325	361833	849330	0	0	0	1.756484	5.272227	2.922548	3.317086	1.756484	5.272227	2.922548	3.317086
Illovo Sugar Ltd.	581706	535346	492488	418766	339644	303047	98727	10226	99889	1.389101	1.576257	1.625132	1.530163	1.153238	1.275174	1.295506	1.241306
Infrasors Holdings Ltd.	869577	814177	761962	795532	622466	698277	12744	14171	16859	1.093084	1.307988	1.091211	1.164094	0.932887	1.080326	0.849772	0.954328
										4.728328	**2.472965**	**3.518313**	**3.573202**	**4.074837**	**2.015821**	**2.862525**	**2.984386**

Table 10 - Receivables and payables turnover (A)

Receivables and Payables days - A																				
	Y1	Y2	Y3	Y1	Y2	Y3	Y1	Y2	Y3	Y1	Y2	Y3	Y1	Y2	Y3	Days	Y1	Y2	Y3	Days
Company	Trade Receivables			Revenue			Trade Accounts Payable			Cost of Sales			Receivables turnover			Average	Payables turnover			Average
Anheuser-Bush InBev	47520000	45620000	32410000	56444000	45517000	43604000	15240000	14071000	11616000	213860000	178030000	171377000	38.1062	38.18755	27.1974	34.4745	260.1047	288.4859	247.4085	265.3331
Barclays Africa Group	24762000	23753000	29219000	85929000	85114000	73603000	5364000	4092000	8669500	43285000	43111000	35196000	10.51814	10.18616	14.48981	11.73137	45.2318 4	34.64499	89.90702	56.59461
Anglo American	15610000	17280000	21400000	26243000	21378000	20455000	2214000	1700000	10241000	20714000	19712000	24567000	21.71112	29.50323	38.18626	29.8002	39.01275	31.47829	152.1539	74.21498
Aspen	109000000	90000000	81000000	412000000	356000000	361000000	52000000	35000000	34000000	213000000	177000000	188000000	96.56553	92.27528	81.89751	90.24611	89.10798	72.17514	66.01064	75.76459
BHP Billiton	18550000	17300000	29820000	38285000	30912000	44636000	3996000	3662000	4857000	27540000	35487000	37010000	17.68512	20.42734	24.38458	20.83235	52.96078	37.66534	47.9007	46.17561
British American Tobacco	33060000	26960000	23550000	20292000	14751000	13104000	2298000	1281000	1056000	77120000	60070000	50720000	59.46629	66.71005	65.59638	63.92424	108.7617	77.83669	75.99369	87.53068
FirstRand	88780000	101520000	80090000	80441000	71561000	51882000	17014000	17141000	17529000	35524000	29520000	21653000	40.28381	51.78072	56.34488	49.4698	174.8145	211.9399	295.4826	227.4123

Glencore	11915000	10482000	10175000	205476000	152948000	152948000	24664000	22438000	19424000	197695000	149763000	149763000	21.16537	25.01458	24.28195	23.4873	45.5366 1	54.68554	47.33986	49.1873 4
Mondi	961000	877000	829000	70960000	66620000	68190000	5320000	5670000	5080000	39810000	37480000	39250000	49.43137	48.04938	44.37381	47.28485	48.77669	55.21745	47.24076	50.4116 3
MTN	19402000	19828000	22764000	132815000	147920000	147063000	11126000	16186000	12430000	55833000	58369000	51327000	53.32026	48.92658	56.49864	52.91516	72.73458	101.2162	88.39305	87.4479 5
Naspers	420000	393000	398000	60980000	59300000	65690000	4870000	4370000	4480000	35740000	33920000	38240000	25.13939	24.18971	22.11448	23.81453	49.73559	47.02388	42.76151	46.5069 9
Nedbank	734720 0	68218 00	60078 00	713110 00	698620 00	551280 00	14047 00	12717 00	99110 0	461100 0	453440 00	327240 00	37.60609	35.64108	39.77737	37.67485	11.11916	10.23665	11.05462	10.8034 8
Old Mutual	422000	220000	203000	42250000	37260000	35890000	3950000	5540000	4490000	53500000	34830000	34500000	36.4568	21.55126	20.64503	26.2177	26.9486	58.05627	47.5029	44.1692 6
Richemont	996000	10210000	98400000	106470000	151000000	291300000	150800	152600	156300	38480000	550000	920000	34.14483	24.6798	12.32956	23.71806	14.303405	101.2709	62.01033	59.1951
Sanlam	2180100	2557100	2808400	587000000	543820000	493650000	31601000	32364000	35875000	71500000	675800000	599900000	13.55599	17.16269	20.76504	17.16124	161.3198	17.47982	21.8276	66.8757 3
Sasol	9316000	20752000	21627000	203610000	172942000	185266000	9400000	12178000	12888000	73600000	713200000	801690000	167.0026	43.79781	42.60822	84.46954	46.61685	62.32431	58.67754	55.8729

Shoprite	1715000	1748000	160400	14100000	13002800	11369400	10141000	10205000	11834000	10717400	99372000	90180000	44.39539	49.06789	51.4943	48.31922	34.5369 7	37.48365	47.89765	39.9727 5
South32	400000	410000	554000	69500000	58120000	38430000	697000	577000	762000	57420000	72470000	52470000	21.00719	25.74845	52.6177 5	33.12446	44.3059 9	29.06099	53.00743	42.1248
Standard Bank	1597980	1280980	862850	10316200	9985700	11014000	635770	481090	433040	57512200	56235500	93710000	56.53852	46.82273	28.5945 4	43.98526	40.3491 5	31.22572	16.86689	29.4805 9
Vodacom	9397000	9644000	959900	81271000	80077000	74500000	1067100	815000	759000	30483000	31594000	30589000	42.20331	43.95844	47.0286 6	44.3968	12.7773 3	9.415554	9.056687	10.4165 3
													44.31517	**38.18404**	**38.5793**	**40.35238**	**68.95278**	**68.44616**	**76.4247**	**71.2745 5**

Table 11 - Receivables and payables turnover (B)

Receivables and Payables days - B																				
	Y1	Y2	Y3	Y1	Y2	Y3	Y1	Y2	Y3	Y1	Y2	Y3	Y1	Y2	Y3	Days	Y1	Y2	Y3	Days
Company	Trade Receivables			Revenue			Trade Accounts Payable			Cost of Sales			Receivables turnover			Average	Payables turnover			Average
Holdsport Ltd.	30879	23994	25619	1828600	1727436	1544844	138376	143808	121229	950080	899421	809883	6.524604	5.669058	6.052996	6.082219	53.161104	58.35968	54.63577	55.3855
International Hotel Properties Ltd.	51184	64402	22192	659160	577616	579541	636383	67795	66243	489600	436135	417809	28.34238	40.61962	13.97672	27.67174	474.4277	56.73742	57.87021	196.3451
Evraz Highveld Steel & Vanadium Ltd.	518	472	684	7713	8767	13061	737	621	774	5521	6583	9734	24.51316	19.65096	19.11492	21.09302	48.723966	34.43187	29.02301	37.39295
Moneyweb Holdings Ltd.	3474	2495	2417	28304	25501	23494	588	1705	416	6175	4044	3371	44.79967	35.71134	37.55023	39.35375	34.756288	153.8885	45.04301	77.89592
M-Fitec International Ltd.	0	0	0	5440	2192	1980	0	0	0	4572	1930	1899	0	0	0	0	0	0	0	0
Metmar Trading Ltd.	318288	507973	541464	1951260	2097435	1522227	232162	176310	314985	186643	196229	140764	59.53851	88.39852	129.8324	92.58981	45.401655	32.79487	81.67485	53.29046
Rockcastle Global Real Estate Ltd.	60793	40539	15410	336977	209890	26550	113553	71536	4966	104892	64358	663	65.84854	70.49757	211.8512	116.0658	395.13833	405.7093	2733.922	1178.256

Oakbay Resources and Energy Ltd.	71641	51277	16981	462622	273214	165049	109750	87679	77675	414022	227757	123161	56.52339	68.50346	37.55288	54.19324	96.755122	140.5131	230.1977	155.8222
The Pivotal Fund Ltd.	7088	11879	0	863547	549171	0	52713	76071	0	124375	77098	0	2.995923	7.895237	0	3.630386	154.69554	360.1379	0	171.6111
Lodestone Reit Ltd.	6921	3258	2620	166529	108490	139130	5950	5134	4785	61594	42197	53922	15.16952	10.9611	6.873428	11.00135	35.259122	44.40861	32.38984	37.35252
Gooderson Leisure Corporation Ltd.	13201574	9842057	9975005	15032999	12831648	12025163	9126590	4631968	4238839	24867357	19598050	18692068	32.05331	27.99602	30.27715	30.10883	133.959	86.26717	82.71781	100.9993
Giyani Gold Corporation	100706	48906	21294	643968	310355	365423	312159	572867	1275663	412733	463602	586200	57.07999	57.517	21.26935	45.28878	276.0575	451.0258	794.2972	507.1268
Datacentrix Holdings Ltd.	644267	439329	465423	2609256	2249661	2279512	252132	180256	203733	17816661	15166466	15326067	90.12433	71.27967	74.52446	78.64282	51.653022	43.38088	48.5203	47.8514
Ascension Properties Ltd.	42200	23412	11950	533595	421566	353101	12680	12112	16533	144947	100562	42570	28.86646	20.27056	12.3527	20.49657	31.930229	43.96174	141.7558	72.54928
Masonite Africa Ltd.	242197	224976	79695	1973964	1871965	618166	96178	96480	76598	15643119	15211114	563746	44.83953	43.86633	47.05641	45.23557	22.44106	23.15093	49.59374	31.72857
Astrapak Ltd.	151412	192080	460211	1348378	1388606	1288422	164227	169298	464080	10468890	10965255	949667	40.98656	50.48891	130.3742	73.9499	57.25	56.35418	178.3669	97.32638

																803			
Keaton Energy Holdings Ltd.	99476	143341	135630	1032079	1181054	1372605	94641	186607	191230	868776	968938	1153868	35.1801	44.2989	36.0664	38.51519	39.761165	70.29506	60.49128	56.84933
Cadiz Holdings Ltd.	55729	61180	66649	863547	708490	659160	39124	30874	73166	77098	53922	42570	23.5552	31.5187	36.9058	30.65996	185.2222	208.9872	627.3336	340.5143
Illovo Sugar Ltd.	22207	16609	13092	162269	217440	229142	21515	20425	19335	164569	165386	171037	49.9513	27.8802	20.8542	32.89528	47.71843	45.07712	41.26169	44.68575
Infrasors Holdings Ltd.	60173	51737	38593	337247	327510	286986	52404	36736	40693	273010	249772	253259	65.1248	57.6593 2	49.0840 8	57.2894	70.06139	53.68352	58.64725	60.79739
													38.5981	**39.0379 6**	**46.0784 8**	**41.23818**	**112.71 91**	**118.4582**	**267.3898**	**166.189**

Table 12 - Inventory turnover (A)

	Inventory days - A									
	Y1	Y2	Y3	Y1	Y2	Y3	Y1	Y2	Y3	Days
Company		**Inventory**			**Cost of Sales**			**Inventory turnover**		**Average**
Anheuser-Bush InBev	4119000	3913000	2862000	21386000	17803000	17137000	70.29996	80.22496	60.95758	70.49417
Barclays Africa Group	5685300	4515300	7827700	43285000	43111000	35196000	47.94119	38.22886	81.17714	55.7824
Anglo American	4441000	3727000	4051000	20714000	19712000	24567000	78.25456	69.01152	60.18704	69.15104
Aspen	13600000	11800000	10800000	213000000	177000000	188000000	23.30516	24.33333	20.96809	22.86886
BHP Billiton	1095000	7640000	4660000	27540000	35487000	37010000	14.51253	78.58089	45.95785	46.35042
British American Tobacco	586400	579300	424700	7712000	6007000	5072000	27.75363	35.19968	30.56299	31.1721
FirstRand	1438000	1251400	735400	35524000	29520000	21653000	14.77508	15.47293	12.39648	14.21483
Glencore	24084000	18347000	18303000	197695000	149763000	149763000	44.46577	44.71502	44.60778	44.59619
Mondi	867000	850000	838000	3981000	3748000	3925000	79.49133	82.77748	77.92866	80.06583
MTN	11493000	13853000	5635000	55833000	58369000	51327000	75.13379	86.62723	40.07199	67.27767
Naspers	154000	194000	262000	3574000	3392000	3824000	15.72748	20.87559	25.00785	20.53697
Nedbank	689637	691925	666807	4611100	4534400	3272400	54.58947	55.69703	74.37494	61.55381
Old Mutual	245000	134000	307600	5350000	3483000	3450000	16.71495	14.04249	32.54319	21.10021
Richemont	530200	534500	516300	3848000	5500000	9200000	50.29184	35.47136	20.48364	35.41561
Sanlam	208130	18106000	18915000	7150000	67580000	59990000	10.62482	97.79062	115.0854	74.50029
Sasol	931600	2379800	2314100	7360000	71320000	80169000	46.20027	12.17929	10.53582	22.9718
Shoprite	17794000	15055000	13321000	107174000	99372000	90180000	60.60061	55.29802	53.91622	56.60495
South32	81000	747000	953000	5742000	7247000	5247000	5.148903	37.62315	66.29407	36.35538
Standard Bank	1048027	1065628	107716	5751200	5623500	9371000	66.51305	69.16586	4.195533	46.62481
Vodacom	1268000	1675000	1189000	30483000	31594000	30589000	15.18289	19.35098	14.18762	16.2405
							40.87636	**48.63332**	**44.572**	**44.69389**

Table 13 - Inventory turnover (B)

	Inventory days - B									
	Y1	Y2	Y3	Y1	Y2	Y3	Y1	Y2	Y3	Days
Company		**Inventory**			**Cost of Sales**			**Inventory turnover**		**Average**
Holdsport Ltd.	511845	459191	365396	950080	899421	809883	196.6397	186.3473	164.6775	182.5549
International Hotel Properties Ltd.	9515	9422	9131	489600	436135	417809	7.093495	7.885242	7.976887	7.651874
Evraz Highveld Steel & Vanadium Ltd.	984	899	1372	5521	6583	9734	65.05343	49.84581	51.44648	55.44857
Moneyweb Holdings Ltd.	13075	18587	18679	6175	4044	3371	772.8543	1677.61	2022.496	1490.987
M-Fitec International Ltd.	0	0	0	4572	1930	1899	0	0	0	0
Metmar Trading Ltd.	429662	547832	423539	1866433	1962293	1407649	84.02478	101.9005	109.8226	98.58265
Rockcastle Global Real Estate Ltd.	32656	1897	758	104892	64358	663	113.6354	10.75865	417.3002	180.5647
Oakbay Resources and Energy Ltd.	188499	183516	208513	414022	227757	123161	166.1799	294.1	617.9492	359.4097
The Pivotal Fund Ltd.	0	0	0	124375	77098	0	0	0	0	0
Lodestone Reit Ltd.	0	0	0	61594	42197	53922	0	0	0	0
Gooderson Leisure Corporation Ltd.	2054350	2022338	2020617	24867357	19598050	18692068	30.1535	37.66463	39.45659	35.75824
Giyani Gold Corporation	0	0	0	412733	463602	586200	0	0	0	0
Datacentrix Holdings Ltd.	154766	31122	44408	1781661	1516646	1532607	31.70614	7.489902	10.57604	16.59069
Ascension Properties Ltd.	159200	0	0	144947	100562	42570	400.8914	0	0	133.6305
Masonite Africa Ltd.	225940	208393	92049	1564319	1521114	563746	52.71821	50.00509	59.59756	54.10695
Astrapak Ltd.	174614	130378	289491	1046890	1096525	949667	60.87947	43.39889	111.2645	71.84762
Keaton Energy Holdings Ltd.	36650	54110	35081	868776	968938	1153868	15.39781	20.3833	11.09708	15.62606
Cadiz Holdings Ltd.	0	0	0	164569	165386	171037	0	0	0	0
Illovo Sugar Ltd.	9877	10226	9989	81608	82061	81087	44.17588	45.48433	44.96387	44.87469
Infrasors Holdings Ltd.	12744	14171	16859	273010	249772	253259	17.03806	20.70855	24.2974	20.68133
							102.9221	**127.6791**	**184.6461**	**138.4158**

Table 14 - Inputs (A)

Inputs - A									
	Y1	Y2	Y3	Y1	Y2	Y3	Y1	Y2	Y3
Company	TA			GNP			TL		
Anheuser-Bush InBev	232103000000	258381000000	134635000000	104.7	100	93.7	160199000000	176956000000	88916000000
Barclays Africa Group	1165979000000	1165067000000	123969000000	104.7	100	93.7	1046919000000	1056759000000	109502000000
Anglo American	54561000000	50149000000	52839000000	104.7	100	93.7	25679000000	25824000000	30671000000
Aspen	116300000000	104300000000	88400000000	104.7	100	93.7	73200000000	61800000000	54300000000
BHP Billiton	117006000000	118953000000	124580000000	104.7	100	93.7	54280000000	58882000000	54035000000
British American Tobacco	141038000000	39773000000	31515000000	104.7	100	93.7	80012000000	31367000000	26483000000
FirstRand	1217707000000	1149277000000	1059266000000	104.7	100	93.7	1100523000000	1041212000000	960662000000
Glencore	135593000000	124600000000	128485000000	104.7	100	93.7	86138000000	80819000000	87142000000
Mondi	7209000000	7310000000	6469000000	104.7	100	93.7	3170000000	3614000000	3282000000
MTN	242415000000	268700000000	313867000000	104.7	100	93.7	148148000000	163469000000	313867000000
Naspers	21930000000	16723000000	12936000000	104.7	100	93.7	6569000000	6069000000	6033000000
Nedbank	903961000000	900061000000	860733000000	104.7	100	93.7	829807000000	832339000000	800779000000
Old Mutual	768495000000	723298000000	620092000000	104.7	100	93.7	724467000000	679865000000	572540000000
Richemont	20160000000	20125000000	20450000000	104.7	100	93.7	6030000000	3960000000	4631000000
Sanlam	681018000	615329000	674508000	104.7	100	93.7	611327000	552218000	614316000

	000	000	000				000	000	000
Sasol	398939000000	390714000000	323599000000	104.7	100	93.7	181705000000	178296000000	127116000000
Shoprite	55723000000	48001000000	43652000000	104.7	100	93.7	27974000000	26862000000	24759000000
South32	14733000000	13374000000	15489000000	104.7	100	93.7	4498000000	3952000000	4454000000
Standard Bank	2027928000000	1951974000000	1983028000000	104.7	100	93.7	1837911000000	1772615000000	1804120000000
Vodacom	81138000000	78703000000	71307000000	104.7	100	93.7	58142000000	55679000000	49664000000

Inputs - A											
Y1	**Y2**	**Y3**	**Y1**	**Y2**	**Y3**	**Y1**	**Y2**	**Y3**	**Y1**	**Y2**	**Y3**
WC			**CL**			**CA**			**X**		
-161780000000	29450000000	-101620000000	34459000000	40116000000	28456000000	18281000000	43061000000	18294000000	0	0	0
302680000000	195160000000	516442690000	219104000000	228944000000	113206580000	249372000000	248460000000	629649270000	0	0	0
72530000000	59240000000	79310000000	73510000000	65250000000	58390000000	14604000000	12449000000	13770000000	0	0	0
33000000000	161000000000	109000000000	34800000000	21100000000	21800000000	38100000000	37200000000	32700000000	0	0	0
96900000000	53740000000	35160000000	11366000000	12340000000	12853000000	21056000000	17714000000	16369000000	0	0	0
-15780000000	5030000000	8080000000	15544000000	11856000000	9006000000	13966000000	12359000000	9814000000	0	0	0
735700000000	687920000000	622500000000	18318000000	18605000000	18795000000	91888000000	87397000000	81045000000	0	0	0
50390000000	450000000	13260000000	44255000000	43367000000	40872000000	49294000000	43412000000	42198000000	0	0	0
5300000000	4260000000	4900000000	15250000000	19180000000	14530000000	20550000000	23440000000	19430000000	0	0	0
-52160000000	18850000000	59130000000	65116000000	77726000000	89519000000	59900000000	79611000000	95432000000	0	0	0
27110000000	11910000000	5190000000	29280000000	20460000000	21810000000	56390000000	32370000000	27000000000	0	0	0
826750000000	1017470000000	693180000000	38150000000	13913000000	44757000000	120825000000	115660000000	114075000000	0	0	0
230980000000	395380000000	211290000000	22058000000	19837000000	53137000000	45156000000	59375000000	74266000000	0	0	0
108400000000	87130000000	105330000000	50880000000	31130000000	39000000000	15928000000	11826000000	14433000000	0	0	0
60120000000	106040000000	104300000000	35574000000	31633000000	55071000000	41586000000	42237000000	65501000000	0	0	0

35781000000	66531000000	65336000000	52173000000	41602000000	41342000000	87954000000	108133000000	106678000000	0	0	0
4550000000	1981000000	5953000000	26482000000	25370000000	19100000000	31032000000	27351000000	25053000000	0	0	0
2588000000	1291000000	1164000000	1744000000	1377000000	1704000000	4332000000	2668000000	2868000000	0	0	0
165558000000	147139000000	88175000000	148365000000	128951000000	182760000000	313923000000	276090000000	270935000000	0	0	0
2292000000	1848000000	-1261000000	26719000000	25770000000	26614000000	29011000000	27618000000	25353000000	0	0	0

Inputs - A											
Y1	**Y2**	**Y3**	**Y1**	**Y2**	**Y3**	**Y1**	**Y2**	**Y3**	**Y1**	**Y2**	**Y3**
NI			**NI_t-1**			**FFO**			**Y**		
853000000	433400000	1246100000	569100000	276900000	986700000	1782100000	1327600000	1376800000	0	0	0
2087900000	2276900000	146214000	1502200000	1650400000	130594900	7330500000	7290000000	458547100	0	0	0
550500000	262400000	-545400000	405900000	192600000	-584200000	552900000	166600000	-411200000	0	0	1
620000000	610000000	650000000	510000000	430000000	520000000	830000000	90000000	840000000	0	0	0
1032200000	-725900000	805600000	622200000	-602700000	439000000	1175300000	-6235000000	867000000	0	0	0
2959100000	624500000	585500000	3770400000	483900000	452200000	647600000	465500000	455700000	0	0	0
3315700000	3068700000	208400000	2613900000	2407500000	1560100000	3320000000	3015900000	5508900000	0	0	0
516200000	-54900000	837900000	516200000	-118700000	-811400000	20547600000	15294800000	14735100000	1	1	1
88700000	94400000	79600000	71400000	68600000	64500000	95700000	94300000	90000000	0	0	0
955500000	524300000	3489200000	454100000	-310300000	2357000000	13940600000	14825500000	6841200000	0	0	0
305200000	126100000	159800000	280800000	100100000	126000000	-36000000	-17700000	16100000	0	0	0
1472100000	1322300000	1103800000	1115800000	993700000	821000000	4207700000	3962500000	3531000000	0	0	0
1085000000	1137100000	351900000	718800000	740200000	305000000	5378100000	5582300000	4743100000	0	0	0
157000000	205800000	170500000	121000000	168800000	133600000	176400000	206100000	267000000	0	0	0
1807800000	1305700000	1476900000	1409300000	1047400000	1091000000	1616100000	1152700000	1403900000	0	0	0

300080000000	237180000000	455930000000	215130000000	150270000000	311620000000	317050000000	242390000000	465490000000	0	0	0
76150000000	72240000000	59820000000	54350000000	48500000000	41340000000	81270000000	72810000000	63280000000	0	0	0
16240000000	-15450000000	-3980000000	12310000000	-16150000000	-5280000000	69500000000	58120000000	38430000000	1	1	0
411940000000	347260000000	265850000000	307150000000	257940000000	207120000000	1275560000000	1212220000000	911130000000	0	0	0
192280000000	188440000000	178510000000	131260000000	129100000000	125100000000	217500000000	210590000000	192350000000	0	0	0

Table 15 - Inputs (B)

Inputs - B									
	Y1	Y2	Y3	Y1	Y2	Y3	Y1	Y2	Y3
Company		**TA**			**GNP**			**TL**	
Holdsport Ltd.	1398743000	1318113000	1250526000	104.7	100	93.7	374691000	341510000	315821000
International Hotel Properties Ltd.	113366936	93636166	16715529	104.7	100	93.7	60859713	41574651	14338655
Evraz Highveld Steel & Vanadium Ltd.	3738000000	3588000000	3667000000	104.7	100	93.7	2569000000	2127000000	1958000000
Moneyweb Holdings Ltd.	22084000	27396000	28805000	104.7	100	93.7	4537000	4926000	3318000
M-Fitec International Ltd.	75576000	778725000	75312000	104.7	100	93.7	1242000	4149000	2017000
Metmar Trading Ltd.	1219340000	1570338000	1642228000	104.7	100	93.7	925628000	1127989000	997826000
Rockcastle Global Real Estate Ltd.	2079302000	2326505000	1606576000	104.7	100	93.7	522664000	1085377000	623392000
Oakbay Resources and Energy Ltd.	11229881000	8308024000	7339792000	104.7	100	93.7	3311190000	2575384000	2597637000
The Pivotal Fund Ltd.	13757896000	10310153886	2398168549	104.7	100	93.7	7266960000	5460650100	1241029300
Lodestone Reit Ltd.	1724961000	1133769000	1137942000	104.7	100	93.7	198389000	361437000	747625000
Gooderson Leisure Corporation Ltd.	304389889	294975693	273966273	104.7	100	93.7	112914080	103772483	87808888
Giyani Gold Corporation	2197453	1052187	1505842	104.7	100	93.7	510314	1233823	2450334
Datacentrix Holdings Ltd.	1185035000	980918000	962531000	104.7	100	93.7	494301000	368493000	424588000
Ascension Properties Ltd.	4331778000	3903830000	3823852000	104.7	100	93.7	1668446000	1601923000	2951118000
Masonite Africa Ltd.	1475861	1499149	604362	104.7	100	93.7	816085	843583	216571

	000	000	000				000	000	000
Astrapak Ltd.	1840507000	2094539000	2297724000	104.7	100	93.7	763863000	1019964000	1082976000
Keaton Energy Holdings Ltd.	1494811387	1877369117	1871867382	104.7	100	93.7	1001968490	1039111491	934397101
Cadiz Holdings Ltd.	6668993000	6663913000	5995861000	104.7	100	93.7	6272488000	6008536000	5322952000
Illovo Sugar Ltd.	15631500000	14826500000	13819800000	104.7	100	93.7	8865300000	7150800000	6351200000
Infrasors Holdings Ltd.	324130000	326506000	368337000	104.7	100	93.7	173976000	188573000	227711000

Inputs - B											
Y1	**Y2**	**Y3**	**Y1**	**Y2**	**Y3**	**Y1**	**Y2**	**Y3**	**Y1**	**Y2**	**Y3**
WC			**CL**			**CA**			**X**		
517330000	301330000	400637000	141432000	276944000	121229000	658762000	578274000	521866000	0	0	0
188795	342020	-5744509	5848305	5610907	6905425	6037100	5952927	1160916	0	0	0
276000000	495000000	697000000	1796000000	1370000000	1169000000	2072000000	1865000000	1866000000	0	0	0
15798000	20484000	24732000	4537000	4926000	3318000	20335000	25410000	28050000	0	0	0
74163000	74576000	73295000	1242000	4149000	2017000	75405000	78725000	75312000	0	0	0
-67321000	51773000	183134000	844062000	1092625000	917107000	776741000	1144398000	1100241000	0	0	0
714566000	-43154000	30297237	145800000	150692000	1068763	860366000	107538000	31366000	0	0	0
-15972000	16735000	13402000	280460000	487415000	431116000	264488000	504150000	444518000	0	0	0
-483096000	68056000	279481422	1076149000	429611000	51382104	593053000	497667000	330863526	0	0	0
9336000	-34740000	87917000	20947000	46345000	60532000	30283000	11605000	148449000	0	0	0
-25681431	-14569219	-8491089	49022271	37479039	29199969	23340840	22909820	20708880	0	0	0
-56447	-1008204	-2364145	510314	1233823	2450334	453867	225619	86189	0	1	1
468856	432135	370869	464919	348604	385321	933775	780739	756190	0	0	0
-357149000	-7934000	-69090000	619109000	175267000	170044000	261960000	167333000	100954000	0	0	0
356559000	326428000	147913000	231178000	232518000	92485000	587737000	558946000	240398000	0	0	0

172468000	73870000	201907000	349087000	398168000	617284000	521555000	472038000	819191000	0	0	0
-120314585	-42932082	-20668649	394390142	350946531	280094984	274075557	308014449	259426335	0	0	0
41096000	154582000	163282000	54325000	36183000	84930000	95421000	190765000	248212000	0	0	0
1629400000	1957200000	1894400000	4187600000	3396400000	3030400000	5817000000	5353600000	4924800000	0	0	0
7405000	19171000	6369000	79552000	62246000	69827000	86957000	81417000	76196000	0	0	0

Inputs - B											
Y1	**Y2**	**Y3**	**Y1**	**Y2**	**Y3**	**Y1**	**Y2**	**Y3**	**Y1**	**Y2**	**Y3**
NI			**NI_t-1**			**FFO**			**Y**		
266053000	304128000	261839000	191195000	218776000	187895000	273688000	308925000	266744000	0	0	0
2336094	-723581	-284806	1904558	-806910	-284806	3438857	831375	-284806	1	1	1
-295000000	-360000000	-898000000	-302000000	-379000000	-943000000	23000000	-293000000	-529000000	1	1	1
-4961000	-3089000	-2529000	-4923000	-3017000	-2636000	-6175	-4044000	-3371000	1	1	1
868000	1196000	262000	619000	861000	189000	868000	1196000	262000	0	1	1
-142155000	-165714000	-146649000	-147059000	-160778000	-129422000	-38505000	34217000	-38684000	1	1	1
274929000	10152000	142618000	268091000	10132000	142011000	277585000	19523000	164792000	0	0	0
-85739000	-38940000	-236025000	-68204000	-38940000	-236025000	-51655000	23172000	-137624000	1	1	1
1145732000	620825560	321404290	833138000	449302221	258358888	1528715000	884437717	394039949	0	0	0
164372000	96682000	122880000	162940000	177662000	100877000	99972000	127066000	188613000	0	0	0
5443142	9911545	8474030	4119742	7560970	6342830	17474055	19985000	10676047	0	0	0
-1324009	351048	-11704170	-1324009	351048	-11704170	-1482514	-1197873	-11746997	1	1	1
173480000	146457000	126464000	123171000	103477000	88925000	173480000	146457000	126464000	0	0	0
515200000	22920000	210072000	515200000	22920000	210072000	366916000	78028000	291537000	0	0	0

126681000	-27569000	-93089000	104142000	-41741000	-70614000	152900000	31604000	-92089000	1	0	0
21567000	3855000	-42936000	6680000	-11036000	-30571000	44289000	61511000	40935000	1	0	0
-170667256	-12889063	102397578	-168499627	-71854907	64422088	-116507434	36853506	150130955	0	0	0
-269381000	10132000	8912000	-251276000	7800000	5109000	-240047000	14099000	20411000	0	0	0
1007000000	1331800000	1605300000	672500000	943800000	1118500000	1410200000	1655100000	1886900000	0	0	0
11344000	184000	-320684000	15360000	4907000	-305608000	20148000	15125000	-27966000	0	1	1

Table 16 - Values (A)

Values - A												
	Y1	Y2	Y3	Y1	Y2	Y3	Y1	Y2	Y3	Y1	Y2	Y3
Company	**Value 1**			**Value 2**			**Value 3**			**Value 4**		
Anheuser-Bush InBev	9.346	9.412	9.157	0.690	0.685	0.660	-0.885	0.068	-0.555	0.148	0.155	0.211
Barclays Africa Group	10.047	10.066	9.122	0.898	0.907	0.883	0.121	0.079	0.820	0.010	0.197	0.091
Anglo American	8.717	8.700	8.751	0.471	0.515	0.580	0.497	0.476	0.576	0.135	0.130	0.111
Aspen	9.046	9.018	8.975	0.629	0.593	0.614	0.087	0.433	0.333	0.299	0.202	0.247
BHP Billiton	9.048	9.075	9.124	0.464	0.495	0.434	0.460	0.303	0.215	0.097	0.104	0.103
British American Tobacco	9.129	8.600	8.527	0.567	0.789	0.840	-0.113	0.041	0.082	0.110	0.226	0.286
FirstRand	10.066	10.060	10.053	0.904	0.906	0.907	0.801	0.787	0.768	0.015	0.016	0.018
Glencore	9.112	9.096	9.137	0.635	0.649	0.678	0.102	0.001	0.031	0.326	0.348	0.318
Mondi	7.838	7.864	7.839	0.440	0.494	0.507	0.258	0.182	0.252	0.212	0.262	0.225
MTN	9.365	9.429	9.525	0.611	0.608	1.000	-0.087	0.024	0.062	0.269	0.289	0.285
Naspers	8.321	8.223	8.140	0.300	0.363	0.466	0.481	0.368	0.192	0.134	0.122	0.169
Nedbank	9.936	9.954	9.963	0.918	0.925	0.930	0.684	0.880	0.608	0.042	0.015	0.052
Old Mutual	9.866	9.859	9.821	0.943	0.940	0.923	0.512	0.666	0.285	0.029	0.027	0.086
Richemont	8.285	8.304	8.339	0.299	0.197	0.226	0.681	0.737	0.730	0.252	0.155	0.191
Sanlam	9.813	9.789	9.857	0.898	0.897	0.911	0.145	0.251	0.159	0.052	0.051	0.082
Sasol	9.581	9.592	9.538	0.455	0.456	0.393	0.407	0.615	0.612	0.131	0.106	0.128
Shoprite	8.726	8.681	8.668	0.502	0.560	0.567	0.147	0.072	0.238	0.475	0.529	0.438
South32	8.148	8.126	8.218	0.305	0.295	0.288	0.597	0.484	0.406	0.118	0.103	0.110
Standard Bank	10.287	10.290	10.326	0.906	0.908	0.910	0.527	0.533	0.325	0.073	0.066	0.092
Vodacom	8.889	8.896	8.881	0.717	0.707	0.696	0.079	0.067	-0.050	0.329	0.327	0.373

Values - A														
Y1	**Y2**	**Y3**	**Y1**	**Y2**	**Y3**	**Y1**	**Y2**	**Y3**	**Y1**	**Y2**	**Y3**	**Y1**	**Y2**	**Y3**
Value 5			**Value 6**			**Value 7**			**Value 8**			**Value 9**		
0	0	0	0.037	0.017	0.093	0.111	0.075	0.155	0	0	0	0.200	0.220	0.116
0	0	0	0.018	0.020	0.012	0.070	0.069	0.042	0	0	0	0.163	0.160	0.056
0	0	0	0.101	0.052	-0.103	0.215	0.065	-0.134	0	0	1	0.151	0.153	0.034
0	0	0	0.044	0.058	0.074	0.113	0.015	0.155	0	0	0	0.097	0.173	0.111
0	0	0	0.088	-0.061	0.065	0.217	-0.106	0.160	0	0	0	0.248	-0.093	0.295
0	0	0	0.210	0.157	0.186	0.081	0.148	0.172	0	0	0	-0.121	0.127	0.128
0	0	0	0.027	0.027	0.002	0.030	0.029	0.057	0	0	0	0.118	0.121	-0.764
0	0	0	0.038	-0.004	0.065	2.385	1.892	1.691	1	1	1	0.000	0.368	1.000
0	0	0	0.123	0.129	0.123	0.302	0.261	0.274	0	0	0	0.108	0.158	0.105
0	0	0	0.039	0.020	0.111	0.941	0.907	0.218	0	0	0	0.356	1.000	0.194
0	0	0	0.139	0.075	0.124	-0.055	-0.029	0.027	0	0	0	0.042	0.115	0.118
0	0	0	0.016	0.015	0.013	0.051	0.048	0.044	0	0	0	0.138	0.142	0.147
0	0	0	0.014	0.016	0.006	0.074	0.082	0.083	0	0	0	0.203	0.211	0.071
0	0	0	0.078	0.102	0.083	0.293	0.520	0.577	0	0	0	0.129	0.099	0.121
0	0	0	0.027	0.021	0.022	0.026	0.021	0.023	0	0	0	0.124	0.110	0.150
0	0	0	0.075	0.061	0.141	0.174	0.136	0.366	0	0	0	0.165	0.224	0.188
0	0	0	0.137	0.150	0.137	0.291	0.271	0.256	0	0	0	0.167	0.197	0.183
0	0	0	0.110	-0.116	-0.026	1.545	1.471	0.863	1	1	0	0.138	0.022	0.140
0	0	0	0.020	0.018	0.013	0.069	0.068	0.051	0	0	0	0.146	0.148	0.124
0	0	0	0.237	0.239	0.250	0.374	0.378	0.387	0	0	0	0.189	0.187	0.176

Table 17 - Values (B)

Values - B												
	Y1	Y2	Y3	Y1	Y2	Y3	Y1	Y2	Y3	Y1	Y2	Y3
Company	Value 1			Value 2			Value 3			Value 4		
Holdsport Ltd.	7.126	7.120	7.125	0.268	0.259	0.253	0.785	0.521	0.768	0.101	0.210	0.097
International Hotel Properties Ltd.	6.035	5.971	5.251	0.537	0.444	0.858	0.031	0.057	-4.948	0.052	0.060	0.413
Evraz Highveld Steel & Vanadium Ltd.	7.553	7.555	7.593	0.687	0.593	0.534	0.133	0.265	0.374	0.480	0.382	0.319
Moneyweb Holdings Ltd.	5.324	5.438	5.488	0.205	0.180	0.115	0.777	0.806	0.882	0.205	0.180	0.115
M-Fitec International Ltd.	5.858	6.891	5.905	0.016	0.005	0.027	0.984	0.947	0.973	0.016	0.005	0.027
Metmar Trading Ltd.	7.066	7.196	7.244	0.759	0.718	0.608	-0.087	0.045	0.166	0.692	0.696	0.558
Rockcastle Global Real Estate Ltd.	7.298	7.367	7.234	0.251	0.467	0.388	0.831	-0.401	0.966	0.070	0.065	0.001
Oakbay Resources and Energy Ltd.	8.030	7.919	7.894	0.295	0.310	0.354	-0.060	0.033	0.030	0.025	0.059	0.059
The Pivotal Fund Ltd.	8.119	8.013	7.408	0.528	0.530	0.517	-0.815	0.137	0.845	0.078	0.042	0.021
Lodestone Reit Ltd.	7.217	7.055	7.084	0.115	0.319	0.657	0.308	-2.994	0.592	0.012	0.041	0.053
Gooderson Leisure Corporation Ltd.	6.463	6.470	6.466	0.371	0.352	0.321	-1.100	-0.636	-0.410	0.161	0.127	0.107
Giyani Gold Corporation	4.322	4.022	4.206	0.232	1.173	1.627	-0.124	-4.469	-27.430	0.232	1.173	1.627
Datacentrix Holdings Ltd.	7.054	6.992	7.012	0.417	0.376	0.441	0.502	0.553	0.490	0.000	0.000	0.000
Ascension Properties Ltd.	7.617	7.591	7.611	0.385	0.410	0.772	-1.363	-0.047	-0.684	0.143	0.045	0.044
Masonite Africa Ltd.	7.149	7.176	6.810	0.553	0.563	0.358	0.607	0.584	0.615	0.157	0.155	0.153
Astrapak Ltd.	7.245	7.321	7.390	0.415	0.487	0.471	0.331	0.156	0.246	0.190	0.190	0.269
Keaton Energy Holdings Ltd.	7.155	7.274	7.301	0.670	0.553	0.499	-0.439	-0.139	-0.080	0.264	0.187	0.150
Cadiz Holdings Ltd.	7.804	7.824	7.806	0.941	0.902	0.888	0.431	0.810	0.658	0.008	0.005	0.014
Illovo Sugar Ltd.	8.174	8.171	8.169	0.567	0.482	0.460	0.280	0.366	0.385	0.268	0.229	0.219
Infrasors Holdings Ltd.	6.491	6.514	6.595	0.537	0.578	0.618	0.085	0.235	0.084	0.245	0.191	0.190

Values - B														
Y1	**Y2**	**Y3**	**Y1**	**Y2**	**Y3**	**Y1**	**Y2**	**Y3**	**Y1**	**Y2**	**Y3**	**Y1**	**Y2**	**Y3**
Value 5			**Value 6**			**Value 7**			**Value 8**			**Value 9**		
0	0	0	0.190	0.231	0.209	0.730	0.905	0.845	0	0	0	0.164	0.163	0.164
0	0	0	0.021	-0.008	-0.017	0.057	0.020	-0.020	0	0	0	0.102	0.054	0.000
0	0	0	-0.079	-0.100	-0.245	0.009	-0.138	-0.270	0	0	1	0.012	0.026	0.024
0	0	0	-0.225	-0.113	-0.088	-0.001	-0.821	-1.016	0	0	0	-0.004	-0.012	0.021
0	0	0	0.011	0.002	0.003	0.699	0.288	0.130	0	0	0	0.167	0.163	0.162
0	0	0	-0.117	-0.106	-0.089	-0.042	0.030	-0.039	0	0	0	0.017	-0.015	-0.062
0	0	0	0.132	0.004	0.089	0.531	0.018	0.264	0	0	0	0.013	0.001	0.002
0	0	0	-0.008	-0.005	-0.032	-0.016	0.009	-0.053	1	1	1	-0.114	0.000	0.000
0	0	0	0.083	0.060	0.134	0.210	0.162	0.318	0	0	0	0.158	0.160	0.109
0	0	0	0.095	0.085	0.108	0.504	0.352	0.252	0	0	0	0.004	-0.295	0.098
0	0	0	0.018	0.034	0.031	0.155	0.193	0.122	0	0	0	0.138	0.135	0.144
0	0	0	-0.603	0.334	-7.773	-2.905	-0.971	-4.794	0	0	0	0.000	0.000	0.000
0	0	0	0.146	0.149	0.131	0.351	0.397	0.298	0	0	0	0.170	0.172	0.174
0	0	0	0.119	0.006	0.055	0.220	0.049	0.099	0	0	0	0.000	0.000	0.000
0	0	0	0.086	-0.018	-0.154	0.187	0.037	-0.425	0	0	0	0.098	0.204	-0.137
0	0	0	0.012	0.002	-0.019	0.058	0.060	0.038	0	0	0	0.527	1.000	-0.168
0	0	0	-0.114	-0.007	0.055	-0.116	0.035	0.161	0	0	0	-0.006	0.696	0.228
0	0	0	-0.040	0.002	0.001	-0.038	0.002	0.004	1	1	0	-0.035	0.130	0.271
0	0	0	0.064	0.090	0.116	0.159	0.231	0.297	0	0	0	0.199	0.171	0.179
0	0	0	0.035	0.001	-0.871	0.116	0.080	-0.123	0	0	0	-0.150	-0.928	-0.024

Table 18 - O-score (A)

O-score - A									
	Y1	Y2	Y3		Y1	Y2	Y3		
Company	O-score			Average	Default probability			Average	Coefficients
Anheuser-Bush InBev	-0.07972	-1.39894	-0.81762	-0.76543	48%	20%	31%	33%	-1.32
Barclays Africa Group	-0.42316	-0.30069	-1.00614	-0.57666	40%	43%	27%	36%	-0.407
Anglo American	-3.44171	-2.74851	-1.43974	-2.54332	3%	6%	19%	9%	6.03
Aspen	-1.6696	-2.27655	-2.24201	-2.06272	16%	9%	10%	12%	-1.43
BHP Billiton	-3.59045	-2.06807	-3.31761	-2.99204	3%	11%	3%	6%	0.0757
British American Tobacco	-2.02743	-0.81532	-0.64144	-1.1614	12%	31%	34%	26%	-1.72
FirstRand	-1.29218	-1.25514	-0.75142	-1.09958	22%	22%	32%	25%	-2.37
Glencore	-5.49006	-4.44505	-4.45491	-4.79667	0%	1%	1%	1%	-1.83
Mondi	-3.11164	-2.64549	-2.64291	-2.80001	4%	7%	7%	6%	0.285
MTN	-3.30216	-3.72813	0.003067	-2.34241	4%	2%	50%	19%	-0.521
Naspers	-3.82905	-3.18063	-2.48611	-3.16526	2%	4%	8%	5%	
Nedbank	-1.0071	-1.24777	-0.81765	-1.02417	27%	22%	31%	27%	
Old Mutual	-0.65518	-0.91267	-0.35205	-0.63997	34%	29%	41%	35%	
Richemont	-4.62967	-5.80121	-5.69349	-5.37479	1%	0%	0%	1%	
Sanlam	-0.27965	-0.39343	-0.23354	-0.30221	43%	40%	44%	43%	
Sasol	-3.62829	-3.85349	-4.80153	-4.09444	3%	2%	1%	2%	
Shoprite	-2.9606	-2.49751	-2.62217	-2.69343	5%	8%	7%	6%	
South32	-6.5163	-5.67373	-5.09411	-5.76138	0%	0%	1%	0%	
Standard Bank	-1.04156	-1.0336	-0.68384	-0.91966	26%	26%	34%	29%	
Vodacom	-2.04947	-2.10256	-2.02929	-2.06044	11%	11%	12%	11%	
	-2.55125	**-2.41892**	**-2.10623**	**-2.3588**	**15%**	**15%**	**20%**	**16%**	

Table 19 - O-score (B)

	O-score - B							
	Y1	Y2	Y3		Y1	Y2	Y3	
Company		O-score		Average	Default probability			Average
Holdsport Ltd.	-5.59302	-5.67202	-5.91514	-5.72673	0%	0%	0%	0%
International Hotel Properties Ltd.	-0.785	-1.19732	8.899257	2.305649	31%	23%	100%	52%
Evraz Highveld Steel & Vanadium Ltd.	-0.2393	-0.69434	-0.35339	-0.42901	44%	33%	41%	40%
Moneyweb Holdings Ltd.	-2.8066	-1.81236	-2.05453	-2.2245	6%	14%	11%	10%
M-Fitec International Ltd.	-6.40389	-6.06291	-5.28185	-5.91622	0%	0%	1%	0%
Metmar Trading Ltd.	0.901508	0.273081	-0.48498	0.22987	71%	57%	38%	55%
Rockcastle Global Real Estate Ltd.	-5.24874	-0.97012	-4.00099	-3.40661	1%	27%	2%	10%
Oakbay Resources and Energy Ltd.	-2.33117	-2.43739	-1.97925	-2.24927	9%	8%	12%	10%
The Pivotal Fund Ltd.	-0.93306	-2.10269	-3.37628	-2.13734	28%	11%	3%	14%
Lodestone Reit Ltd.	-5.15396	1.323315	-1.85335	-1.89467	1%	79%	14%	31%
Gooderson Leisure Corporation Ltd.	-0.52589	-1.41499	-1.79531	-1.2454	37%	20%	14%	24%
Giyani Gold Corporation	5.261038	11.57879	73.32197	30.05393	99%	100%	100%	100%
Datacentrix Holdings Ltd.	-3.47121	-3.86261	-3.16238	-3.49873	3%	2%	4%	3%
Ascension Properties Ltd.	-0.82134	-1.9672	0.9072	-0.62711	31%	12%	71%	38%
Masonite Africa Ltd.	-2.3482	-1.80233	-1.58421	-1.91158	9%	14%	17%	13%
Astrapak Ltd.	-2.63306	-2.20841	-1.75482	-2.19876	7%	10%	15%	10%
Keaton Energy Holdings Ltd.	0.944385	-1.14045	-1.69829	-0.63145	72%	24%	15%	37%
Cadiz Holdings Ltd.	1.028837	-0.0163	-0.23531	0.259076	74%	50%	44%	56%
Illovo Sugar Ltd.	-2.15479	-2.96808	-3.31903	-2.81397	10%	5%	3%	6%
Infrasors Holdings Ltd.	-1.04488	-0.4756	1.919362	0.132962	26%	38%	87%	51%
	-1.71792	**-1.1815**	**2.309933**	**-0.19649**	**28%**	**26%**	**30%**	**28%**

Coefficients
-1.32
-0.407
6.03
-1.43
0.0757
-1.72
-2.37
-1.83
0.285
-0.521

Table 20 - Liquidity accuracy (A)

Liquidity Accuracy - A										
Company	**CR**	**S/D**	**QR**	**S/D**	**RT**	**S/D**	**PT**	**S/D**	**IT**	**S/D**
Anheuser-Bush InBev	0.7927	D	0.6887	D	34.4745	S	265.3331	D	70.4942	D
Barclays Africa Group	2.2979	S	1.9320	S	11.7314	S	56.5946	S	55.7824	D
Anglo American	2.0843	S	1.4612	S	29.8002	S	74.2150	D	69.1510	D
Aspen	1.1696	S	0.7776	D	90.2461	D	75.7646	D	22.8689	S
BHP Billiton	1.6691	S	1.5871	S	20.8323	S	46.1756	S	46.3504	S
British American Tobacco	1.3179	S	0.5146	D	63.9242	D	87.5307	D	31.1721	S
FirstRand	1.6660	S	1.5151	S	49.4698	S	227.4123	D	14.2148	S
Glencore	1.0524	S	0.5807	D	23.4873	S	49.1873	S	44.5962	S
Mondi	1.3023	S	0.7728	D	47.2849	S	50.4116	S	80.0658	D
MTN	1.0034	S	0.8642	S	52.9152	D	87.4480	D	67.2777	D
Naspers	1.5820	S	1.4928	S	23.8145	S	46.5070	S	20.5370	S
Nedbank	1.1028	S	0.2134	D	37.6748	S	10.8035	S	61.5538	D
Old Mutual	0.5348	D	0.5006	D	26.2177	S	44.1693	S	21.1002	S
Richemont	2.6404	S	1.6656	S	23.7181	S	59.1951	S	35.4156	S
Sanlam	1.0838	S	0.6371	D	17.1612	S	66.8757	D	74.5003	D
Sasol	2.3681	S	1.7520	S	84.4695	D	55.8729	S	22.9718	S
Shoprite	1.1872	S	0.5329	D	48.3192	S	39.9728	S	56.6050	D
South32	3.1978	S	2.4691	S	33.1245	S	42.1248	S	36.3554	S
Standard Bank	1.1960	S	0.4183	D	43.9853	S	29.4806	S	46.6248	S
Vodacom	1.0367	S	0.9843	S	44.3968	S	10.4165	S	16.2405	S
Total Safe		**18**		**10**		**16**		**13**		**12**
Accuracy		**90%**		**50%**		**80%**		**65%**		**60%**

Legend	
Safe	S
Distress	D
Rules of Thumb	
Current ratio	1
Quick ratio	0.8
Receivables turnover	50
Payables turnover	60
Inventory turnover	50

Table 21 - Liquidity accuracy (B)

Liquidity Accuracy - B										
Company	**CR**	**S/D**	**QR**	**S/D**	**RT**	**S/D**	**PT**	**S/D**	**IT**	**S/D**
Holdsport	3.6835	S	0.9198	D	6.0822	S	55.39	S	182.5	D
International Hotel Properties	0.7538	D	0.7522	D	27.6717	S	196.35	D	7.651	S
Evraz Highveld Steel & Vanadium	1.3704	D	0.5778	D	21.0930	S	37.39	S	55.44	D
Moneyweb Holdings	6.0314	S	1.9365	S	39.3537	S	77.90	D	1491	D
M-Fitec International	39.0085	S	39.0085	S	0.0000	D	0.00	D	0	D
Metmar Trading	1.0558	D	0.5650	D	92.5898	D	53.29	S	98.58	D
Rockcastle Global Real Estate	2.2147	S	1.4237	S	116.065	D	1178.2	D	180.5	D
Oakbay Resources and Energy	1.0028	D	0.4921	D	54.1932	D	155.82	D	359.4	D
The Pivotal Fund	0.5698	D	0.5698	D	3.6304	S	171.61	D	0	D
Lodestone Reit	1.3828	D	1.3828	S	11.0014	S	37.35	S	0	D
Gooderson Leisure Corporation	0.5989	D	0.5438	D	30.1088	S	101.00	D	35.75	S
Giyani Gold Corporation	0.3691	D	0.3691	D	45.2888	S	507.13	D	0	D
Datacentrix Holdings	2.0702	S	1.8911	S	78.6428	D	47.85	S	16.59	S
Ascension Properties	0.6572	D	0.5715	D	20.4966	S	72.55	D	133.6	D
Masonite Africa	2.5152	S	1.5589	S	45.2356	S	31.73	S	54.10	D
Astrapak	1.3356	D	0.9033	D	73.9499	D	97.33	D	71.84	D
Keaton Energy Holdings	0.8329	D	0.7088	D	38.5152	S	56.85	S	15.62	S
Cadiz Holdings	3.3171	S	3.3171	S	30.6600	S	340.51	D	0	D
Illovo Sugar	1.5302	S	1.2413	S	32.8953	S	44.69	S	44.87	S
Infrasors Holdings	1.1641	D	0.9543	D	57.2894	D	60.80	D	20.68	S
Total Distressed		**12**		**12**		**7**		**12**		**14**
Accuracy		**60%**		**60%**		**35%**		**60%**		**70%**

Legend	
Safe	S
Distress	D
Rules of Thumb	
Current ratio	1.5
Quick ratio	1
Receivables turnover	50
Payables turnover	60
Inventory turnover	50

Table 22 - O-score accuracy (B)

O-score Accuracy - B		
Company	**O-score**	**S/D**
Holdsport	-5.72673	S
International Hotel Properties	2.305649	D
Evraz Highveld Steel & Vanadium	-0.42901	S
Moneyweb Holdings	-2.2245	S
M-Fitec International	-5.91622	S
Metmar Trading	0.22987	D
Rockcastle Global Real Estate	-3.40661	S
Oakbay Resources and Energy	-2.24927	S
The Pivotal Fund	-2.13734	S
Lodestone Reit	-1.89467	S
Gooderson Leisure Corporation	-1.2454	S
Giyani Gold Corporation	30.05393	D
Datacentrix Holdings	-3.49873	S
Ascension Properties	-0.62711	S
Masonite Africa	-1.91158	S
Astrapak	-2.19876	S
Keaton Energy Holdings	-0.63145	S
Cadiz Holdings	0.259076	D
Illovo Sugar	-2.81397	S
Infrasors Holdings	0.132962	D
Total Distressed		**5**
Accuracy		**25%**

Table 23 - O-score accuracy (A)

O-score Accuracy - A		
Company	**O-score**	**S/D**
Anheuser-Bush InBev	-0.76543	S
Barclays Africa Group	-0.57666	S
Anglo American	-2.54332	S
Aspen	-2.06272	S
BHP Billiton	-2.99204	S
British American Tobacco	-1.1614	S
FirstRand	-1.09958	S
Glencore	-4.79667	S
Mondi	-2.80001	S
MTN	-2.34241	S
Naspers	-3.16526	S
Nedbank	-1.02417	S
Old Mutual	-0.63997	S
Richemont	-5.37479	S
Sanlam	-0.30221	S
Sasol	-4.09444	S
Shoprite	-2.69343	S
South32	-5.76138	S
Standard Bank	-0.91966	S
Vodacom	-2.06044	S
Total Safe		**20**
Accuracy		**100%**