ASSESSING CORPORATE FINANCIAL DISTRESS IN SOUTH AFRICA

By

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DECLARATION

I, Bothwell Farai Hlahla declare that the research work reported in this dissertation is my own, except where otherwise indicated and acknowledged. It is submitted for the degree of Master of Management in Finance and Investment in the University of the Witwatersrand, Johannesburg, South Africa. This thesis has not, either in whole or in part, been submitted for a degree or diploma to any other universities.

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ABSTRACT

This study develops a bankruptcy prediction model for South African companies listed on the Johannesburg Stock Exchange. The model is of considerable efficiency and the findings reported extend bankruptcy literature to developing countries. 64 financial ratios for 28 companies, grouped into failed and non-failed companies, were tested using multiple discriminant analysis after conducting normality tests. Three variables were found to be significant which are: Times Interest Earned, Cash to Debt and Working Capital to Turnover. The model correctly classified about 75% of failed and non-failed in the original and cross validation procedures. This study went on to conduct an external validation of the model superiority by introducing a sample of failed companies, which showed that the model predictive accuracy is more than chance.

Despite the popularity of the topic among researchers this study highlighted the importance and relevance of the topic to corporate managers, policy makers and to investors especially in a developing market perspective, thereby contributing significantly towards understanding the factors that lead to corporate bankruptcy.

Keywords: corporate financial distress, financial ratios, failed firms, non-failed firms, prediction model and multi discriminant analysis.

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1 CHAPTER ONE - INTRODUCTION

1.1 Purpose of the Study

The main purpose of this study is to analyse and verify if a different set of variables determine corporate failures in South Africa relative to the set of variables found in developed countries. The primary objective of the research is therefore to develop a verifiable bankruptcy prediction model that will identify significant attributes of firms in a developing economy, South Africa. The bankruptcy prediction model developed may be different compared to bankruptcy models for developed economies studied to date. The study also extends corporate failure studies to developing economies, because corporate failure is problematic to both developed and developing economies.

1.2 Context of the Study

The sudden global financial crisis in 2008, where financial market liquidity dried up, caused numerous companies with historically strong financial standing to go out of business because they were caught off guard and could not meet their financial obligations. This has increased the importance of understanding the reasons behind the collapse of a firm, as this will enable timely bankruptcy preventative action to be taken as precaution. Over the past fifty years practitioners and academics have widely researched corporate failure prediction without drawing consensual conclusions. Despite the popularity of the topic the corporate failure problem remains a topical issue, as to which is the most accurate and reliable method for predicting firm failure, thereby remaining contestable.

To highlight the extent of corporate failures in South Africa, a sample of Statistics South Africa 10 year historical company liquidation data for the month of September showed that an average of 627 companies liquidated in that one month. There are significant downstream effects of a company failing, as the firms' main stakeholders, i.e. the shareholders, financiers, suppliers, customers and employees, endure heavy losses financially and economically. Further downstream, at a larger scale, are the households that would lose income vital for livelihoods, creating socio-economic problems and unrest. Corporate failure and its subsequent job loss effect are causes of concern for South Africa's Government, whose key objective is job creation, as a tool of alleviating the widespread poverty of its electorate. Because the problem of firm failure persists, it presents a problem to economic growth and is a source of concern for a developing economy such as South Africa.

1.3 Problem Statement

Empirical research on corporate failures has largely been conducted in developed countries. Although corporate failures are a common problem of both developing and developed economies (Altman et al., 1979), there is minimal research that has focussed on developing markets; this means we still do not know which factors significantly predict bankruptcy in developing economies such as South Africa particularly during period of global economic crisis. This study goes further to analyse and verify if a different set of variables determine corporate failures in South Africa, a developing country, relative to developed countries. Corporate failure

normally occurs when a firm is unable to meet its liabilities, especially as is currently the case where firms are exposed to a global economic crisis.

By developing a bankruptcy prediction model for South African firms, this study identifies the significant attributes of firms and verifies if corporate failure is determined by different set of variables. The developed model and the subsequent variables will play a pivotal role in providing localised early warning signals that are compatible to the South African environment and to stakeholders of South African firms, which sets the stage for corrective action to be taken in advance, ultimately preventing firms from experiencing distress.

1.4 Significance of the Study

Previous studies have focused on developed economies; therefore there are few studies that have been conducted for developing countries, which is a key motivation for this paper. The research findings from developed economies may not be suitable for application in South Africa due to differences in market structures, socio-economic factors, politics, legal frameworks and accounting standards. The study also seeks to make a contribution to the bankruptcy literature available to developing countries, by verifying if a different set of variables determine corporate failure.

This study seeks some important results that will be relevant to policy makers at both the company and the national levels. The South African authorities and

stakeholders, mainly the fiscal and monetary policy makers, will benefit significantly from this paper in their formulation of developmental oriented policies and strategies that seek to avoid regression of businesses, by anticipating corporate bankruptcy, understanding and appreciating the factors that contribute to corporate financial failure. This paper aims at creating a signal of the health of companies, which in turn allows prompt corrective action to be taken in advance of any rot setting in the business.

At company level this paper will be of benefit to corporate stakeholders; the main ones being investors, creditors, debtors and employees. Investors and investment professionals will benefit from this paper as they will be able to make informed investment decisions. Corporate managers will be able to devise and implement appropriate strategies that prevent the companies they manage from failure beforehand by anticipating and rectifying failure related problems.

1.5 Assumptions of the Study

Researchers have defined corporate failure and failure prediction differently, through the usage of financial ratios. Beaver (1966) defined corporate failure as one of the following: recourse to the judicial procedure of bankruptcy; default of debt repayment; excessive use of the banking overdraft; not paying dividends on preferred shares.

Altman (1968), Deakin (1972) and Edmister (1972) define bankruptcy as the declaration of bankruptcy as a restrictive definition of failure. South Africa Companies Act states that actual commercial insolvency, in this context, is denoted by the debtor's liabilities actually exceeding the value of his assets. Definitions widely used are discontinuation of the business, or the business does not earn an adequate return, or insolvency via the court. Due to the difficulty in obtaining adequate data on companies that have declared bankruptcy, the study adopts the definition of distress used by Sharenet (Data source database for this research) stated as follows:

1. Firms that have agreed to undertake a restructuring scheme to revive their financial conditions by the South African authorities.
2. Firms that were put under receivership.
3. Companies that have been incurring losses for three years continuously or more.
4. Companies that have exhibited negative position in cash flow for three years continuously or more.

1.6 Delimitations of the Study

The study considers listed industrial firms on the Johannesburg Stock Exchange ("JSE") and excludes the financial services sector. The financial services sector is heavily regulated therefore failure is more predictable and when diagnosed swift corrective action is typically undertaken by regulatory authorities to avoid contagion

that can easily affect the whole industry and the whole economy. Excluding the financial services sector reduced the sample of companies that were analysed. Analysing the JSE companies further excludes analysis of private and smaller companies, which are significant contributors to the economy in totality. At individual level these companies may be less established than their larger counterparts and tend to be more vulnerable to corporate failure due to early stage of the business cycle or smallness in size.

Another limitation is that the model cannot be used in portfolio selection as there is large concentration bias presented by the pairing approach. The use of a matched sample of failed and non-failed firms might introduce a potential firm failure bias (Palepu, 1986). The bias may not be important if the model is used to rank the firms according to bankruptcy likelihood but the bias will be important if the model is used for portfolio selection in the investment process. However, Platt and Platt (1990) found that the one-to-one sampling technique is an acceptable method in failure prediction studies.

The rest of the paper is structured as follows; Chapter Two provides a review of corporate bankruptcy literature, Chapter Three highlights the methodology the study utilises, Chapter Four is the analysis of the study and discusses the findings and Chapter Five draws conclusions, recommendations and areas for future research.

2 CHAPTER TWO – LITERATURE REVIEW

2.1 Introduction

This section provides a background discussion of bankruptcy prediction and review the bankruptcy literature and studies that have been conducted by other researchers. Research on predicting corporate bankruptcy is anchored on the early pioneering studies of Beaver (1966) and Altman (1968) and subsequently Altman's (1984) Z-score model. Section 2.2 presents prediction of corporate failure process and reasons for failure. Section 2.3 presents prediction of corporate failure and section 2.4 summary of literature review at the end of the introduction.

2.2 Corporate Failure Process and Reasons for Failure

Business failure has been a central topic of business studies for many decades. In recent months there have been high profile corporate collapses that have either contributed to the global financial crisis or has been a consequence of the global financial crisis, such as the Lehman Brothers collapse. Typically, the stakeholders of a business are concerned with the financial health of an organisation and the consequences of failure. Argenti (1976) defined three types of business, which are: failure of an unsuccessful start-up, failure process of an ambitious growth company and failure process of a dazzled growth company. Ooghe and De Prijcker (2007) added a fourth type of business failure process, being failure process of an apathetic established corporation.

There are numerous reasons why corporates fail which include; poor working capital management, ineffective management, poor budgetary control and financial planning, loss of key personnel, inadequate corporate governance, inadequate risk assessment, new competition, poor industrial relations, poor quality products, supplier and product concentration, legislation changes and fraud. Similarly there are many ways of assessing and reviewing corporate failure. Financial ratios and how they evolve over time provides important indications of whether corporate bankruptcy is looming.

There is a sequence to the business failure process where the initial stages of failure are internal organisational problems followed by financial signals arising from weak performance and finally corporate failure itself. Failure symptoms appear when the firm is in a downward spiral, not only because of deficient resources but also because of the inadequate deployment of resources, leading to weaker strategic positioning, Crutzen and Van Caillie (2007). The weaker strategic positioning is evidenced by poor sales, high expenses, poor profitability, poor cashflow and poor liquidity. In the context of this study, the poor financial performance is highlighted by financial ratios and the ratios are then used to predict failure. The immediate factors that cause business failure are summarised by Ooghe and De Prijcker (2007) in Table 1 below.

Table 1: Immediate Factors of Business Failure

	Type 1	**Type 2**	**Type 3**	**Type 4**
	Failure process of an unsuccessful start-up	**Failure process of an ambitious growth company**	**Failure process of a dazzled growth company**	**Failure process of an apathetic established company**
Management				
Competencies and skills	Insufficient competencies and skills in many areas	Wrong estimation turnover		
		Lack of financial background		
Motivation		Enduring motivation	Very Motivated	Insufficient motivation and commitment
Personal characteristics	Rashness	Persuasiveness	Over-optimism	Inertia
	Authoritarian leadership	Risk lovers	Dazzled	
		Over-optimism		
Corporate policy				
Strategy	No strategic advantage			No adjustments to environment
Capital expenditures	Inappropriate	Exaggerated	Exaggerated	Unadjusted
Commercial policy	Lack of customers	Overestimation sales		Loss of customers
	Customer dissatisfaction			Customer dissatisfaction
Finance and administration	Insufficient financial planning	Lack of expertise	Extreme gearing	
Operational policy	Severe operational errors		Unadjusted management and operational structure	Operational inefficiencies
Human resources management	Insufficient training			
	Minor influence			
Corporate governance	Moderate influence			

Source: Ooghe and De Prijcker (2007)

2.3 Prediction of Corporate Failure

A lot of attention has been extended to bankruptcy prediction modelling literature ever since the pioneering work of Beaver (1966). Most of the work has been strongly influenced by a small number of early papers conducted on quoted companies in the United States of America, which include Altman (1968), Ohlson (1980) and Zavgren (1985). The models largely included accounting ratios in the form of liquidity, leverage, performance, efficiency and size ratios of the sample firms. Bankruptcy research that has been conducted has identified numerous ratios that have been deemed important in predicting bankruptcy. However, there has not been conclusive consensus on which ratios were most useful in foreseeing corporate failure and no absolute test for the importance of variables (Barnes, 1987). This lack of theoretical support for choosing the appropriate variable that can predict bankruptcy has led researchers to search for other significant variables.

Beaver (1966) was among the first to show that corporate failure could be reliably predicted through the combined use of sophisticated quantitative techniques using numerous financial ratios. Beaver followed a univariate approach in that each ratio was evaluated in terms of how it could be used to predict failure on its own without consideration of the other ratios. Using a sample of seventy nine failed and non-failed firms as well as thirty financial ratios averaged over five years prior to failures, he claimed that cash-flow-to-total-debt ratio was significant in predicting failure. This ratio misclassified only 13% of the sample for one year before bankruptcy and 22% of the sample for five years before bankruptcy. Beaver found that a number of

indicators could discriminate between matched samples of failed and non-failed firms for as long as five years prior to failure. Beaver's univariate analysis of a number of bankruptcy predictors set the stage for the use of multivariate approach to studying corporate distress and failure.

Altman (1968) extended Beaver's interpretation by investigating a set of financial as well as economic ratios to determine the possible determinants of corporate failures using multiple discriminant analysis ("MDA"). MDA is superior to univariate analysis because it analyses all characteristics and interrelations of all the variables simultaneously. The study used sixty-six failed and non-failed corporations selected from manufacturing industries where twenty two ratios were grouped under five categories; liquidity, profitability, leverage, solvency and activity ratios. Five ratios finally emerged as good predictors of corporate bankruptcy. These were working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, market value of equity to book value of total debt and sales to total assets. A Z-score was determined and companies with a score greater than 2.99 were non-bankrupt. Companies having a Z-score below 1.81 were in the bankrupt group. Altman referred to the area between 1.81 and 2.99 as the grey area or the ignorance area. The model correctly classified 95% of the total sample, one-year prior to bankruptcy, being 94% bankrupt firms and 97% as non-bankrupt firms. However misclassification of failed firms increased significantly as the prediction time increased, with misclassifications of 28% at two years, 52% at three years and 71% at four years. This formed the beginning attempts to build predictive models, and led

to the well-known Z-score procedure which is widely used by both credit practitioners and researchers.

MDA has widely been accepted as a business failure prediction tool since its use by Altman (1968). However there is some criticism regarding the statistical procedures of using MDA. The main critique is that the MDA procedure can only be optimal if normality conditions are met; if not, the conclusions would not be reliable. Karels and Prakash (1987) investigated whether the financial ratios used in the other studies satisfy the normality conditions of the MDA procedure. Fifty financial ratios were tested and only nine were found normal and six ratios found lognormal. The normalised ratios were used to construct the MDA model, which correctly classified 98% of the non-bankrupt group and 100% of the bankrupt group. They concluded that MDA procedures do not necessarily produce better results if the variables lack normality. However the problem of lack of normality can be reduced through transformation of the variables (Hair *et al,* 1995), similar to the study carried out by Altman *et al* (1977). This study adopts transformation techniques where the variables are transformed to both lognormal and square root normal and also uses dummy variables to alleviate the problem of multivariate non-normality.

Comparing four prediction models, Mossman et al. (1998) made an important contribution to the efficiency of these types of models. They tested four bankruptcy models, namely: Altman's Z-score model based on financial ratios; Aziz et al.'s (1988) model based on cash flows; Clark and Weinstein's (1983) market return model

and Aharony et al.'s (1980) market return variation model. They found that in the year prior to bankruptcy, the Altman Z-score model was the most effective in predicting likelihood of bankruptcy. Over three years preceding bankruptcy, the cash flow model consistently discriminated bankrupt and non-bankrupt firms. These findings suggest different uses of the models, as some stakeholders might be particularly interested in cash flow variables as early warning signals of failure. A large negative shift in accounting ratio variables could be a useful indicator of imminent financial collapse.

Corporate failure is not a sudden event but evolves over a period; however firms with strong balance sheets attaining consistently high profits are not likely to fail in the wake of adverse economic conditions. Corporate failure is typically a result of many years build-up of adverse corporate performance, which is reflected in the firms accounting statements. In addition, double entry system of accounting ensures that when accounting policies are changed or when the accounts are window dressed, there will be minimum impact on the accounting information utilised in bankruptcy prediction.

Agarwal and Taffler (2007) compared market based models against the Z-Score model and extended the analysis to compare the market shares, revenues and profitability of banks that utilised these competing models in the UK. They found that the two approaches capture different inherent characteristics of bankruptcy risk even though there is minimum difference in predicting ability. They also found the

Z-Score model led to higher profits being realised by the bank, where decision error costs and loan prices were taken into account. They also found that the more conventional accounting ratio based models, which produce significant economic benefit, are more robust and not dominated by such models as the market based approach. Their findings justify the relevance of accounting ratio based Z-Score models and go on further to support this paper and the methodology adopted where the predicting model is based on accounting ratios.

Altman (1984) showed that the total costs of bankruptcy are substantial and firms incur bankruptcy costs in the range of 11% to 17% of the firm value three years prior to bankruptcy in developed economies. Excluding the multinationals, most firms in South Africa generally have shorter history, which contributes to the complexity of predicting bankruptcy. Most emerging markets experience high growth yet firms normally have smaller growth rates compared to the broader economic growth. This further justifies the need to conduct this study to verify if a different set of variables determine corporate failures in an emerging market context. Sori, Karbhari and Kassim (2001) used MDA to develop a bankruptcy prediction model of considerable efficiency for Malaysia, a developing economy, which predicted failure four years ahead and found that failure was due to excessive borrowing, excessive investment and low profitability.

2.4 Summary of Literature Review

There have been numerous attempts to predict bankruptcy but all these studies have not reached a reliable consensus since Altman's (1968) study. Current bankruptcy literature is not conclusive and cannot be generalized for emerging markets, let alone for South Africa. It is against this backdrop that developing a verifiable prediction model will play a key role in determining the attributes of companies in South Africa and also provide some insight into the failure process thereby allaying financial distress and abating bankruptcy costs. This study is implemented to fill the literature gap in South Africa and identify the symptoms that lead to bankruptcy, to prevent the economic and social consequences that arise when companies fail.

3 CHAPTER THREE – RESEARCH METHODOLOGY

3.1 Introduction

This chapter describes how the research is conducted and explains the hypothesis of this study, the research design and development of the econometric model. In addition, this section describes the data sources and data analysis methodology.

3.2 Data, Data Source and Sample Selection

The sample data was limited to the income statements, balance sheets and cashflow statements of the sampled firms. A sample of 14 distressed companies was compiled from Sharenet and SENS, which are both JSE information portals, using this papers' definition of financial distress. As a start of the data collection, a comprehensive list of companies that were delisted and suspended from the JSE was compiled. A sample of the raw data obtained from Sharenet of the companies that failed is shown in Table 2 below. Companies that were suspended or delisted for reasons that were not associated with financial distress, were eliminated from the sample to remain with 14 failed companies. The companies were eliminated from the sample for reasons such as voluntary winding up, mergers and schemes of arrangements. Financial statements of these companies were then collected in standardized format for five years prior to financial distress from information portal of BFA McGregor. The financial statements were then grouped according to the year prior to distress. The financial statements of the non-distressed firms was matched with the same fiscal years as those of the distressed companies and then sorted into years before distress, equivalent to the years assigned to the distressed companies. The sample of

non-failed companies was selected randomly. 14 non-failed companies were matched to the failed companies thereby assigning each failed company with a non-failed "partner" in the sample. The firms were paired under the criteria that the firms had to be in the same industry as the failed companies and similar in asset size to minimise the bias in the failure prediction model that may arise from the size of selected sample firms. The one-to-one match is consistent with previous studies of Beaver (1966) and Altman (1968).

Table 2: Sample of Delisted or Suspended JSE companies

DATE	CODE	COMPANY	DATE	CODE	COMPANY
2010/03/08	EMG	Emergent Properties Ltd	2003/06/02	PTH	Planit Investments Holdings Limited
2010/03/08	EUR	Eureka Industrial Ltd	2006/03/13	OAI	Omega Alpha International IT Holdings
2007/06/18	BRY	Bryant Technology Ltd	2005/05/03	ADT	Advanced Technical Systems Ltd
2007/06/12	EXO	Exxoteq Ltd	2005/05/03	CAL	Chariot Land Ltd
2007/06/07	ALD	Aludie Ltd	2005/05/03	COI	Choice Holdings Ltd
2007/06/06	RNT	Rentsure Holdings Ltd	2005/05/03	DNM	Dynamo Retail Ltd
2007/06/06	RCO	Rare Earth Extraction Co Ltd	2005/05/03	FSH	Fashion Africa Ltd
2007/06/06	APE	APS Technologies Ltd	2005/05/03	LST	Leisurenet Ltd
2007/04/16	VKG	Viking Investments	2005/05/03	PML	Premier Group Ltd, The
2007/04/16	TOT	Top Info Technology Holdings Ltd	2005/05/03	STK	Siltek Holdings Ltd
2007/04/16	TGN	Tigon Ltd	2005/05/03	UNG	Universal Growth Holdings Ltd
2007/04/16	TRF	Terrafin Holdings Ltd	2005/05/03	WTS	Whetstone Industrial Holdings Ltd
2007/04/16	TRX	Terexko Ltd	2003/06/02	COR	Core Holdings Ltd
2007/04/16	SCH	Stocks Hotels & Resorts Ltd	2003/06/02	CNY	Century Carbon Mining Ltd
2007/04/16	SWL	Shawcell Telecommunications Ltd	2003/06/02	ACR	Accord Technologies Ltd
2007/04/16	RHW	Richway Retail Properties Ltd	2003/06/02	COR	Core Holdings Ltd
2007/04/16	RAG	Retail Apparel Group Ltd	2003/06/02	ABR	Afribrand Holdings Ltd
2007/04/16	MLL	Millionair Charter Ltd	2010/04/26	SJL	S&J Land Holdings Ltd
2007/04/16	ICT	Incentive Holdings Ltd	2010/01/11	ELE	ElementOne Ltd
2007/04/16	CCG	CCI Holdings Ltd	2009/09/14	CFO	Country Foods Ltd
2007/04/16	ALC	Amlac Ltd	2009/04/20	STI	Stilfontein Gold Mining Company Ltd
2006/04/03	MUM	Mouldmed Medical Supplies Ltd	2009/04/20	GLL	Global Village Holdings Ltd
2004/08/23	ZRR	Zarara Energy Ltd	2009/04/20	TIW	Tiger Wheels Ltd
2003/09/04	OTR	OTR Mining Ltd	2009/04/09	CNX	Conafex Holdings Societe Anonyme
2003/07/14	REF	Ref Finance Corporation Ltd	2009/03/16	PAL	Pals Holdings Ltd
2003/06/02	TUF	Taufin Holdings Limited	2009/02/23	CVS	Corvus Capital (SA) Holdings Ltd
2003/06/02	PDM	Paradigm Capital Holdings Limited	2009/02/16	PFN	Consolidated Property & Finance Ltd
2003/06/02	UAM	Union Alliance Media Limited	2009/02/16	NEI	Northern Engineering Industries Ltd
2003/06/02	PDH	Prada Technologies Limited			

To avoid distortions of the data sample, the data cut-off point is December 2007, which is prior to the peak of the global financial crisis when world stock markets were negatively affected. Lev and Thiagarajan (1993) concluded that the link between unexpected information in accounting data and abnormal returns is sensitive to the business cycles, which would distort the sample data analysed if it included the global financial crisis period. Beaver *et al.* (1968) showed that accounting data is associated with risk premium variations since risk premiums are not stationery across business cycles. In addition, Richardson *et al. (*1998) found that information contents of accounting data of failed compared to non-failed companies differ in recession and normal periods.

3.3 Research Design

The aim of this study is to assess the likelihood of failure of firms operating in different accounting, legal and economic environments such as firms found in a developing economy, South Africa. The study utilizes financial ratios obtained from published financial statements of a sample of financially distressed companies listed on the JSE, an exchange which started in 1887 and is the largest stock market in Africa. As at October 2010, the JSE market capitalisation was $718 billion with 337 listed companies. The number of companies listed was 364 in 2006 and dropped to 347 in 2007.

3.4 Multiple Discriminant Model

The method utilised by this study to analyse the data is a Multiple Discriminant Analysis (MDA), where the dependent variable is a dummy variable of failed or non-failed firms and the independent variables are 64 selected financial ratios used by Beaver (1966) and Altman (1968) as shown in Table 3 below.

Table 3: Financial Ratios Examined

Code	Ratio Name	Code	Ratio Name
R01	Cash flow to Sales	R33	Inventory Growth
R02	Cash flow to Assets	R34	Sales Growth
R03	Cash flow to Net Worth	R35	Depreciation Growth
R04	Cash flow to Total Debt	R36	Dividend Growth
R05	Return on Sales (ROS)	R37	Return on Opening Equity (ROOE)
R06	Percentage Change in ROS	R38	Percentage Change in ROOE
R07	Return on Assets	R39	Equity to Debt
R08	Return on Equity	R40	Percentage Change in Equity to Debt
R09	Net Income to Total Debt	R41	Equity to Long Term Debt
R10	Current Liabilities to Total Assets	R42	Percentage Change in Equity to Long Term Debt
R11	Long Term Liabilities To Total Assets	R43	Equity to Fixed Assets
R12	Total Liabilities To Total Assets	R44	Percentage Change in Equity to Fixed Assets
R13	Cash To Total Assets	R45	Times Interest Earned
R14	Quick Assets To Total Assets	R46	Percentage Change in Times Interest Earned
R15	Curent Assets To Total Assets	R47	Profit Before Depreciation to Sales
R16	Working Capital To Total Assets	R48	Percentage Change in Profit Before Depreciation to Sales
R17	Cash to Current Liabilities	R49	Pre-tax Income to Sales
R18	Quick Ratio	R50	Percentage Change in Pre-tax Income to Sales
R19	Percentage Change in Quick Ratio	R51	Sales To Inventory
R20	Curent Ratio	R52	Percentage Change in Sales to Inventory
R21	Percentage Change in Current Ratio	R53	Sales to Fixed Assets
R22	Cash Turnover	R54	Percentage Change in Total Assets
R23	Receivable Turnover	R55	Percentage Change in Working Capital to Total Assets
R24	Quick Asset Turnover	R56	Operating Income to Assets
R25	Current Asset Turnover	R57	Percentage Change in Operating Income to Asset
R26	Working Capital Turnover	R58	Percentage Change in Long Term Debt
R27	Percentage Change in Sales to Working Capital	R59	Dividends to Cash Flows
R28	Net Worth to Sales	R60	Net Income to Cash Flow
R29	Asset Turnover	R61	Operating Profit to Sales
R30	Percentage Change in Sales to Total Assets	R62	Return on Owners Equity
R31	Days Sales in Receivable	R63	Total Assets to Net Worth
R32	Inventory To Total Assets	R64	Earning Power

3.5 Chapter Summary

The chapter described the research methodology where a sample of 57 failed companies was analysed and only 14 failed companies were found to be appropriate to be used as a data sample of failed companies prior to the peak of the global financial crisis. The failed companies were matched to randomly selected non-failed companies using a one to one approach. 64 selected financial ratios were used as independent variables in a Multi Discriminant Model, with the dependent variable being a dummy variable of failed or non-failed firms.

4 CHAPTER FOUR – ANALYSIS OF FINDINGS

4.1 Introduction

The findings of this paper are discussed in this chapter using a Univariate Analysis and goes on to use Multiple Discriminant Analysis (MDA). A Univariate Analysis is carried with the description for a single variable. MDA is a statistical technique used to classify an observation into one of several from the former groupings dependent upon the observation's individual characteristics. MDA is primarily used to make predictions in problems where the dependent variable takes a qualitative form. The results of both assessments are discussed and validated using an external validation experiment.

4.2 Univariate Analysis

A total sample of 28 companies was assessed comprising a sample of 14 failed and 14 non-failed companies which were paired according to the same fiscal year. The averages of the financial indicators were calculated as shown in the Table 4 below.

Average Total Assets for failed companies was lower than the average Total Assets for non-failed companies, where the average for non-failed companies is R252 million and that for failed companies is R165 million. This implies that failure can be directly linked to size of the companies listed on the JSE where smaller companies in asset size are more susceptible to failure compared to the larger companies in asset size which may be able to ride out potential bankruptcy, either by stripping off some assets or utilising their assets more effectively compared to the failed companies.

Table 4: Mean Financial Indicators of Failed and Non-Failed Companies

	Failed Firms	Non-Failed Firms	Combined Sample
	n=14	**n=14**	**n=28**
	Mean	**Mean**	**Mean**
	ZAR'000	**ZAR'000**	**ZAR'000**
Total Assets	165 076.57	252 190.24	208 633.41
Fixed Assets	28 473.99	52 331.81	40 402.90
Quick Assets	83 618.40	110 790.53	97 204.46
Current Assets	117 172.04	179 725.47	148 448.76
Equity	56 401.96	91 131.17	73 766.56
Total Debt	60 483.81	60 757.24	60 620.53
Short Term Debt	35 812.60	29 444.03	32 628.31
Long Term Debt	24 671.21	31 313.21	27 992.21
Inventory	33 553.64	68 934.94	51 244.29
Account Receivable	23 239.80	55 018.79	39 129.29
Total Liabilities	104 527.90	161 059.07	132 793.49
Long Term Liabilities	24 671.21	31 313.21	27 992.21
Current Liabilities	79 856.69	129 745.86	104 801.27
Sales	209 337.16	388 802.40	299 069.78
Net Income	-1 001.57	7 976.36	3 487.39
Income Before Interest & Tax	9 286.16	17 221.57	13 253.86
Retained Earnings	-3 155.97	968.49	-1 093.74
Total Interest	9 354.19	2 995.13	6 174.66

Fixed Assets for failed companies were significantly lower than for non-failed companies, which indicate that failed companies may have invested less in assets. Quick Assets, Current Assets, Inventory and Accounts Receivable averages were lower for failed companies compared to their non-failed counterparts, signalling that failed companies made less investment and therefore had fewer assets available to generate sustainable returns.

Total Liabilities, Long Term Liabilities and Current Liabilities averages were smaller for failed companies than for non-failed companies concretising the conclusion that failed companies generally have a smaller balance sheet and therefore are more susceptible to financial distress in the wake of adverse factors that affect the company's performance. It is clear that failed firms had significantly higher Debt than non-failed companies in proportion to each group's Equity and Total Assets. Failed firms had significantly higher Gearing (Debt over Debt plus Equity) of 52% compared to 40% for non-failed companies. Short Term Debt, which is typically more expensive than long term debt, was higher at R35 million for failed firms compared to R29 million for non-failed. The opposite applies for long term debt where failed firms had R24 million compared to R31 million for non-failed firms. The heavy gross borrowing and the costs thereof incurred by failed firms was a significant contributor to financial distress of the failed firms.

Sales for failed companies was lower compared to non-failed companies at R209 million compared to R388 million, respectively. Failed companies had significantly lower Income before Interest and Tax at R9 million compared to R17 million for non-failed companies; and also taxation was lower for failed companies at R2 million compared to R4 million for non-failed companies. Net Income was negative R1 million for failed companies compared to positive R8 million for non-failed companies. This indicates that failed companies had a higher debt and higher interest bill than non-failed companies which is clearly shown as R9million for failed companies and R3 million for non-failed companies. Retained earnings was

significantly lower and negative R3 million for failed companies compared to positive R1 million for non-failed companies. South African firms generally pay out dividends consistently, which explains the low retained earnings for both failed and non-failed companies.

The inferred conclusion from the univariate analysis is that failed companies are generally less profitable. Failed firms borrowed more than their non-failed counterparts, and had significantly higher short term borrowings. Providers of capital require higher returns for short term funds loaned to such companies, in the form of higher interest charges, which adversely impacts profitability and therefore causes financial distress. The financial behaviour of companies that have been discussed above avails justification that the major causes of financial distress for South African companies is excessive borrowing, little investment in cash generating assets, expensive sources of capital and low profitability.

4.3 Estimation of Multiple Discriminant Model

In this paper, as in Sori *et al* (2001), the dependent variable is dichotomous and relates to a sample of failed and non-failed firms, where the variable takes the value 1 if the firm failed and 0 if the firm did not fail. The independent variables used in the analysis are financial ratios of the sample firms. The 64 ratios were selected on the basis of their importance in assessing the success or failure of a company. A stepwise discriminant model was used to assess the discriminating power of the independent variables. In this analysis, normal variables are used in the discriminant

analysis where the independent variables were tested for normality. None of the independent variables were found to be normal, 26 variables were found to be lognormal and 1 variable was found to be square root normal. The independent variables that were not normal in all procedures were excluded and therefore not analysed further. A correlation test was conducted on the normal variables. Only three variables were found to have strong correlations and were therefore dropped from further analysis. By having a panel of ratios, the degrees of freedom can be expected to increase thereby increasing the reliability of the final estimated results. The independent variables were entered into the multi-discriminant model, which are shown in Table 5 below.

Table 5: Normalised Variables used in MDA

Code	Ratio Name	Code	Ratio Name
R01	Cash flow to Sales	R34	Sales Growth
R03	Cash flow to Net Worth	R36	Dividend Growth
R04	Cash flow to Total Debt	R37	Return on Opening Equity (ROOE)
R05	Percentage Change in ROS	R38	Percentage Change in ROOE
R08	Return on Equity	R44	Percentage Change in Equity to Fixed Assets
R09	Net Income to Total Debt	R45	Times Interest Earned
R10	Working Capital To Total Assets	R46	Percentage Change in Times Interest Earned
R17	Cash to Current Liabilities	R48	Percentage Change in Profit Before Depreciation to Sales
R19	Percentage Change in Quick Ratio	R50	Percentage Change in Pre-tax Income to Sales
R21	Percentage Change in Current Ratio	R52	Percentage Change in Sales to Inventory
R26	Working Capital Turnover	R58	Percentage Change in Long Term Debt
R27	Percentage Change in Sales to Working Capital	R59	Dividends to Cash Flows
R30	Percentage Change in Sales to Total Assets	R62	Return on Owners Equity

Again in line with Sori *et al* (2001), the Mahalanobis Distance measure is used to select the variable with the greatest separation for the pair of groups which were closest at a particular step. The model selects the variable which maximises the Mahalanobis distance between the groups and an F-test is used as an additional means of interpreting the relative discriminating power of the independent variables. The results of the MDA analysis are presented in Table 6 below.

Table 6: Summary of Interpretative Measures

Variable	Standard weights value	Discriminant loading		Univariate F Ratio	
		Value	Rank	Value	Rank
R45	0.711	0.674	1	11.411	1
R04	0.537	0.543	2	9.967	2
R26	0.448	0.512	3	8.192	3

This study identifies the Times Interest Earned ratio, the Cash-to-Debt ratio and the Working Capital to Turnover ratio as the significant variables. The Cash to Debt ratio is in line with the early work of Beaver (1966), where he found this variable to be significant. The stepwise procedure employed here prevents insignificant variables from entering the discriminant function. The discriminating power of each of these variables is identified using the discriminant loadings (Pearson coefficients) as well as the Univariate F statistics. The variables are then ranked according to the absolute value of the discriminant loadings and the Univariate F statistical values. From the estimated model and the subsequent statistics, it can be seen from Table 6 that the Times Interest Earned has the greatest discriminating power followed by the Cash-to-Debt ratio. The Working Capital Turnover ratio has the lowest discriminating power of the three variables.

These findings show that the Times Interest Earned ratio, Cash-to-Debt ratio and the Working Capital Turnover ratio of failed firms are significant indicators of differences between failed and non-failed firms. The Times Interest Earned ratio is a financial ratio used to measure a company's ability to pay its debts; the Cash-to-Debt ratio is used to compare a company's operating cashflow to its total debt and the Working Capital Turnover ratio compares the usage of working capital to revenue generation. These ratios relay some important information about the effects of a failure where firms may fail if they fail to generate significant cash flow to cover interest payments as well as covering their debt.

The analysis discussed in the preceding section results in an estimated discriminant function or equation which operates like a regression equation. Using the discriminant function coefficients, this function can be written as:

$$Z = -0.115 + 0.057\,X1 + 0.207\,X2 + 0.033\,X3$$

Where:

Z = the overall discriminant function

X1 = the Times Interest Earned ratio (lognormal)

X2 =the Cash-to-Debt ratio (lognormal)

X3 = the Working Capital to Turnover ratio (lognormal)

Also calculated during the same analysis are group centroids, which are the group means of the predictor variables. These group centroids are 0.525 and -0.493 for non-failed and failed firm groups, respectively. These result in a cutting score of 0.016, which is the average of the two group centroids. Firms are classified as failed if they have a negative discriminant score and non-failed if their discriminant score is positive. Classification matrices generated during the analysis are used to assess the predictive accuracy of the discriminant function as shown in Table 7 below.

Table 7: Comparison of Classification Accuracy

		Failed or Non-Failed	Predicted Group Membership [b,c]		Total
			0	1	
Original	Count	0	38	9	47
		1	15	35	50
	%	0	80.9	19.1	100.0
		1	30.0	70.0	100.0
Cross-validated[a]	Count	0	38	9	47
		1	16	34	50
	%	0	80.9	19.1	100.0
		1	32.0	68.0	100.0
a. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.					
b. 75.3% of original grouped cases correctly classified.					
c. 74.2% of cross-validated grouped cases correctly classified.					

The overall model classification accuracy is 75.3%, which is an average of the correct classification of the dependent variables ("DV"); DV=0 at 80.9% and 70% for DV=1. This is almost similar to the model classification accuracy of 74.2% obtained from the cross-validation. The cross-validation accuracy is an average of 80.9% and 68% for DV=0 and DV=1 respectively. This overall predictive accuracy of the discriminant function (75.3% for original and 74.2% for cross-validation) is called the 'hit ratio'

and is acceptable when compared to the 50% probability that a firm would fail based on chance (when two samples of failed and non-failed firms being compared are equal, there is a 50% chance of picking either a failed or non-failed firm).

These findings demonstrate the importance of managing working capital and ensuring efficiency of turning over stock to enhance profitability and ability to meet debt servicing obligations. In addition, the results are consistent with the univariate analysis where cost of debt funding is very important. In general when firms have excess borrowings the likelihood of financial distress increases; financiers demand large collateral in return for loans which are typically expensive and carry the highest priority on the companies funding pecking order. In the absence of adequate collateral, these loans become very expensive; this may lead to financial distress. It appears that for failed firms, debt funding was for working capital requirements, yet the working capital was not efficiently turned over leading to haemorrhage when servicing loans.

4.4 External Validation

In order to confirm the validity of the discriminant function developed in the preceding section and assess whether generalisation based on this model is justifiable, an external validation experiment was undertaken. A sample of 8 failed companies was used for the external validation procedure.

Table 8: External Validation Procedure

External Validation Procedure		
Panel A: Accuracy Rate		
Distress Year (DY)	**Correct Classification (%)**	**Misclassification (%)**
DY	100	0
1 year before DY	100	0
2 years before DY	62.5	37.5
3 years before DY	50	50
4 years before DY	50	50

Table 8 above summarises the validation procedure. The model correctly classified the entire new sample as failed in the first year before financial distress. The external validation findings provide evidence of the accuracy of the predictive model which is consistently above the chance benchmark of 50% for the distress year which was 100%, year one 100%, year two 62.5% before failure. The model accuracy prediction was 50% for years three and four before failure as shown in Table 8 above. This performance is consistent with the sample analysis performance and the cross-validation process highlighted in Table 7.

Table 9: Analysis of Accuracy of Validity

Panel B: Detailed Analysis of Accuracy Rate of Validity Procedures (%)						
Range of Z-Score	***Description***	**DY**	**1**	**2**	**3**	**4**
Z > 0.525	Non-Distressed	0	0	25	0	12.5
0.016 < Z < 0.525	Grey area non-distressed	0	0	12.5	50	37.5
-0.493 < Z < 0.016	Grey area distressed	87.5	37.5	37.5	25	37.5
Z < - 0.493	Distressed	12.5	62.5	25	25	12.5

Table 9 highlights the existence of an overlap in the Z-Scores for failed and non-failed firms. Altman (1968) referred to the overlap area as the grey area or ignorance zone. This study has the centroids as 0.525 for non-failed companies and -0.493 for

failed companies and therefore the Z-Scores between these two centroids falls into the overlap. The cutting score is 0.016 and the Z-Scores in Table 9 can be interpreted as follows:

- Distressed if $Z < -0.493$,
- Grey Area Distressed if $-0.493 < Z < 0.016$,
- Grey Area Non-Distressed if $0.016 < Z < 0.525$ and
- Non Distressed if $Z > 0.525$.

It is evident from Table 9 that firms' performance gradually deteriorated to failure when approaching the failure year as the accuracy rate of the validity deteriorated from distress year (DY) to year 4. In the distress year the model correctly classified all failed firms with 100% accuracy, combining grey area distressed and distressed. Table 10 below shows the Z-Scores of the companies that were included in the external validity. It is therefore important to identify companies in the grey area when applying this model. Using this model developed corrective action can be taken on companies that are expected to fail in the grey area, as their performance can be assessed in advance.

Table 10: External Validity

External Validity					
Company Name	**(DY)**	**1st**	**2nd**	**3rd**	**4th**
CHARIOT LAND LTD	-0.468	-0.637	0.845	0.280	-3.203
CONSOLIDATED LTD	-0.460	-0.460	-0.460	-0.468	-0.467
CORVUS HOLDINGS LTD	-0.214	-0.548	-0.602	0.181	0.235
EMERGENT LTD	-0.119	-0.083	-0.140	0.133	0.081
JIGSAW HOLDINGS LTD	-0.494	-1.108	0.381	0.362	0.039
PALS HOLDING LIMITED	-0.248	-0.514	0.541	-0.863	2.292
ZARARA LTD	-0.073	-0.933	-0.556	-2.331	-0.130
S & J LAND HOLDINGS LTD	-0.111	-0.111	-0.096	-0.089	-0.112

4.5 Chapter Summary

A total sample of 28 companies was assessed comprising 14 failed and 14 non failed companies. The univariate analysis conducted suggests that failed fails are less profitable, invest less in assets and borrow excessively compared to their non-failed counterparts. An MDA was carried out and identifies the Times Interest Earned, Cash-to-Debt and the Working Capital to Turnover ratios as significant ratios. The significant variables suggest that firms may fail if they fail to generate significant revenue and cashflow to cover debt obligations. The overall classification accuracy of the model is 75.3% which is not too distant from the model classification of 74.2% obtained from a cross validation process. An external validation experiment was undertaken using a sample of 8 failed companies and provided strong evidence of the accuracy of the predictive model. The developed model can be used to diagnose companies that have potential to fail and corrective action can be taken in advance.

5 CHAPTER FIVE – CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This study successfully developed a model to predict corporate bankruptcy of South African companies, which was tested for both internal and external validity. The model has an exceptionally high correct classification accuracy rate of more than 74% in the original and cross-validations that were carried out. The model's performance was further tested by an external validation where a sample of eight new failed companies was introduced. The findings highlight that the model is reliable and is helpful for policy makers to make decisions on anticipating firm failure and thereby providing remedial action in advance. The external validation further highlights that the model performed better than chance with 50% or more accuracy regarding five years before actual failure.

5.2 Discussion

Out of the sixty four financial ratios used in this study, three were found to be significant in discriminating between failed and non-failed companies, which are:

1. Times Interest Earned
2. Cash-to-Debt
3. Working Capital to Turnover

Beaver (1966) found the Cash to Debt ratio as a significant variable in predicting corporate failure, which is similar to the Cash to Debt ratio that this study found significant after the Times Interest Earned ratio but before the Working Capita; Turnover ratio. There may be some inferred similarities to developed economy

studies that have been carried out to date. In this case the jurisdiction of the firm does not matter in determining which variables are significant as similarities exist. The similar ratio highlights that all companies' financial health, in both developed and developing countries can be determined by the level of cash a firm generates and the level of debt that the firm carries.

Apart from Beaver (1966), where cash and debt appear universal for both developed and developing countries, later studies, such as Altman (1968) showed different results; with none of the significant variables being similar. Not all the variables are similar in determining corporate failure in South Africa relative to the set of variables found in developed countries and therefore a different set of variables discriminate between failed and non-failed firms. Although not all significant variables can be generalised or used universally in predicting corporate financial distress, this study highlights that cash and debt are pillars of any business, and the subsequent Cash to Debt ratio can be taken as a key indicator of a firm's health in line with Beaver (1966).

A univariate analysis was conducted which supports these variables suggesting that failure was due to high cost of debt financing which was not matched by optimal usage of working capital. Failed companies did not have adequate cash available to meet their loan servicing requirements, which explains the significance of the Cash to Debt ratio. The results link lack of profitability and efficiency of the failed companies with lack of cashflow.

5.3 Conclusion

This study showed that there are four states of a corporate's performance and evolution to failure, which are "distress", "grey area – distress", "grey area – non-distress" and "non-distress". The grey area was defined by Altman (1968) as the "zone of ignorance", where a firms distress and non-distress characteristics overlap. The zone of ignorance should be analysed with caution as it provides early warning signals that can be used to avert failure, which may impact the application of fresh samples into the developed model (Adya & Collopy, 1998).

The study has its limitations: mainly, cashflow ratios were excluded as well as variables that had the potential to be negative, as this presented problems in transforming the data. Most of the failed companies recorded losses bringing negative values, which may not have been captured fully in the study.

5.4 Recommendations

The topic remains very relevant to the parties stated above as corporate bankruptcy carries significant socio-economic connotations, therefore predicting bankruptcy and allows guided remedial action to be undertaken in advance. Corporate managers can use this model for budgeting and corporate finance planning, where they can take action such as restructuring, mergers and acquisitions to avert bankruptcy. Policy makers are enabled to develop early warning systems to avoid corporate failure. Bankers and creditors can use the model for credit appraisals for borrowers or customers respectively, as part of their credit risk assessment and management. It is

important that stakeholders of the firm should constantly consider the financial health of the companies that they are involved with. In the assessment of corporate failure likelihood a more detailed analysis of the corporate should be carried out including assessing the financial statements using quantitative techniques and other qualitative methods that include assessing external factors that may affect the firm.

Even though this topic has been widely researched there is still a myriad of issues to be resolved relating to corporate failure in South Africa, such as the micro and macro factors that lead to corporate bankruptcy and more importantly linking this topic to capital structures of South African firms. This study exhibited the importance of capital structures as debt and its financing thereof were significant variables. Future research should focus on these areas. In addition, research areas of interest could include whether management and organisational practices can be used to predict bankruptcy.

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