UNIVERSITY OF CAPE TOWN

A Corporate Failure Prediction Model For Non-Financial South African Corporates Incorporating Best Practices Used By The Credit Industry

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Abstract

In the context of the current macroeconomic environment there is an expectation of an increase in South African non-financial corporate failure, where advance prediction thereof will become even more important. A number of South African non-financial corporate failures have occurred following the financial crisis. In addition, South Africa experienced a watershed moment with the first default on a non-financial corporate bond in 2013. At the same time, with the adoption of the International Financial Reporting Standards (IFRS) framework there have been significant advances in the quality of financial information which should improve its usage in predicting corporate failure.

This study used the latest sample to date of listed South African non-financial corporates that met the definition of failure but limited the universe of financial information to that which was prepared under IFRS. At the same time, adjustments were made to the financial data based upon pre-selection of independent credit statistic variables most commonly used in ranking relative credit risk for non-financial corporates. Additionally, equity market price data was introduced into the model to add a forward-looking information consideration. This resulted in an eleven variable model where differentiation of corporate failure was facilitated through the use of multiple discriminant analysis.

The initial model resulted in an 82.95% classification rate (overall accuracy rate for correctly classifying failed and non-failed firms), but this was further improved by using a three variable model comprising Revenue measured in US dollars, Debt/ Market Capitalisation and Debt/EBITDA. The inclusion of Debt/Market Capitalisation assured the consideration of forward-looking information but also factored distance to default theory employed by market-based models. This model, although with a slightly lower classification rate of 80.68% significantly improved the bias of the model to having a greater tendency to correctly classify failed firms. This was further validated through splitting the original sample in two with in sample and out of sample testing undertaken on each sample. The inclusion of outliers in financial data was shown to improve the ability to predict corporate failures.

The study also concluded that samples using only financial data prepared under IFRS resulted in higher classification rates and therefore samples should only rely upon such financial data.

Foreword

A word of gratitude first and foremost to Professor Carlos Correia, who has believed in me and had faith in my ability right from the beginning when I entered the Masters in Financial Management program. This submission would not have been possible without his continued and unwavering support.

Secondly, to the program itself, which sparked my interest in non-financial corporate failure prediction and lead me to follow the career path that I have been on covering non-financial corporate credit for over five years now at Moody's Investors Service. Also to Associate Professor Dr Glen Holman for always inspiring me to go Citius - Altius – Fortius in my career endeavours.

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Not forgetting, Emeritus Professor Tim Dunne, Dr Kutlwano Ramaboa and Dr Ian Durbach, who brought about my love for statistical sciences and for Kutlwano for encouraging me to share my knowledge with students as a teaching assistant at the Graduate School of Business. Most importantly, to Ian for growing my knowledge in multivariate statistics and giving me the opportunity of a tutoring position on the third year research and survey statistics course, which only reinforced my understanding and grew my knowledge. This undertaking would have not been possible without the comprehensive knowledge that I gained in the application of discriminant analysis.

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Chapter 1 | Introduction to the study

a) Background to the study

The need to predict corporate failure well in advance of its occurrence has been a focus for financial circles in an industry and academic context dating back to the early 1900's. In an industry context, corporate failure prediction began in 1841 with the formation of The Mercantile Agency in New York City. This was the precursor to Dun & Bradstreet, Moody's Corporation's previous owner from 1962 until 1999. Moody's Corporation was itself only established as the first bond credit rating agency by John Moody in 1909. In an academic context, the first mention of corporate failure prediction is credited to Smith and Winakor's (1935) study on changes in financial structures in unsuccessful corporations, which created a platform for further academic discourse.

Greater emphasis on the need to accurately predict corporate failure has become increasingly important following the global financial crisis which began in 2008 and continued into 2009 with widespread corporate failure and further ripple effects leading to the European sovereign crisis beginning in 2010 and running to present day. Similar impetus on the need to predict corporate failure has been driven by a number of sizeable corporate failures. These commenced in and around 2000 with the Enron and WorldCom financial collapses.

More recently corporate failure prediction has become increasingly important in a South African context. This follows the first non-financial corporate bond default in 2013. First Strut (Pty) Ltd could not service the coupon payment that fell due on its floating rate note maturing on 5 September 2016. The company was put into provisional liquidation on 16 July 2013. This was then followed in 2014 by the financial failure of African Bank Investments Limited which led to the imposition of a 10% haircut for senior bond holders and a complete write down for preference share and subordinated debt holders. Senior bondholders would have likely sustained higher capital losses had it not been for South African Reserve Bank intervention. In addition there have been a number of high profile liquidations in South Africa recently, most notable of which have been Evraz Highveld Steel and Vanduim and Chemical Specialities, which occurred during the course of 2015.

b) Key objectives and research questions for the study

i) Use of latest research knowledge, more uniform data and a larger sample of failed firms

The study intends building on the most recent international and South African academic and industry literature available to date. Applying observations and modelling conclusions drawn, the intention is to improve on the quality of South African corporate failure prediction models that have been developed to date using multiple discriminant analysis.

Modelling improvements should be facilitated through using updated data available for failed non-financial corporates. This will result in a larger sample of failed firms given the occurrence of further corporate failures following previous studies. This should improve upon model fit and accuracy simultaneously. Small samples of failed firms used in prior South African studies have been identified as inhibitors of accuracy for corporate failure prediction models.

Prior South African corporate failure prediction models that have used multiple discriminant analysis have been limited in the extent of their application of market related data. This study will attempt to include equity market price movement data to reflect changes in the business risks and conditions that investors see, and where they actively dimension these into equity prices. Market data for the purpose of this study is limited to listed equity prices, given that most South African corporate debt is unlisted and not publically traded. Inclusion of publically traded debt data, had it been available, would have likely further added significant explanatory power to the model.

The benefits of the inclusion equity market data as a variable for assessing corporate failure will be discussed in detail when reviewing market-based models. This will also include the economic rationale underlying the information content pertaining to default propensity contained in equity market prices. Equity prices are by nature forward-looking and fluid, constantly reflecting an investor's assessment of the underlying financial strength and prospects of a business. This will provide further discriminatory power for the multiple discriminant analysis in differentiating between failed and non-failed firms.

Financial corporates, such as banks and financing corporations, are excluded from this study because they have different credit characteristics such as higher leverage, different funding and business models and are subject to unique financial regulation and regulatory oversight. Also, the South African Reserve Bank will often intervene or act as a lender of last resort to protect the integrity of the country's financial system, as was seen recently with African Bank Investments Limited. This can in turn distort default parameters and the determination of corporate failure. Corporates, which are not government owned, do not benefit from the same level of implicit financial support, as they are not deemed to be as systematically important to the economy.

This study will also use data exclusively prepared under International Financial Reporting Standards (IFRS). Application of IFRS as the basis for preparing their annual financial statements became a legal requirement effective 1 January 2005. Although, from 2003 the option for all companies in South Africa; listed, unlisted, and private companies, was available to prepare annual financial statements under IFRS.

This study is able to use uniformly consistent financial data under this single set of transparent, principle-based and globally comparable accounting standards. Many previous studies, in order to develop statistically significant samples, have relied upon a mix of financial data prepared under IFRS and Statements of South African Statements of Generally Accepted Accounting Practice (SA GAAP). Comparability of variables across time periods suffered as a result. This in turn ultimately skewed various parameters that were used in assessing the propensity for corporate failure. These variations that resulted from the analysis often were therefore not unique to a company's financial risk profile, but rather attributed to data variances as a result of differences in the financial reporting.

This study also recognises the nuanced changes under IFRS from one financial reporting period to the next. These have followed from the evolution of the IFRS framework with new guidance introduced periodically to align with developments in the corporate landscape that it covers. These differences in IFRS over time still pale in comparison to the variation in data that resulted from annual financial statements being prepared under two different reporting frameworks, SA GAAP followed by IFRS.

Collection of data could prove problematic for a number of reasons. First, many companies often will cease filing financial statements as result of or in the run up to their financial failure. Second, given the lack of large-scale corporate failure within South Africa, collecting homogenous data will prove challenging where both size and business sector are likely to differ in each case. Third, failure for some corporates was attributed to accounting scandals, such as Leisurenet. In such instances financial data in the run up to failure is unreliable in any case and therefore not effective in reflecting financial pressures that the company is under at the time. Although, this can often be overcome through close analysis of the financial statements where in the case of Leisurenet, upfronting of revenue could be picked up through ballooning of the accounts receivable balance.

Once a sample of failed non-financial South African corporates have been collected these will then be paired with non-failed South African corporates, with a preference first for corporates in the same sector and then secondly for the same scale of operations. In creating pairs of non-financial South African corporates operating in the same sector this will ensure that similar business risks are captured in the independent variables or credit statistics used in the corporate failure prediction model. This will then allow for a better aligned assessment of those credit statics that have a higher unique contribution to being able to predict corporate failure. This is facilitated by excluding sector specific risk as a consideration.

A limitation of this approach is the challenge of pairing of non-failed and failed non-financial South African corporates with equivalent scale of operations. This is a result of the relatively small scale of the Johannesburg Stock Exchange when compared to large equity markets such as those in the United States and the United Kingdom.

Although this could often be a differentiator in the model, as larger scale often means greater diversity of operations both from a business and geographic perspective, leading to lower corporate failure propensity. This may not end up being a limitation to sample selection.

ii) Introduction of Moody’s best practices for assessing South African corporate credit risk

Moody’s Investors Service uses a number of techniques to allow for better credit analysis of non-financial corporates. These include adjustments to financial statements so that they factor all considerations for assessing the credit risk profile for non-financial corporates. Additionally, structural elements, which often mask credit risk exposure, are also factored in this analysis. Similarly, financial ratios frequently occurring in sixty-three unique non-financial corporate rating methodologies will be used. At the same time, an attempt will be made to include forward-looking expectations for the evolution of these financial ratios.

In combination, through inclusion of these techniques used by Moody’s Investors Service model predictive power should improve. Previous studies have, in the most part, overlooked or only touched the surface when it came to including additional measures used by rating agencies and banks providing loans. This will be discussed in greater detail in *Chapter 3*.

iii) Addition of equity market price movements in variable set

As part of the variable set that will be used in this study, the percentage change in equity market prices over the same period used for financial ratios will also be included along with a Debt/Market Capitalisation ratio. These should benefit the accuracy of the model from four perspectives.

This will add a forward-looking indicator, given that equity valuations will always factor the forward-looking expectations of investors.

At the same time equity prices also provide an independent appraisal of business risk reflected through the volatility of equity price returns. This also allows for insights into the propensity for equity values to fall below net asset value or assets less liabilities.

Thirdly, equity prices are also an independent check on financial information where auditors could overlook some misstatements. Investors in some cases are made privy to accounting concerns before they become known and also conduct their own independent analysis as to the reliability and realism of financial information provided by companies. This will also factor non-financial information which can be equally important to investors in arriving at a valuation of a company. Examples of these could be new legislation that is about to be passed which will benefit a company, or a soon to be concluded deal which will enhance the company's value. Beaver (1968) observed that financial ratios are not the only source of information on a company's solvency.

Lastly, and in line with the importance identified by Altman (2000) in assessing the value of a business once its liabilities have been settled, Altman's (1968) market value of equity to book value of liabilities will also be used. This introduces an alignment to that of market-based models and their focus on distance to default analysis.

Together these considerations introduce both a distance to default, through using a market value of equity to book value of liabilities ratio, and propensity to use up distance to default analysis in the model, through the inherent volatility that a company faces in its valuation relative to its liabilities expressed through the percentage change in equity market prices over the same period used for financial ratios. This will be discussed at length in *Chapter 3 | e) and f)*.

iv) Liquidity analysis as an additional forward-looking predictor of default

Disclosure around company liquidity has gradually improved overtime. Liquidity is often one of the best forward-looking predictors of non-financial corporate default. With adequate liquidity - companies can often "ride out the storm" and have sufficient time to take the necessary measures to keep their business from failing. This headroom is often reflected through cash and cash equivalent balances, committed banking facilities, and a long dated staggered debt maturity profile. Together these buy time through the ability to erode cash in the short term as remedial steps are taken, without the pressure of having to refinance or pay debt maturing, so that the business can be cash flow generative in the long-term.

Remedial actions often required to keep businesses under financial pressure from failing include sale of non-core loss making assets or business units, cost cutting measures, delaying or cancellation of capital expenditure, reengineering of business processes so that they are returned to being profitable, renegotiation of key supplier and customer contracts and closing of loss making operations. This list is certainly not exhaustive, but the key point is that many of these remedial actions take time to implement.

Often businesses have failed because they have simply run out of cash to keep their operations going. Given a bit more time, these business would likely have implemented the necessary measures to restore their operations back to generating cash flow, and therein be saved from failure.

Most companies now disclose both committed banking facilities and their draw down allowing for the calculation of debt financing availability. Similarly tables for debt maturing in one year, one to two years and two to five years, are often provided.

By using the cash flow statement as well as information from the company’s guidance statement around capital expenditure, a sources and uses analysis for the next twelve months can be generated. Sources typically include cash and cash equivalents, marketable securities, committed bank facility availability along with cash flow from operations. In the interests of prudence it is advisable to apply a 25% haircut to marketable securities, as although reflected at fair value, they could be sold for less depending on the state of the market.

These sources of liquidity should then be assessed against forecast uses over the next twelve months by the non-financial corporate. This typically includes capital expenditure, normally made available in a company’s full year guidance statements, dividend payments and debt repayments. Dividend policy can be estimated using the company’s dividend policy, if this is in existence and communicated to the market, against forecast full earnings guidance, upon which most dividend policies are based. In the case where a company pays out a flat dividend or maintains a progressive dividend policy, prior period dividend payments can be used and in the case of the latter grossed up at the progressive rate. Debt repayment as mentioned earlier can be calculated from debt maturity tables disclosed by companies often under their risk management disclosure note in their audited financial statements.

The intention of this study will be to generate coverage metrics for use in the multiple discriminant analysis model expressed as sources divided by uses. The expectation is that this should always exceed one for non-financial corporates that are not expected to fail within the following twelve month period.

c) Summary, conclusions and interlude

Corporate failure is multidimensional and often its prediction should consider a number of factors. Any analysis should consider both qualitative and quantitative information, which is both forward and backward looking. Also of key importance should be the key economic drivers of any business in both a micro and macro sense. These should receive equal importance in weighing up the likelihood of a corporate failing.

Chapter 1 has introduced the background to the study along with the key objectives, the rationale therein, and research questions. *Chapter 2* details Moody's Investors Service best practices, based on what is public knowledge, and the motivation behind various considerations. This overview begins with financial statement adjustments that are applied for better alignment in assessing credit risk. It then continues onto a discussion on structural considerations in assessing non-financial corporate credit risk. This is followed by considerations for including forward-looking information and concludes with the use of credit metrics seen to have broad applicability and predictive power across sectors.

Chapter 3 is a literature review introducing studies, which laid the foundation for corporate prediction using multiple discriminant analysis. This section also covers the varying definitions of corporate failure that have been applied in prior studies and data issues which have been noted at the same time. This will cover models developed in the United States and in other countries, comprising both developed and developing markets. A separate discussion on research undertaken on South African corporate failure prediction has also been included. Furthermore, across the entire discussion both accounting and market-based models and their inherent strengths and weaknesses are reviewed.

Chapter 4 analyses the sample of failed South African non-financial corporates and associated data. The initial research design included data with respect to liquidity and forecast information. However, this was shown not to be practicable given the lack of uniform financial information provided by non-financial South African corporates that were included in the sample. At the same time the most common credit statistics used by Moody's Investors Service along with two equity price based metrics are introduced to add forward-looking considerations into the model.

Chapter 5 discusses the results of multiple discriminant analysis which initially included eleven independent credit statistic variables. It was found that revenue, debt/Market Capitalisation and debt/EBITDA were the most pervasive discriminators of South African non-financial failure. These variables appear in most discriminant functions through the various optimisation runs to improve upon the initial research design model, therein demonstrating their unique contribution in differentiating between the two groups of failed and non-failed South African non-financial corporates. This was further supported by out of sample testing, where the initial sample was split into two to create a learning sample and a test sample. At the same time it was also shown that by using IFRS based financial information only, that classification rates improved, as opposed to using a sample reliant upon financial information prepared under both IFRS and the prior SA GAAP standards.

This study sets out to determine whether South African non-financial corporate prediction models using a larger sample of failed firms and using financial information prepared only under IFRS will improve classification rates, when compared to previous research. At the same time, additional enhancements will be added through adjusting certain financial information to better align its usage to that of credit analysis. Lastly, an attempt will be made to introduce an analysis of liquidity and forward-looking information, both through using equity price information and financial forecasts, into the research model design. Multiple discriminant analysis, the technique of choice and most commonly used for corporate failure prediction which is backed by extensive research on its application, will be used to facilitate the discrimination between failed and non-failed South African non-financial corporates.

Chapter 2 | Using Moody's best practices for assessing corporate credit risk

a) Rationale

Practitioner perspectives and insights, which are public knowledge, from covering South African corporates as a credit analyst for Moody's Investors Service in South Africa over the past 5 years will be incorporated in developing the model. The modelling approach will set out to capture some of the practical considerations based on experience in the non-financial corporate credit environment, which should be considered in developing a non-financial corporate failure prediction model but often have been overlooked in prior academic studies. This study only makes use of literature, which is made publically available by Moody's Investors Service, and therefore no proprietary or non-public content has been used.

b) Financial statement adjustments for better alignment in assessing credit risk

This includes making adjustments to financial statements using supporting financial notes to align accounting numbers to better reflect the true credit exposures of companies. Wingo and Dillow (2015) identified salient financial statement adjustments for the credit analysis of non-financial corporates. These adjustments are made to meet three objectives. Firstly, to align accounting principles to more faithfully capture underling economics, and secondly, to improve upon the comparability of accounting principles. This is more specific to comparing non-financial corporates on a consistent basis, where some report under IFRS, and others report under US Generally Accepted Accounting (US GAAP). Therefore this is not applicable to this study, which, as discussed earlier, will rely purely on data prepared under IFRS. Lastly, these adjustments aim to reflect estimates or assumptions, which are more appropriate to credit analysis. The common financial statement adjustments, which are applicable and will be used in this study are provided in the table on the following page:

Adjustment[1]	Rationale for making adjustment
Defined benefit pension plans	Removes artificial smoothing of pension expense, which is allowed under accounting standards and adds any underfunded or unfunded pension obligations to debt. Cash contributed to the pension trust is also reclassified in the cash flow statement.
Capitalised interest	Capitalised interest is treated as an expense and moved to operating activities in the cash flow statement from investment activities. This better reflects the credit substance of the transaction, which otherwise would be underplayed.
Capitalised development costs	Reflected as an operating expense and adjusted out of intangible assets while at the same time such investment is treated as an operating cash flow. This prevents any distortion of the financial risks when calculating financial ratios.
Interest expense related to discounted long- term liabilities other than debt	This reclassifies non-debt like long-term liabilities out of interest expense, and instead reflects these as an operating expense. This improves the delineation of finance related and operating activities in assessing the credit fundamentals of a business.
Hybrid securities	Adjusts for hybrid instruments or debt instruments that have debt and equity like characteristics, such as Payment-In-Kind (PIK) instruments, shareholder loans and convertible bonds with mandatory conversion or similar equity like features.
Operating leases	Operating and off balance sheet finance lease arrangements with legal contractual obligations are recognised and added

Adjustment[1]	Rationale for making adjustment
	to debt. At the same time the operating lease/rent expense is re-characterised in the income statement to better reflect the credit implications following conclusion of such transactions.
Securitizations and factoring arrangements adjustments	Classifies off balance sheet securitisations and factoring arrangements as debt where there is not a true sale. This occurs when not all risks and rewards are transferred.

[1]Where these adjustments have featured more prominently in this study or require further explanation as to how they are applied, an extended discussion has been provided.

In assessing defined benefit obligation exposures when it comes to pension fund obligation, this study, in line with the Moody's Investors Service's framework, will make the following adjustments as set forth on the next page with respect to the Income Statement, Balance Sheet and Cash Flow Statement:

Balance Sheet	» Add to debt any amount that is unfunded or underfunded and remove any intangible pension assets or liabilities.
Income Statement	» Reverse all pension costs and recognise service cost- this is the best estimate of the cost of operating the plan and is normally reflected as percentage of cost of sales, operating expenses and selling, general and administrative expenses. » Allocate an interest expense to pension related debt based upon the long term borrowing rate of the corporate (In this study interest expense as percentage of total interest bearing debt will be used where this is normally calculated from imputed data relating to the credit rating) » Exclude any interest expense above that which is recognised through the above calculation along with any gains/losses relating to the plan assets as an unusual non-recurring item.
Cash flow Statement	» Contributions to the plan beyond the calculated service costs are moved to the financing activities section. There is no adjustment made in instances where there is a deficit contribution relative to calculated service costs.

It is worth noting that most pension plans in South Africa are defined contribution plans rather than defined benefit plans. However this is not always the case, especially where South African companies have expanded internationally and in doing so assumed the pension obligations of companies that have been acquired.

Capitalisation of interest relating to property, plant and equipment (PP&E) is allowed in certain circumstances under IFRS. This commingles the operating and financing activities of a business. The study will align with the adjustment as set forth by Moody's Investors Service in decoupling this effect, which results in a better representation of the underlying economics for non-financial corporates:

Balance Sheet	» Reduce PP&E by the amount of interest capitalised during the period, adjusting for deferred taxes and reducing retained earnings by the after-tax cost of the additional interest expense recognised in the income statement
Income Statement	» Increase interest expense by the amount of interest capitalised and reduce applicable tax expense
Cash Flow Statement	» No adjustment required

Similarly, provided certain criteria are satisfied, capitalisation of development costs are mandatory under IFRS, which are seen to be operating costs and should be included in any credit assessment of operating performance. Therefore the following adjustments applied by Moody's Investors Service will be applied to this study:

Balance Sheet	» Reduce intangible assets by the cumulative amount of development cost, which have been capitalised whilst adjusting deferred taxes accordingly. These adjustments are then balanced with a reduction of retained earnings by the same amount.
Income Statement	» Operating expenses are increased by the amount capitalised to development costs for the period accompanied by respective adjustments to depreciation and tax
Cash Flow Statement	» Capitalised development costs are moved from investment activities to operating activities

Under IFRS, companies discount certain liabilities other than debt obligations to present value where this unwinding mechanism is treated as an interest expense. This distorts the relationship of interest expense and debt of companies and therein interest coverage ratios, which are an input in the credit assessment of any corporate. This study, in line with the approach practiced by Moody's Investors Service, will alter this effect by moving costs associated with the unwinding of these obligations to operating expenses. No adjustments are required in the balance sheet or cash flow statement where there is no impact.

In assessing debt instruments, which have both debt and equity like characteristics, Moody's Investors Service, along with this study, will apply its Hybrid Equity Credit assessment framework. A basket approach developed by Havlicek, Kessler and Bianchi (2015) is used and has been outlined below:

Basket	**Debt Component**	**Equity Component**
A	100%	0%
B	75%	25%
C	50%	50%
D	25%	75%
E	0%	100%

For further detail regarding the framework for the categorisation of hybrid instruments into their respective baskets please refer to appendix A and B.

Depending on the basket treatment the following adjustments will be made to the respective financial statements which are presented on the next page:

Standard adjustments for reclassification to equity for hybrid securities classified as debt

Balance Sheet	Hybrid securities reflected as debt are reclassified as equity (normally under preferred stock) in proportion to the equity weighting based upon the hybrid basket that is assigned.
Income Statement	Interest expense is reclassified to preferred dividends in proportion to the hybrid basket decided upon.
Cash Flow Statement	Interest expense, assuming that it has been reported under operating activities, is moved in proportion to its hybrid basket treatment to financing activities.

Standard adjustments for reclassification to debt for hybrid securities classified as equity

Balance Sheet	Hybrid securities reflected as equity are reclassified as debt (normally under subordinated debt) in proportion to the debt weighting based upon the hybrid basket that is assigned.
Income Statement	Preferred dividends are reclassified to interest expense in proportion to the hybrid basket decided upon.
Cash Flow Statement	Preferred dividends are moved in proportion to their hybrid basket treatment to operating activities from financing activities.

In assessing operating lease obligations, the framework adopted by Moody's Investor's Service will be used to better reflect this obligation through various adjustments. These include an apportionment of the rent expense in the Income Statement of one-third to interest expense and two-thirds to depreciation expense.

At the same time, the greater of a multiple of the rent expense or present value of future lease obligations is applied to debt. Multiples are applied based upon the respective sector of a company's operations. For more information on sector multiples that are applied please see Appendix C. Discount rates are derived from a company's long term borrowing rate based on the rating category which is then mapped to corresponding bond yields derived from Moody's Analytics proprietary data.

This study will instead use the company's interest expense as a percentage of interest bearing debt. This is due to the limited universe of listed South African corporates rated by Moody's Investors Service and that corresponding bond yield data from Moody's Analytics is proprietary in nature. The adjustment process is summarised below:

Balance Sheet	Debt and fixed assets by an amount that equals the greater of (i) the present value of minimum lease commitments, capped at 10x, or (ii) a sector multiple times annual rent expense.
Income Statement	Rent expense reclassified to interest and depreciation expense using the following calculation, and operating expenses adjusted (or cost of goods sold and selling, general & administrative expenses) proportionally: » Lease Interest Expense = Lease debt times an intermediate term interest rate based on the issuer's rating (capped at rent expense) Lease Depreciation Expense = Rent Expense less Lease Interest Expense
Cash Flow Statement	Lease depreciation expense reclassified from operating cash flow to capital expenditures.

When a company sells any form of receivables forward, Moody's Investors Service views this as being the same as a collateralised borrowing activity. This is commonly referred to as a securitisation of assets or factoring. Such activity results in a temporary inflation of a company cash balance, which at the same time could be applied to reducing debt, often resulting in credit ratios looking stronger, either way, than they actually should be. To align with Moody's Investors Service's analytical view this study will make the following adjustments to avoid this distortion from occurring which are provided on the next page:

Balance Sheet	The amount sold forward is restored to its respective line item in the asset section of the balance sheet and the equivalent amount added to debt
Income Statement	An interest expense is added based upon the non-financial corporate's short term borrowing rate and other operating expenses are increased by the same amount
Cash Flow Statement	Cash inflow from the sale of receivables is moved from operating activities to financing activities. Any deficiency or surpluses resulting from collection of the receivables going forward are added to operating activities or added to financing activities, respectively.

Further considerations for Moody's Investors Service in its assessment of non-financial corporates are non-reoccurring and unusual items, equity accounted income, and subsidiary investments where there are significant minority investors. These considerations often may result in significant variations between information derived from the Income Statement and the Cash Flow Statement or the ability to control cash flow or capital structure decisions at subsidiary investments where there are significant minority investors. This is often primarily due to their accrual or non-cash based nature or a limited ability to fully control financial decisions at subsidiary investments where there are significant minority investors.

In most cases Moody's Investors Service will adjust out non-recurring and unusual items from the Income Statement and Cash Flow Statement to avoid distortion of operating performance. Examples include assets sales, revaluation of assets, non-operating expenses such as information technology upgrades and fines or penalties to name a few. Any transaction that does not constitute normal operating activities for a business or is not expected to reasonably occur again in the future, is generally treated as unusual or non-reoccurring in nature. This is done so that ratios when calculated, offer a better indication of the on-going profitability of the business under what is deemed to be normal operating conditions. This gives a better indication of the long-term ability of a business to sustainably generate sufficient cash flow to service its debt. Broadly this is done using the following approach:

Balance Sheet	Adjusted when material to any credit analysis
Income Statement	Unusual or non-recurring revenues, gains or costs, are included net of tax to a special line item below net profit after tax. This is then excluded from any financial ratios using income statement figures.
Cash Flow Statement	Unusual or non-reoccurring cash inflows or outflows are reclassified to a special line item under operating activities. This is then excluded from any financial ratios using cash flow statement figures.

c) Structural considerations and adjustment to better reflect credit risk

Moody's Investors Service moves equity accounted income to a line item after earnings before interest, tax depreciation and amortisation (EBITDA). This study will do the same. The rationale behind this is to allow for better alignment of EBITDA with cash flow generation, while at the same time allowing for the income statement to still build up to the non-financial corporate's reported net profit. Equity accounted profits are included under a special line item, after tax, before the corporate's reported net profit.

Equity accounted income in most cases does not reflect the underlying dividend flows and therefore cash received from equity accounted investments. If this were the case, this would have to be supported by companies having dividend policies targeting payment of all earnings for each reporting period. In the long-term this is unsustainable, as profits need to be reinvested in the business. Reinvestment of profits is essential for sustaining and maintaining the quality of current operating assets and growing the company's asset profile to capitalise on growth opportunities. This is particularly evident in growth companies, especially those focused on the technology sector, where dividends are not paid out in favour of growing the business. These are often directed towards continued investment in research and development, as well as, plant, property and equipment to ensure that products and service ranges remain competitive.

Where companies are regular dividend payers, a view can be taken to replace equity accounted income with dividends received during the reporting period. This is then also included in the calculation of EBITDA. This approach normally relies upon a dividend policy to payout a pre-specified percentage of earnings that has been agreed by an independent board of company directors. In some instances historical dividend payout ratios can also be used. Notwithstanding that dividend policies can be changed, albeit with a degree of rigmarole, reliance purely on dividend history offers less certainty of dividends being paid in the future.

Where there is a realistic expectation that dividends will be received from respective associate investments it makes sense to include dividend flows in the calculation of EBITDA as an indication of on-going cash flow to companies. This is based on the premise that positive earnings continue to be reported. Equity accounting reporting with respect to the cash flow statement and balance sheet are still seen to be representative of the credit picture faced by the company. South African non-financial corporate examples, where Moody's Investors Service has elected to include dividends received in place of equity accounted income, include Naspers Limited.

On 14 May 2015 Naspers had a 34% investment in Tencent and 30% investment in Mail.ru group. Both companies represent significant investments for Naspers and generate material cash flow for the company through dividend payments. They both have operations with a core focus on internet services, which have required significant investment in technology and marketing to grow their offerings to the market. Excluding once-off special dividends, dividend payments remain low as a proportion of earnings, due to reinvestment of the earnings. Notwithstanding this consideration, given the percentage of total share capital held in Tencent and Mail.ru group, Naspers would also unlikely be successful in forcing a continual or even just a once-off 100% dividend declaration of earnings. This again supports the notion of not recognising equity accounted profits in their entirety. This is due to equity accounted profits often being loosely linked to the underlying cash flows that are ultimately received from these investments.

Despite no formal dividend payout ratio policy, given the materiality of these investments for Naspers' credit profile, a decision was taken to substitute equity accounted income for dividends received. This better aligned EBITDA with the cash that was received from dividends flowing from these investments. This also recognised alignment with the true cash flow potential of the business that can differ vastly from reported equity accounted profits. If reported equity accounted profits had been included in EBITDA this would have resulted in a significantly inflated number which was representative of cash flowing to Naspers that was not under its control.

Moody's Investors Service will closely examine subsidiary investments where there are significant minority holding which decrease the ability of the controlling company to fully control cash flows and capital structure decisions. Under IFRS, subsidiary investments controlled by the parent company are consolidated across all of its three financial statements. This gives the financial picture that subsidiary investments are effectively one and the same in the context of the organisational structure of the controlling parent company.

There are a number of shortcomings in this approach when it comes to credit analysis. Firstly, this ostensibly assumes the controlling parent company is part and parcel of revenue and expenses and all cash flow movements, which is not the case. This results from combining the income statement and cash flow of subsidiary investments line item by line item with that of the controlling parent company, excluding any intergroup transactions, which may occur. In reality the controlling parent company is limited in the extent to which it can look to the cash flow of its subsidiary investment as a full dividend declaration of earnings. Any cash flow movement beyond this is unlikely, as this would circumvent corporate governance considerations. This would be seen as a breach of fiduciary duties by the board of directors, who, at all times, have to act in the best interests of the subsidiary investment company. The presence of significant minority investment holders will also put up barriers to such an occurrence.

At the same time, there are limitations with respect to the controlling parent company's ability to influence investment and capital structure. Oversight of assets is limited to the management team overseeing the operations of the subsidiary investment. The liability and equity composition of the subsidiary investment company also falls under the discretion and determination of the same team. The only situations where some degree of influence could be exerted would be at the time when executive officers are reappointed, where they could be replaced with a more parent company friendly representation, notwithstanding that this would need to be done in consensus with the significant minority investment holders and in line with fiduciary duties.

Therefore in forming a true credit picture the analysis should then strip out all effects of a combination of all subsidiary investments in the controlling parent company's income statement and cash flow statement, only including equity accounted income in the income statement and dividends received in the cash flow statement. For the aforementioned reasons, it also does not make sense to simply consolidate the balance sheet structure of the subsidiary investment into that of the controlling parent company, given the limited control that can be exerted in this regard. Such examples of where this analysis has been applied include Steinhoff International Holdings N.V. and MTN Group Limited.

Steinhoff in their initial asset swap transaction concluded in 2013 with KAP Industrial Holdings Limited and JD Group Limited, obtained controlling equity stakes in both listed investments. Under IFRS these investments were consolidated. However, both investments had significant minority shareholders, representing around 40% of the total listed share capital, independently for both companies. Moody's Investors Service was of the view that there was limited influence, which could be exerted over these investments' cash flows and capital structure. At best Steinhoff could only use its influence to bring about a 100% declaration of earnings in any one given period.

Moody's Investors Service followed up analytically with this view by fully deconsolidating these two investments from the financial statements. They were then limited in their recognition to something that came close to an equity accounting approach. In line with this adjusted approach the following were reflected: (1) equity accounted profits/losses in the income statement, (2) investment value in the balance sheet recognised as the share in the listed valuation at reporting date whilst applying a 25% haircut in the interests of conservatism and recognising equity market volatility; and (3) dividends received in the cash flow statement. This aligned with the view that, at best, EBITDA could benefit from a 100% dividend declaration of earnings and that the value attributed to the investment, notwithstanding any control premium and in interest of conservatism, would below the market valuation at the reporting date. At the same time given the amount of subsidiary debt exposure it did not make sense to fully consolidate this either.

MTN presented similar analytical challenges. A unique analytical approach was adopted given that the primary debt raising entity is MTN Group Limited rather than the ultimate parent and reporting entity, MTN Holdings Limited. This at the same time recognised MTN's geographic diversity of operations. MTN's portfolio of operations comprise a number of subsidiary investments with the presence of minority investors, which are often required by the markets where it operates. The inclusion of minority investors often meets indigenisation or government ownership requirements imposed by telecom regulators. As such, and with a similar rationale to Steinhoff but extended to cash flow repatriation requirements, consolidation of subsidiary investments was deemed not to be representative of the underlying cash flow supporting the business along with financial statement exposures.

MTN's funding model is focused on raising debt at operating subsidiary levels with no recourse back to the South African entity on the strength of the balance sheet of these operating subsidiaries. MTN Group Limited in turn funded the initial investments from these markets along with continued funding of South African operations.

Under this situation Moody's Investors Service elected to focus purely on MTN Group Limited on a standalone company financial statement basis and then recognise dividend and management fee flows to the company from its various subsidiary investments. This was seen to be more representative of the actual 'true' credit profile of MTN Group Limited, not only in terms of its debt obligations but also the cash flow dynamics underpinning the ability to service this debt.

This study will also introduce factors, which Moody's Investors Service considers when incorporating any credit uplift or credit pressures that may not be immediately evident when looking at a company on a standalone basis. This includes government ownership, which Moody's Investors Service captures under Government-Related Issuers methodology developed by Wilson, A., Coley, W., Lemay, Y., Marion, S., Benedicte, A. and Ferrer-Vidal, S. (2014) along with any accompanying implicit or explicit assumptions.

In the case of non-financial corporates that are government owned, they either benefit from a demonstrated track record of credit support, or a sovereign that is reliant upon the corporate entity to meet its own strategic objectives or to contribute cash to the government.

In the case where there is credit support being offered, the credit profile on a standalone basis does not fully represent the credit strength of the entity. Under such instances there is an assumption that were the non-financial corporate to come under any unforeseen financial pressure, that the sovereign would step in with an appropriately measured cash injection or provision of guarantees to debt holders. These non-financial corporates are often strategic in nature for the government. The impact of their financial failure would have broader, often dire, economic consequences for the sovereign or country. Hence, the need to provide financial support, if required. Under these circumstances it is not in the sovereign's interest to allow such a corporate to go into financial failure.

This equally can work the other way. Some non-financial corporates owned by governments may be tasked with meeting broader social objectives. This can range from targeting capital expenditure on certain strategic regions or sectors to charging its customers below market rates. In turn, this can often result in a credit profile, which otherwise would have been assessed as being strong on a standalone basis, being viewed more weakly. This is due to the resulting drag effect on the corporate that follows from government interference in its day to day functioning. Similarly, a government, which is heavily reliant on dividend flows from a corporate, can also place pressure on its standalone credit profile. By having high dividend payout requirements this leads to a weaker overall assessment of financial strength. Lastly, government ownership can also result in weaker governance oversight. This occurs when the board is primarily comprised of government officials, which in some instance leads to less scrutiny than had the corporate been in private hands. This can also lead to the company being run under social considerations rather than for profit considerations.

It is worth noting that given the current universe of South African corporate failures there are no government related non-financial corporates, which have failed. These entities are also not publically listed, so this would limit usage in the context of this study's independent credit statistic variables. However, the above considerations are worth noting for future studies where the universe may have changed. South African government owned non-financial corporates, such as Eskom SOC Ltd and Transnet SOC Ltd, continue to be significant debt capital market issuers in South Africa. To overlook this consideration, would be to ignore a large portion of the debt capital market, to which these state owned companies continue to contribute.

However, this consideration aside, this analytical framework should not be overlooked in the context of the non-financial corporate being part of a broader organisational structure. In such instances financial support received and provided should always be considered in assessing the credit strength of an entity.

Some corporates may benefit from guarantees being extended to their debt often from an entity with a stronger financial profile. This occurs whereby the extension of a guarantee by another entity provides credit enhancement to the entity benefiting from the guarantee. This can be both upstream in nature, commonly from operating subsidiaries, and downstream in nature, from parent entities or shareholders. These are also important considerations in the earlier discussion of investment subsidiaries with significant minority shareholders. It is worth noting that it is rare but not uncommon for a parent to guarantee debt of non-wholly owned subsidiaries. Similarly, the same applies to investment subsidiary with significant minority shareholders guaranteeing the debt of a parent. In both situations it makes sense then not to decouple the credit profiles of these entities given their interlinkage.

Therefore the financial risks borne by investment subsidiaries with significant minority shareholders should be reflected in the credit assessment of the parent, which has extended the guarantees. This is a simple assessment as it then makes sense to align with the IFRS consolidated approach. Similarly, risk exposures of investment subsidiaries with significant minority shareholders extending upstream guarantees to a parent, should similarly reflect the financial risks of the parent. This occurs often when the parent is a shell entity with investments in cash generating operating subsidiaries and associates. This is a slightly more complex analytical setup and often involves adding parent guaranteed debt to the debt of the operating subsidiaries. This however also considers the likelihood of the guarantee being called upon as well as the relative strength and exposure of each operating subsidiaries, providing debt guarantees.

Examples of downstream guarantee arrangements include Steinhoff International Holdings N.V. prior guarantee of legacy debt, which KAP Industrial Holdings Limited assumed as part of an asset swap transaction recognised by Moody's Investors Service (2011). An example of an upstream guarantee would include Sibanye Gold Limited's prior guarantee of Gold Fields Limited's US$1 billion senior unsecured bond the impact of which was dimensioned by Rowlings (2015). The guarantees resulted from the unbundling of Sibanye Gold from Gold Fields, which was then separately listed on the Johannesburg Stock Exchange. Sibanye Gold has previously formed part of the restricted group guaranteeing Gold Fields' debt and therefore had to continue to do so under the terms of the bond indenture. Sibanye Gold was subsequently removed as a guarantor in March 2015 as part of a consent and solicitation offer.

This study in developing a multiple discriminant analysis model will also attempt to control for these unique credit considerations, which can often lead to an improvement in corporate failure prediction power offered by financial ratios being tied to the true credit profile of a corporate when these qualitative considerations are reflected.

d) Incorporation of forward-looking expectations in assessing robustness of credit strength

Moody's Investors Service benefits from the provision of company forecasts on a confidential non-public basis which provides analysts with the ability to assess the evolution of a company's credit profile factoring their expected financial performance and business plans. These are often sensitised, depending on the degree of conservatism that management builds into their financial forecasting. A conservative approach to financial forecasts ensures the robustness of ratings through business cycles. At the same time this also builds-in cushioning for performance misses and overshooting on costs or capital expenditures against expectation. This forward-looking information is critical in determining any deterioration in a company's financial strength in advance of its occurrence.

Although such information will not be made available for this study, given Moody's Investors Service confidentiality practices, a work-around approach will be explored. Most companies now provide regular full year trading guidance, which is updated at each financial reporting date and includes financial year-end expectations for key metrics applicable to the business. For example, miners will often provide guidance on revenue, costs and capital expenditure based upon their view of production, prevailing commodity prices, currency exchange rates and reserves which rely upon technical reports prepared by independent mining consulting firms. This information, when available, will be used as a proxy to generate forward-looking expectations to be used as additional data points for variables included in the multiple discriminant model to determine if this improves accuracy.

These key indicators, when combined, will ultimately determine free cash flow generation, which is calculated using cash flow from operations minus dividends and capital expenditure. Negative free cash flow will have to be funded through depletion of cash balances, raising of debt through bond issuance or drawing on bank facilities or, if shareholders agree, an issuance of equity. Similarly, these will also determine the evolution of banking covenant levels, which if imposed and breached, will result in banking facility lines being cancelled, which will put a company under liquidity pressure. The strength of a company's liquidity position often provides one of the best early warning signs of failure. Without sufficient cash to fund its operations, a company cannot survive. Using guidance, when made available, an additional overlay for the multiple discriminant model will be considered which factors expected liquidity sources versus uses over the next twelve months. Most management commentary now includes a specific discussion of the company's liquidity position allowing for this analysis to be undertaken as part of the study.

By including forwarding looking equity prices, expectations of variable evolution, and a twelve-month view on liquidity, this model specification is expected to improve the accuracy in predicting corporate failure. Most prior South African corporate failure models developed using multiple discriminant analysis have relied upon historical financial statement data, which provides limited information on the future financial strength of a company.

e) Use of credit metrics with strong explanatory power and adaptability across sectors

Moody's Investors Service's non-financial corporate rating methodologies, spanning sixty-three unique non-financial corporate sectors, will be used to develop an initial sample of credit metrics. Credit metrics occurring most frequently will be included in the initial sample of variables that will be used in the multiple discriminant analysis model. This will ensure the inclusion of variables, which are more broad-based in nature and capture movements in the credit strength of companies regardless of the nature or sector of their operations.

Qualitative inputs will also be considered for inclusion in the initial sample of variables. Factors such as quality of management, financial policy and competitive strength are often determinants for the range of responses available to companies in protecting their credit profiles when adverse or challenging operating or financial conditions present themselves. These are often subjective in nature and derived through forming a consensus view amongst rating analysts. However, they provide valuable insights into behavioural characteristics often glossed over in corporate failure analysis, which only focuses on quantitative considerations. Moody's Investors Service under such instances normally makes use of a pre-agreed grid, which is used as a guide in assigning a risk score to various qualitative factors. A similar approach will be used in this study.

At the same time, often the sector in which a company operates will determine their financial risk profile. Companies that operate in more cyclical sectors or sectors that are transitory in nature, such as technology companies, are subject to a greater degree of business risk. This study will also attempt to include a qualitative risk input, based upon the company's business profile, to control for business risk

Together these qualitative inputs often offer alternative, but equally import, inputs into assessing corporate failure when combined with quantitative considerations.

Chapter 3 | Literature on corporate failure prediction

The chapter will discuss the various definitions and interpretations of corporate failure that have been applied to studies undertaken in South Africa and internationally. At the same time some of the data issues experienced by researchers in the field of corporate failure prediction will be highlighted.

The focus will then shift to a summary of accounting-based corporate failure prediction research undertaken in the United States, which continues to be a leader in this field. This will be followed by studies undertaken outside of the United States split into developed and developing markets.

In addition, market-based models for corporate failure prediction will be surveyed and the theory underlying their development explained. Their application and accuracy will then be compared to that of accounting-based models.

Having considered international studies, a full discussion will follow on South African research to date carried out on market-based models and accounting-based models used in corporate failure prediction.

The chapter concludes with a discussion on multiple discriminant analysis and financial research applications.

a) Definition of corporate failure

Varying definitions of corporate failure have been applied to studies over time. Beaver (1966) defined a group of failed companies as those that defaulted on a loan obligation or missed preferred dividend payments in addition to any form of bankruptcy or insolvency problems. Altman (1968) decided to limit his bankrupt group in his sample of companies to manufacturers that filed a bankruptcy petition under the United States' Chapter X of the National Bankruptcy Act. Deakin (1972) opted for a categorisation as companies which had experienced bankruptcy, insolvency or liquidation. Later Altman, Haldeman and Narayanan (1977) broadened Altman's original definition of corporate failure to include bond defaults and non-payment of dividends.

Taffler and Tisshaw (1977), in a study of English companies, defined failure as firms entering receivership, voluntary liquidation imposed by creditors, compulsory winding up order by a court of law or steps taken by government to avoid financial collapse. In a study of Brazilian companies, Altman, Baidya and Ribeiro-Dias (1979) defined corporate failure as filing for liquidation, undertaking legal reorganisations and indicating 'out of court manifestations of serious problems'. Ta and Seah (1981) in their study identified failed firms as those that were either in receivership, voluntary liquidation or in a court winding up procedure. In an Australian context, Castagna and Matolcsy (1982) defined corporate failure as the occurrence of an appointment of a liquidator or receiver.

Bhatia (1988) aligned the definition of corporate failure with that which is stipulated by the Industrial Development Bank of India in their classification criteria of 'sick' firms. These were limited to firms that had two years of cash losses or a had experienced continual erosion of net worth of around 50% or defaulted on debt servicing four times in succession. These also included firms that had made irregular use of credit lines on a persistent basis or were one to two years of tax payments in arrears.

In an international context Altman and Narayanan (1997) broadly recognised corporate failure as constituting either a bankruptcy filing, bond default, bank loan default, delisting or, government intervention via special financing to avoid failure or liquidation. This was based upon their review of corporate failure prediction model studies across a number of countries.

An observation made by Altman and Narayanan (1997) relates to the importance of the sample's cut-off date identified for corporate failure events occurring. This gained prominence when it came to Type II errors (incorrectly classifying a non-failed firm as being financially distressed), where some of these firms did fail at a later time. This was attributed to healthy firm's data in essence being censored because all that could be said was that the firm was healthy at the time the data was collected.

In a South African context Court, Radloff and van der Walt (1999) described corporate failure as those companies that were forced to delist from the Johannesburg Stock Exchange (JSE) due to poor financial performance leading to liquidation. Bruwer and Hamman (2006), interpreted failure as a company that "will not survive in its existing structure, and therefore encompasses a delisting or a major structural change". Muller, Steyn-Bruwer and Hamman (2009) applied the same definition of corporate failure in their study.

With the introduction of the new South African Companies Act financially distressed companies were defined in Chapter 6 of the Companies Act No. 71 of 2008 by the Parliament of the Republic of South Africa (2008)and the Companies Amendment Act No. 3 of 2011 Section 128 by Parliament of the Republic of South Africa. (2011). These were defined as companies, which were expected to become insolvent within six months, or being reasonably unlikely to pay all of their debts as they became due and payable within the immediately ensuing six months. At the same time companies under the act in financial distress are required to either (1) enter into business rescue proceedings; (2) liquidate; or (3) compromise with creditors. If the company elects to proceed with the first option it is placed under temporary supervision of the court. This provides for relief against its creditors until such time that a business rescue plan has been devised.

This in many respects is similar to the United States' Chapter 11 Bankruptcy Code enacted by the U.S. House of Representatives (1978) commonly referred to as a "reorganisation" bankruptcy. Under the Chapter 11 Bankruptcy Code corporates are also given protection from creditors. Proceedings are similarly overseen by the courts, where a reorganisation plan has to be presented and accepted.

Through alignment of the processes for managing corporate failure between South Africa and the United States, there is rationale that United States research should be applicable and comparable in this respect. However, it is worth noting that there are nuances, which cannot be ignored, most notable of which is the fundamental difference in legal systems. South Africa follows a common law approach to its bankruptcy proceeding whereas the United States adheres to civil law. This is discussed further in *Chapter 3 | d)* as part of the overview of international studies on corporate failure prediction.

In a South African practical setting Dywer and Wang (2010) in their creation of Moody's Analytics RiskCalc v3.2, South Africa did not define corporate failure but rather defined default. The meaning of default was extended to also include missed payments and other credit events. There was also recognition that there is debate arising from the process of assigning an appropriate definition of default, which has arisen for the process of developing the Basel Capital Accord. In this instance RiskCalc chose to conform to the criteria for default, which is prevalent in most advanced economies in the world. This was characterised as payments that are 90 days past due, bankruptcy or liquidation, and placement on an internal non-accrual list. This was further extended to any write-downs resulting from unlikely payment, charged-off loans, facilities which had been called, special provisions or restructured debt.

In another related Moody's Analytics study Sun, Munves and Hamilton (2012) in their explanation of the Expected Default Frequency (EDF™) model defined default as including the failure to make scheduled principal or interest payments, bankruptcy, administration, receivership, or their legal equivalent. This also encompassed any form of distressed debt restructuring and/or government bailouts enacted to prevent a credit event such as a default on debt obligations.

Emery (2015) in Moody's Investors Service's Rating Symbols and Definitions constitutes debt default as occurrence of any one of four events. The first being missed or delayed payment of a legally contracted interest or principal payment as defined in credit agreements or a bond indenture, but not including missed payments which occurs within a contractually allowed grace period. The second being bankruptcy filing or legal insolvency by a debt obligor meaning future contractually-obligated debt service payments will either be delayed or missed. The third being distressed exchange whereby (1) the obligor offers creditors a new or restructured debt instrument, securities package or cash or assets that would amount to a diminished financial obligation relative to the original obligation; and (2) the exchange allows the obligor to avoid bankruptcy or a default on payments in future. The fourth being change in payment terms of credit agreement or bond indenture imposed by a sovereign resulting in a diminished financial obligation e.g. forced currency re-denomination (imposed by a debtor, themselves or their sovereign or any forced change of the original promise such as indexation or maturity).

This definition excluded technical defaults arising from maximum leverage or minimum debt coverage covenants with lenders being violated, unless the obligor fails to remedy the violation or honour any resulting acceleration in payment of debt. This would also exclude payments owed on debt obligations which are missed purely due to a technical or administrative error and are (1) not related to the obligor's ability or willingness to make debt repayments; and (2) are remedied in a very short-order (typically one to two business days). Lastly based on select facts and circumstances, missed payments on financial contracts or claims could also be excluded if their validity is legally disputed.

b) Data issues

As Altman and Narayanan (1997) identified, good data was often hard to come by in their survey of corporate failure prediction model studies undertaken across the world. Data on failed firms was often difficult to collect in smaller economies of some developed countries and in the case of most developing countries.

The sample of South African corporate failures faces similar challenges where many failures are limited to small private companies. This means that financial data is not easily accessible and not subject to the same degree of rigour in its preparation and scrutiny. Most of these companies are not regulated and their financial statements are not subject to the same degree of detailed audit examination as listed companies, notwithstanding that they are often not audited by top tier accounting firms.

Fosu (2013) highlighted that given the conservative nature of financial management in the South African corporate arena, many companies are predominantly equity financed. This preference to fund companies through equity instead of debt lowers the likelihood of a company finding itself in a situation of financial distress. As result, this also leads to a lack of large-scale defaults in the South African corporate sector.

Altman and Narayanan (1997) observed that the size of the sample used and the sources of data are critical in assessing the statistical reliance which can be placed upon results. This is a further limitation when it comes to replication or extension studies based upon prior foundation studies. This also presents challenges when it comes to the randomness and size requirements for any statistical analysis along with the confidence of the conclusions that are reached.

c) Research on accounting-based models for corporate failure prediction in the United States

The first prominent academic attempt to develop a corporate failure prediction model can be attributed to accounting researcher, Beaver (1967). This model used a univariate analysis of financial ratios matching failed and non-failed companies which demonstrated the ability to predict corporate failure up to five years in advance of failure occurring. This set the stage for further multivariate approaches.

Altman's (1968) application of multiple discriminant analysis followed using a similar methodology to that of Beaver's (1967) univariate approach. The expectation was that the introduction of a multivariate framework would result in greater statistical significance than the technique of sequential comparisons.

Altman's (1968) model was referred to as the Z-Score model which correctly predicted 94 per cent of the initial sample as having failed. Out of sample testing had an even higher 96 per cent classification, where the upward bias was supported by the initial sample test upward bias normally present not having manifested in the investigation and/or the initial model not being optimised. The initial sample comprised sixty-six US manufacturing corporations with two a priori groupings of thirty-three failed and thirty-three non-failed companies. Non-failed companies were paired with failed companies and chosen on a stratified random basis. This recognised that this group was not completely homogenous due to industry and size differences. Firms were stratified according to industry and their size, with total assets size restricted to US$1-US$25 million. Similarly small firms were excluded (under US$1 million in total assets) as were large asset-size firms exceeding $25 million to match that of the sample of failed firms.

Deakin (1972) used the same fourteen variables that Beaver analysed but instead applied a multivariate discriminant model. Profitability, liquidity and solvency ratios were the most significant indicators of corporate failure. A further evolution of the Z-Score model by Altman, Haldeman and Narayanan (1977), brought about the introduction of the ZETA® model. This introduced several enhancements to the original approach most notable of which was the incorporation of developments around business failure and refinements in the utilisation of discriminant statistical techniques. In addition, the ZETA® model also settled on the use of seven ratios whereas the Z-Score model relied upon five ratios.

The ZETA® model recognised the change in financial profile and size of business failures. Most prior studies models had used relatively small firms in their samples, which were not representative of the population to which they would be applied. Furthermore, these studies also tended to concentrate on manufacturers or specific industries. With appropriate analytical adjustments to make company financial data comparable across different industries this would allow for better alignment to that of the population.

The ZETA® model introduced various adjustments to inputs in the financials in line with a similar approach adopted by credit rating agencies to better reflect the credit fundamentals of each company. These included (1) the capitalisation of leases; (2) the inclusion of reserves in equity; (3) minority interests and other liabilities on the balance sheet netted off against other assets; and (4) the consolidation of captive finance companies and other non-consolidated subsidiaries. The ZETA® model enhanced the accuracy of predicting corporate failure to 96.2% versus the Z-Score model's 93.9%. It is worth noting that the incremental benefit of the ZETA® model versus the Z and Z'' models is not significant, which add credibility to the Z and Z'' models being used in the study.

Altman (1993) then developed the Z'' model. This model substituted book value of equity for market value first to derive what was referred to as the Z' model, which in turn then allowed the model to also be used for private companies. This resulted in a slightly lower accuracy for predicting bankruptcy of 91% versus the original model's 94%. The Z'' model went on to remove the asset turnover ratio (sales/total assets) from the Z' model to allow for more wide spread applicability to corporates across industries by removing this manufacturing focused ratio. A summary table of the ratios used in each of Altman's models is provided below:

	Z Score Model		***ZETA® Model (proprietary hence no weightings)***	
	Ratio	***Weighting (W)***	***Ratio***	***Weighting (W)***
X_1	$\frac{Working\ Capital}{Total\ Assets}$	0.012	$\frac{EBIT}{Total\ Assets}$	N/A
X_2	$\frac{Retained\ Earnings}{Total\ Assets}$	0.014	$S_e{}^4 = \frac{S^5\left[\frac{EBIT^1}{Total\ Assets}\right]}{\sqrt{n}}$	N/A
X_3	$\frac{EBIT^1}{Total\ Assets}$	0.033	$\frac{Retained\ Earnings}{Total\ Assets}$	N/A
X_4	$\frac{MV^2\ Total\ Equity}{BV^3\ Total\ Liabilite}$	0.006	$\frac{EBIT^1}{Total\ Interest\ Payments}$	N/A
X_5	$\frac{Sales}{Total\ Assets}$	0.999	$\frac{Current\ Assets}{Current\ Liabilities}$	N/A
X_6			$\frac{BV^3\ Total\ Equity}{BV^3\ Total\ (Equity + Liabi}$	N/A
X_7			$Total\ Assets$	N/A
	Z' Model		***Z'' Model***	
	Ratio	***Weighting (W)***	***Ratio***	***Weighting (W)***
X_1	$\frac{Working\ Capital}{Total\ Assets}$	0.717	$\frac{Working\ Capital}{Total\ Assets}$	6.56
X_2	$\frac{Retained\ Earnings}{Total\ Assets}$	0.847	$\frac{Retained\ Earnings}{Total\ Assets}$	3.26
X_3	$\frac{EBIT^1}{Total\ Assets}$	3.107	$\frac{EBIT^1}{Total\ Assets}$	6.72
X_4	$\frac{BV^3\ Total\ Equity}{BV^3\ Total\ Liabilite}$	0.420	$\frac{BV^3\ Total\ Equity}{BV^3\ Total\ Liabilites}$	1.05
X_5	$\frac{Sales}{Total\ Assets}$	0.998		

[1]Earnings Before Interest and Tax; [2]Market Value; [3]Book Value; [4]Standard Error; [5]Sample Standard Deviation; where $Z = \sum_i^n W_i X_i$ with Z>0 being classified as non-failed and Z<0 as failed

d) Research on accounting-based models for corporate failure prediction outside of the United States

The studies included in this review are limited to markets that share broad similarities to the South African corporate sector. Markets with similar corporate legal frameworks and accounting standards have been included in this study given that their findings are seen to be more applicable and transferable to South African corporate failure prediction. This is the case in many respects for other former English colonies such as Australia, Canada, India and Singapore, which have their corporate legal foundations originating from English common law. Although South Africa's legal system comprises aspects of both English common law and Roman Dutch civil law, as a general rule company law follows that of the English legal system. Most major lending agreements and therefore liquidation proceedings generally fall under English common law.

The applicable legal framework can have significant bearing on both the definition and declaration of corporate failure. The University of California at Berkeley, School of Law (2010) identifies the main theoretical differences between common law and civil law as follows: common law is generally uncodified (not rule based), where there is reliance rather on precedent, and civil law as codified (rule based), where there is a reliance rather on prescribed framework for dealing with all legal matters.

Roman Dutch civil law has limited bearing on contractual law in South Africa with lending agreements normally conforming to an English commercial legal agreement template. Brazil and Mexico have legal systems that align with civil law which has its origins in Roman law.

Although all of these markets now conform to IFRS, many seminal studies were undertaken in these markets prior to the introduction of IFRS. Each market mostly had their own set of financial reporting standards and framework which they applied.

Today, the United States is the only notable exception for following a different set of accounting standards to IFRS, namely US GAAP. Although it is worth mentioning that there continues to be an increasing convergence between these two sets of accounting standards.

PwC (2014) does however point out that although IFRS is required in the case of listed Canadian firms for their interim and annual financial statements; however for companies with United States listings US GAAP continues to be acceptable.

Altman and Narayanan (1997) outline the main characteristics observable for developed country models. Most notable is that failure prediction studies have a long history and that corporate failure data is more readily available. Furthermore failure was easier to identify because of the existence of clearly defined bankruptcy laws and banking infrastructure. Government intervention is also somewhat less but not non-existent. Economies were viewed as being subject to a greater degree of privatisation and less state interference. However, regulatory oversight for companies is more sophisticated, onerous and transparent, therefore making the circumstances under which corporate failure could occur more predictable.

The above factors are notably absent from developing country models. Similarly, developing countries have not yet evolved to the same degree of economic liberalisation. Governments still provide protection against failure and are seen to be more interventionist in their approach. This does not mean that in the case of developed economies this behaviour is completely absent, only a lot rarer in its occurrence.

i) Studies undertaken in developed markets

Australia | Common law legal system | IFRS compliant

Castagna and Matolcsy (1982) using twenty-one failed industrial companies (which would have been larger with the inclusion of mining companies) from 1963 to 1977 developed a corporate failure model using discriminant analysis. Prior studies by Castagna and Matolcsy (1978 and 1979) had reduced the number of variables used to ten, which were then used in linear and quadratic classification models. Based on Lachenbruch's (1967) validation tests the linear model was shown to be best at classifying failed firms. However, the same could not be said for classifying non-failed firms. Similarly, a stepwise procedure showed the ten-variable model was better than a proposed five-variable model. Actual classification rates were not stated nor were out of sample tests undertaken given size limitations.

Izan (1984) and Altman and Izan (1983) using a larger sample of fifty failed firms developed a model along the lines of Alman's (1968) initial model. Type I errors or incorrectly classifying a failed company as healthy and Type II errors or incorrectly classifying a non-failed firm as being financially distressed were also discussed. Type I accuracy prior to default was 94.1% for one year, 75% for two years and 63.5% for three years. Type II accuracy was 89.6% for one year, 89.6% for two years and 85.4% for three years. The final model uses the following variables from ten initial candidate variables:

$$Z_A = 0.53(X_1) - 0.44(X_2) - 0.25(X_3) + 0.24(X_4) + 0.23(X_5)$$

Where:

$$Z_A = Australian\ Z - score$$

$$X_1 = \frac{Earnings\ before\ interest\ and\ tax}{Interest\ expense}$$

$$X_2 = \frac{Market\ value\ of\ equity}{Total\ liabilities}$$

$$X_3 = \frac{Funded\ debt}{Shareholder\ funds}$$

$$X_4 = \frac{Earnings\ before\ interest\ and\ tax}{Total\ assets}$$

$$X_5 = \frac{Current\ assets}{Current\ liabilites}$$

When applied to a small hold out sample comprising ten firms the following Type I results were observed: 100% for one year, 70% for two years and 40% for three years. In absence of reporting of Type II accuracy the overall accuracy of the model cannot be ascertained. However, it was concluded that the predictive power was sufficiently strong to be applied to a cross-section of firms and industries.

Canada | Common law legal system | IFRS compliant, US listed firms can report under US GAAP

Knight (1979), as with many other Canadian studies faced the challenge of a predominantly small business population. This inherently limits the ability to assimilate a statistically sufficient number of corporate failures and publically available data on those firms. As part of the study a large number of small business failures were analysed, complemented by interviews with key persons involved. The focus of the research was to establish why small businesses fail and in doing so suggest an approach as to how corporate failure could be prevented. This was against the backdrop of a rising number of failed small businesses in Canada.

A discriminant analysis model was developed comprising seventy-two failed small firms with average annual sales and assets of about US$100,000. Results from the five variable models showed low classification rates. From the original leaning sample of thirty-six failed and thirty-six non-failed firms only 64% were correctly classified. Similarly from the remaining test sample of firms only 54% were correctly classified. It was concluded that the discriminant analysis was not successful. This was most likely explained by the industry effects, where inclusion of multiple industries often contributes to estimation problems.

Altman and Lavallee (1981) examined fifty-four publically traded firms split equally between failed and non-failed firms. A ten year period spanning 1970 to 1979 was used with an average tangible asset size for failed firms of US$12.6 million one reporting date prior to failure leading to an average lag of sixteen months. The sample included both manufacturers and retail-wholesalers; however sufficient financial information was not available to adjust for operating leases. Non-failed firms were stratified based upon industry, size and data period with average assets of US$15.6 million. Asset scale was similar to that of Altman's earlier United States studies for the 1950s and 1960s.

Classification rates were higher when combining manufacturing and retailing firms but a single model for both sectors was not advocated. Manufacturers' classification was also adversely impacted when the model contained industry sensitive variables. The following model resulted based on a forward stepwise procedure:

$$Z_c = -1.626 + 0.234(X_1) - 0.531(X_2) + 1.002(X_3) + 0.972(X_4) + 0.612(X_5)$$

Where:

$$Z_c = Canadian\ Z - score$$

$$X_1 = \frac{Sales}{Total\ assets}$$

$$X_2 = \frac{Total\ debt}{Total\ assets}$$

$$X_3 = \frac{Current\ assets}{Current\ liabilites}$$

$$X_4 = \frac{Net\ profit\ after\ tax}{Total\ debt}$$

$$X_5 = \frac{Rate\ of\ growth\ of\ equity}{Rate\ of\ asset\ growth}$$

The model presented an overall classification rate of 83.3%. Applying Lachenbruch's (1967) test replications on prior years, data prior year accuracies were 73% for Year 2, 53% for Year 3 and 30% for year 4. The model was deemed to be accurate at predicating failure up to two financial reporting periods in advance. There were parallels with Altman's (1968) model with regards to data quality and diversity of industries represented in the sample.

Simultaneously various simulations on prior probabilities of group membership and costs of error were undertaken. Type I errors could be eliminated whereas Type II errors were unacceptably high and vice versa when Type II errors were eliminated. At the same time, the modelled results were compared to Joy and Tollefson's (1975) naïve classification strategy. This approach showed that the model was more efficient with lower expected costs than the naïve approach of assigning all observations to a non-bankrupt category. It was also noted that most failed firms were retailers and most non-failed firms were manufacturers. The following variable misclassified failed retailers with high sales turnover and misclassified manufacturers with low sales turnover:

$$X_5 = \frac{Rate\ of\ growth\ of\ equity}{Rate\ of\ asset\ growth}$$

However, omitting this from the model did not improve classification rates, rather, it made them worse. Further areas for improvement were identified as introducing operating lease adjustments, and in time construction of a model using a larger sample of failed firms, assuming their greater frequency of occurrence.

England | Common law legal system | IFRS compliant

Taffler (1976) approached corporate failure primarily from a security analysis perspective. This was adapted through further studies by Taffler and Tisshaw (1977) and Taffler and Houston (1980). Primarily its applications were identified for auditors in assessing the going concern assumption for financial reporting. In addition it also could be used in assisting liquidators and receivers assuming judicial responsibility for failed firms.

Taffler and Tisshaw (1977) used linear discriminant analysis on a sample of forty-six failed and forty-six financially sound non-listed manufacturing companies from 1969 to 1975. These were paired by size and industry. From an initial sample of eighty different ratios, only four measure were selected for the final model:

» $\frac{Profit\ before\ tax}{Current\ liabilities}$

» $\frac{Current\ assets}{Total\ liabilities}$

» $\frac{Current\ liabilities}{Total\ assets}$

» $No - credit\ interval$

No-credit interval is the duration which the company can continue to fund its operations without support of short-term financing. This was calculated as follows: $\frac{Assets - current\ liabilities}{Operating\ costs}$, where operating costs excluded depreciation. This was seen to have similar characteristics to the acid test ratio.

The model yielded a correct classification rate of 97% versus Taffler's (1976) 96%, one year prior to failure. This differed significantly to the assessment of the going concern assumption by auditors of 22%. It was also recognised that 15% to 20% of firms that displayed a profile which was similar to failed companies, did in fact fail.

Taffler (1976) established accuracies of 70%, 61% and 35% for two years, three years and four years prior to failure, respectively. Although the steep decline in accuracy as the sample date moved further away from default, a one-year disinvestment horizon was deemed to be adequately sufficient. Additional observations made were that many failed firms were kept afloat as a result of government intervention. The value attached to financial reports by accountants was low but overlooked the enhanced information content through a combination of various parts of this financial information. A multivariate approach to financial analysis was recommended.

Taffler (1982) presented a revised failure discriminant model using principal component analysis concentrating on a smaller sample of twenty-three failed companies from 1968 to 1973 and forty-five non-failed firms. From 150 variables, five were selected:

» $\frac{Earings\ before\ interest\ and\ taxes}{Total\ assets}$

» $\frac{Total\ liabilities}{Net\ capital\ employed}$

» $\frac{Quick\ assets}{Total\ assets}$

» $\frac{Working\ capital}{Net\ worth}$

» $Stock\ inventory\ turnover$

No weights were provided for the variables above. Prior probability and cost-of-error estimates were included. It was concluded that the model was best applied in an operational context as a means of short listing firms which might experience financial distress. Furthermore, actions or behaviour by creditors and financial institutions were key determinants thereafter of actual bankruptcy.

Marais (1979) as part of a study undertaken by the Bank of England tested several previously published United States and United Kingdom models using univariate and multivariate approaches, where the following variables were identified as the best differentiators of corporate failure:

» $\frac{Current\ assets}{Gross\ total\ assets}$

» $\frac{1}{Gross\ total\ assets}$

» $\frac{Cash\ flow}{Current\ liabilities}$

» $\frac{Funds\ from\ operations - working\ capital}{Total\ debt}$

Although the $\frac{1}{Gross\ total\ assets}$ appears to be unusual this was supposed to introduce a scaling consideration for the discriminant function to consider, where the inverse of gross total assets was aimed at reducing the size of figures included.

Discussion around the accuracy of classification was limited to the results being deemed satisfactory. Firm scores below a certain cut-off point were categorised as indicating future problems, and a Z score was identified to be a sophisticated screening device.

Earl and Marais (1982) expanded upon this analysis. Classification results of 93%, 87% and 84% three years prior to failure were reported. Cash flow data was seen to improve upon accuracy with cash flow to current liabilities being the most successful discriminator.

Ireland | Common law legal system | IFRS compliant

Cahill (1981) analysed eleven listed failed firms from 1970 to 1980 with three primary issues explored. Firstly, variables showing significant deterioration in advance of failure were identified. Secondly, adverse opinions from auditor reports on the going concern assumption were considered along with other unique considerations which could be attributed to failure.

Variables were identified that aligned with the first point deviating from their aggregate one year prior to failure. However, this was not as prominent two years prior to failure.

Only one audit report expressed uncertainty surrounding going concern, with five less serious qualifications present in other failed-firm reports. This was mainly attributed to auditor reluctance to raise going concern issues and Irish accounting conventions of the time. It was felt that variable deterioration should have been a red flag for auditors where it was difficult to envisage that was overlooked.

Debt financed acquisitions and expansion along with mergers were seen to be key ingredients for corporate failure. Several failed firms continued to pay dividends one year prior to their failure, with one firm paying unsecured creditors after failure.

Singapore | Common law legal system | Singapore Financial Reporting Standards aligned with IFRS

Ta and Seah (1981) considered twenty-four financial ratios for use in the discriminant analysis. Twenty-two failed firms where identified from 1975 to 1983. These were then matched with twenty-one non failed-firms, with only commercial and industrial firms considered. Mean asset size of the firm in the sample was \$89.5 million with the following four financial ratios used in the model:

» $\frac{Total\ debt}{Total\ equity}$

» $\frac{Profit\ before\ tax}{Sales}$

» $\frac{Profit\ before\ tax}{Equity}$

» $\frac{Interest\ payment}{Profit\ before\ interest\ and\ taxes}$

The model achieved the following results:

	Original sample			**Holdout sample**		
Prediction Horizon	**Type I Accuracy**	**Type II Accuracy**	**Overall Accuracy**	**Type I Accuracy**	**Type II Accuracy**	**Overall Accuracy**
One year	77.3%	93.5%	86.8%	75%	90.5%	86.2%
Two years				62.5%	85.7%	79.3%

ii) Studies undertaken in developing markets

Brazil | Civil law legal system | IFRS compliant

Altman, Baidya and Ribeiro-Dias (1979) used twenty-three failed firms from January 1975 to June 1977, which spanned textiles, furniture, pulp and paper, retail stores, plastics, metallurgy and other sectors. These were included with thirty-five non-failed firms. Average asset size ranged between

US$25-30 million. Wherever possible privately owned Brazilian firms were used to avoid skewness arising from the inclusion of multinationals and government owned firms.

Altman's (1968) original model was used with the modification of X_2 and X_4 variables. For X_2 the following was calculated given that there was no Brazilian equivalent of retained earnings in their financial reporting at the time:

$$\frac{Total\ equity - capital\ contributed\ by\ shareholders}{Total\ assets}$$

Given that most Brazilian firms are privately held, often with a majority ownership held by a single family, market value of ownership could not be calculated. For X_4 book value of equity was used in place of market value of equity.

Two models were derived. The first model excluded X_1 given that the stepwise program showed that it did not have any explanatory power. The second model also excluded X_2. This was excluded because, as previously indicated, it was difficult to calculate given the disclosure practices of Brazilian financial reporting and also that it was seen to be similar to X_4. The models were specified as follows:

$$Z_1 = 1.44 + 4.03(X_2) + 2.25(X_3) + 0.14(X_4) + 0.42(X_5)$$

$$Z_2 = 1.84 - 0.51(X_1) + 6.23(X_3) + 0.71(X_4) + 0.56(X_5)$$

The reader is referred to the section *c) Research on accounting-based models for corporate failure prediction in the United States in this section* for a detailed account of Altman's (1968) model along with variable definitions.

Both models had a critical cut-off score of zero i.e. a score above zero indicated non-failure, a score below, failure.

Results of both models were mostly identical for one-year prediction. Type I errors were 13% and Type II errors were 11.4%. Overall classification accuracy was 88% with the first model performing slightly better two and three years out. Further tests were undertaken on a hold out sample, which showed high levels of accuracy. Accuracy also remained unchanged after applying the Lachenbruch (1967) tests. Additional advance accuracy tests showed classification rates of 84.2% for two years and 77.8% for three years. Extension of the model discussion and its application included its ability to offer limited early assistance to avoid at all costs significant government assistance further down the line.

India | Common law legal system | IFRS compliant

Bhatia (1988) examined a sample of eighteen failed and eighteen non-failed firms in India. These were matched according to the type of product and gross fixed assets, comprising firms for the cement, electrical, engineering, glass, paper and steel industries. The model employed the following variables:

» $\frac{Inventory\ of\ finished\ goods}{Sales}$

» $\frac{Inventory\ of\ finished\ goods}{Sales}$

» $\frac{Profit\ after\ tax}{Net\ asset\ value}$

» $\frac{Interest\ expense}{Value\ of\ output}$

» $\frac{Cash\ flow}{Total\ debt}$

» $\frac{Cash\ flow}{Total\ debt}$

» $\frac{Trade\ receivables\ days}{365} x\ credit\ sales$

Type I accuracy was 87.1% and Type II accuracy was 86.6%. An out of sample test on twenty-eight failed and twenty non-failed firms validated the model's accuracy and applicability.

Mexico| Civil law legal system | IFRS compliant

With the growing prevalence of emerging market corporate bonds, Altman (1995) introduced an emerging market bond scoring system which relied upon the Z'' score model. The resulting Z'' score output was used with certain adjustments made to align the corporate failure prediction outcome with those characteristics unique to emerging markets. Altman (2005) later examined the applicability of the model in the context of its application to Mexican corporates as well as allowing for outcomes to be compared to that of credit ratings provided by the big three rating agencies, Fitch Ratings, Moody's Investors Service and Standard and Poor's. The emerging market bond scoring system adhered to the following 6- step process in its application:

1) Calculated an EM Z'' Score and a bond equivalent rating compared to the United States bond market
2) Adjusted the Bond Equivalent Rating for foreign currency revaluation vulnerability
   - High vulnerability= -1 rating class (3 notches)
   - Neutral vulnerability= -1 notch
   - Low vulnerability= no change
3) Adjusted the Bond Equivalent Rating for industry specific risk particular to the emerging market not prevalent in the same industry in the United States
   - ±-1 or 2 notches
4) Adjusted the Bond Equivalent Rating for competitive positioning
   - Dominant company in the industry= +1 notch
   - Average company in industry= no change
   - Poor competitive position= -1 notch
5) Assessed the impact of special collateral and guarantees on the Bond Equivalent Rating
   - Upgrade particular debt issue if there are legal guarantees extended by a higher credit quality guarantor or the existence of special collateral
6) Assessed the corporate yield spread between similar bonds in the United States versus the United States sovereign. This was then compared to the yield spreads of similar bonds issued

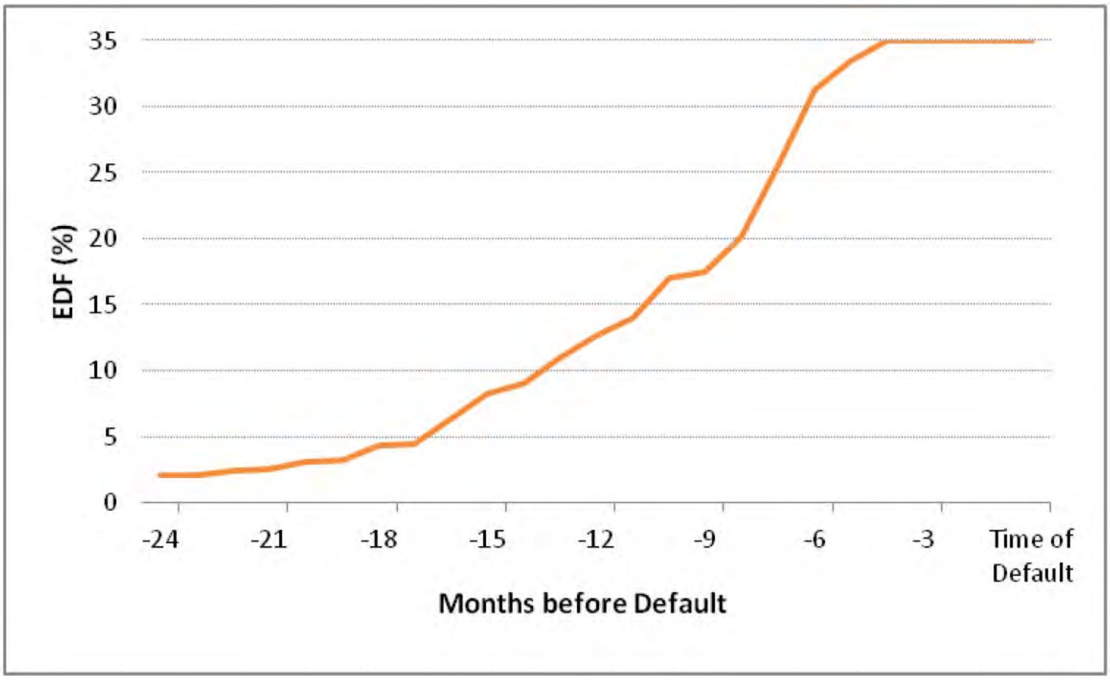
by the United States sovereign versus the emerging market sovereign. Both resulting differences, if any, were then added.

- » If the outcome on the Z'' model is BBB and similar quality bonds in the United States are trading at 1% over United States treasuries (assumed yield of 4.5%) and comparable duration of the emerging market sovereign treasuries are trading 2% over United States treasuries, then the required yield would be 7.5% or 1%+4.5%+2%
- » If the actual yield is greater than the calculated yield of 7.5% then the bond issue would be considered attractively valued by the market

In its application to Mexican corporates both in a pre and post Mexican peso crisis period, the model showed encouraging results. The outcomes often aligned with the credit rating assigned and in some cases provided the credit rating outcome in advance of a credit rating agency taking a rating action based on a recent development. This therefore gave the EM Z'' Score model the added advantage of being both forward-looking and offering the ability to profit from this forward-looking view in the case of fixed income traders and investment managers. Profits could be made or value protected by taking a beneficial position in advance of a rating agency action. This could be done either shorting/selling in the case of an anticipated credit rating downgrade or going long/buying the bond issue in the case of an anticipated credit rating upgrade.

e) Market-based models for corporate failure prediction for international markets

The first and most widely recognised market based model, the Expected Default Frequency (EDF™), model was introduced by KMV Corporation, which was acquired by Moody's Corporation in 2002. The EDF™ model has been an industry leading Probability of Default (PD) model since it was introduced in the early 1990s. The EDF model determines the default probabilities by directly modelling the evolution of the economic variables driving defaults. The model takes a similar focus to credit risk as fundamental credit analysis but also considers market-based valuation of the economic drivers. This adds an additional enhancement to pure fundamental techniques by adding in financial market information, which ensures up to date estimates of risk and value for companies. This also increases the advance warning of potential defaults given the forward-looking nature of such information. This compares favourably to historical looking data used primarily in fundamental based models.



Source: Moody's Analytics

The model focuses on two key areas that drive a company's risk of default (1) financial risk; and (2) economic risk.

As Sun, Munves and Hamilton (2012) outline, EDF is a measure used to assess the probability that a company will default over a specified period of time, typically one year. Merton (1974) led the pioneering development of the EDF model which belongs to a class of structural risk model.

Under the EDF model approach common equity is deemed to be the only loss-absorbing layer of the company's capital structure. Any other capital structures which have losses imposed on them are seen to trigger a default. In other words, any obligations that are senior to common equity subject to broken promises are considered a default. Government bailouts are assessed within a framework of whether a default would have certainly occurred without government intervention. This considers unique cases, such as the financial crisis, where some banks were required to accept 'bailout funds' but were not in any risk at the time that they would default. This is further extended under this model to include instances where the market value of assets or the value of ongoing business falls below the liabilities payable or the default point.

Default often follows from liabilities exceeding assets. This provides a conceptual starting point for the EDF model. The EDF model attempts to determine the probability that a company's liabilities exceed its assets. There are a number of shortcomings with a pure balance sheet approach to determining default risk. The first obstacle is determining a market related value for assets. Under IFRS most assets are reflected at historic acquisition cost or book value less accumulated depreciation and impairments, if there are any. This often does not align with the net realisable value that the asset would sell for or its future cash flow generation ability.

Some assets will generate less cash flow than was forecast at the time they were purchased. Such an example would be assets purchased for the United States automotive industry in the 1970's, which saw a steady decline in demand in years following this period. Many assets stood idle or were not functioning at their full capacity. This lead to the present value of future cash flow generation potential being below the amount originally paid for the asset. Asset impairment requirements have gone a long way to addressing differences in historical asset value and market asset value. There are limitations in that they are still dependent on a judgment call by companies and their auditors. Both parties exert a certain degree of subjectivity and interpretation as to when and by how much an asset should be impaired.

The greater risk to developing an accurate corporate failure prediction model often is on the upside to asset valuations. Historic cost approaches to valuing assets often do not take into account the goodwill and intangible properties of assets. Such an example would be the secret formula used by Coca Cola, which underestimates the future cash flow potential of this asset and degree of market share protection that it affords the company.

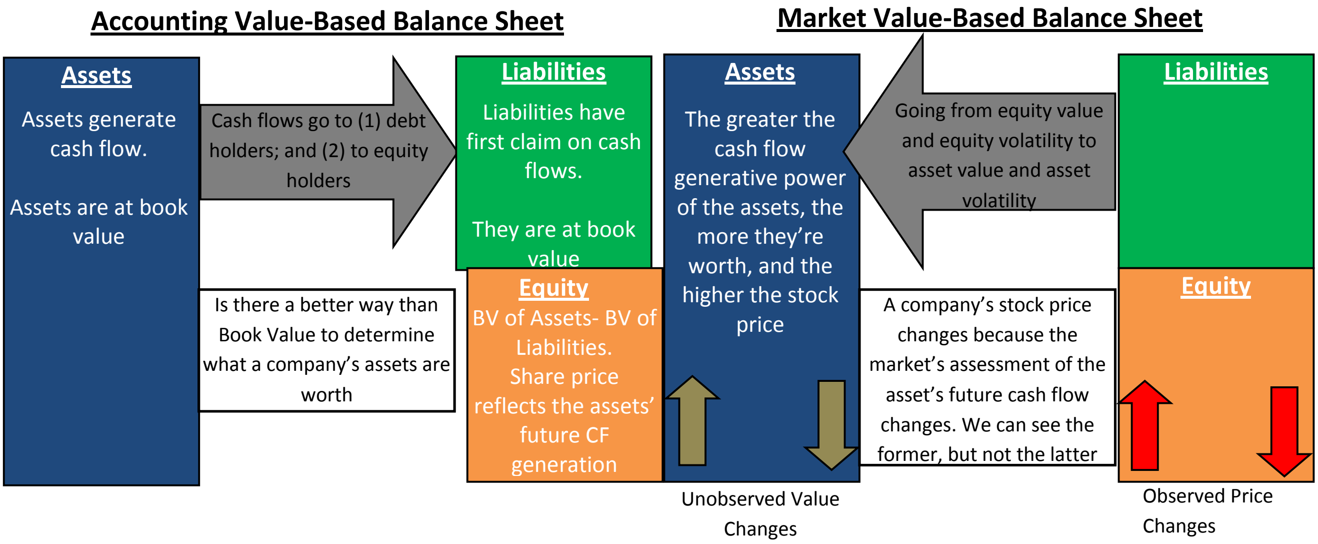
Projected value of a firm's asset potential often does not align with its reported value under accounting standards. Another shortcoming is that financial reports are at best prepared on a quarterly basis and are based on historical information and not forward-looking information. This often means that corporate failure prediction relying upon this data will signal default risk when it is already too late.

The value of a company can be estimated by markets, which is seen to be a better alternative. These are forward-looking, demonstrate efficiency at assimilating information, and capture the collective wisdom of many investors. The market value for various assets is not always readily available as there may not be public markets for these assets. Another challenge is where a public market for similar assets exists it is often difficult to match these assets. This means finding assets that are equivalent in age and specification, which is often impossible, to allow for a valuation based on comparatives. Supply demand factors present at the time of sale of other similar assets are also likely to differ in the future resulting in propensity for differences in valuation. However, if the company is publically traded we can indirectly infer the market value attached to the assets.

A company's equity and its assets are valued in the same way. The present value of future cash flows generated by the assets is the company's asset value. The present value of the portion of total cash flows received by equity holders after the company's debts have been settled is the company's equity value. In this way there is an indirect link between a company's equity value, which can be measured through public valuations, and its asset value, which cannot. Again this is also an imperfect solution as not all companies have publically available equity valuations. It is often straight forward to determine the market value of debt so adding this to the value of equity attributed by equity capital markets allows for the market value of assets to be imputed.

In assessing default risk, the likelihood that a company's liabilities exceed that of its assets needs to be determined. This becomes a function of two primary factors (1) the difference in market value between assets and liabilities, as previously mentioned; and (2) the volatility of a company's assets. The greater the volatility of a company's assets, the greater the risk of extreme movements in asset values and the greater the default risk given the potential for assets to be valued less than liabilities. Companies in sectors with more stable operating environments, such as utilities, pharmaceuticals and defence, exhibit lower asset volatility compared to less stable operating environments such as the technology and mining sectors. The same challenge is faced with regards to determining asset volatility. Asset volatility is often not directly observable, given that the market values of assets over time required to calculate this, are also often not available.

Where market values for equity are available these often offer the best proxy for a company's default risk. Forward-looking expectations of a company's financial longevity are reflected through these market valuations which investors influence through their views on valuation of the equity price. A liquid equity market which ensures that current and future expectations are always reflective in the prevailing price. This at the same time reflects the volatility of company's underling business conditions, their financial strength and the impact of both the current and expected future macroeconomic environment on fundamentals.



Source: Moody's Analytics

Building upon this contextual foundation, the EDF model needs to derive the probability that the market value of assets will fall below its liabilities. This allows for an assessment for the probability of default in the future for a company. This is a function of two factors. The first being the difference between the market value of a company's assets and the book value of its liabilities. The second being the volatility of the company's assets.

This is bundled into three component inputs in calculating a company's EDF credit measure (1) the current market value of the company or the market value of assets; (2) the level of the company's obligations or its default point; and (3) the vulnerability of the market value of the company's assets to change significantly referred to as asset volatility.

Given that the above inputs are constantly current, objective non-judgmental variables, EDF credit measures have consistently outperformed the rating agencies in distinguishing between defaulting and non-defaulting companies according to Moody's Analytics (2011). Not only that, they have proven to be a consistent leading indicator of agency rating upgrades and downgrades.

By way of demonstrating the application of the EDF model, two companies are selected. The first, Johnson &Johnson, is fundamentally strong and in a defensive pharmaceutical business sector. The second, RadioShack, is weak and in a cyclical electronics retail business sector. As of April 2012 the two inputs were calculated for both companies:

Metric/ Input	Johnson & Johnson (Aaa stable)	RadioShack (In default)
1 year EDF measure	0.01%	3.58%
Default Point (DP)	US$39 bn	US$1.042 bn
Market Value of Assets (MVA)	US$236 bn	US$1.834 bn
Market Value Leverage (DP/MVA)	17%	57%
Asset Volatility	11%	24%

As shown below there are three key inputs which are used to determine Johnson & Johnson's default in one year's time, being (1) the estimated market value of Johnson &Johnson assets; (2) its default point; and (3) asset volatility. The last variable, which has not been calculated is estimated through the assumption that Johnson & Johnson's equity returns are normally distributed.

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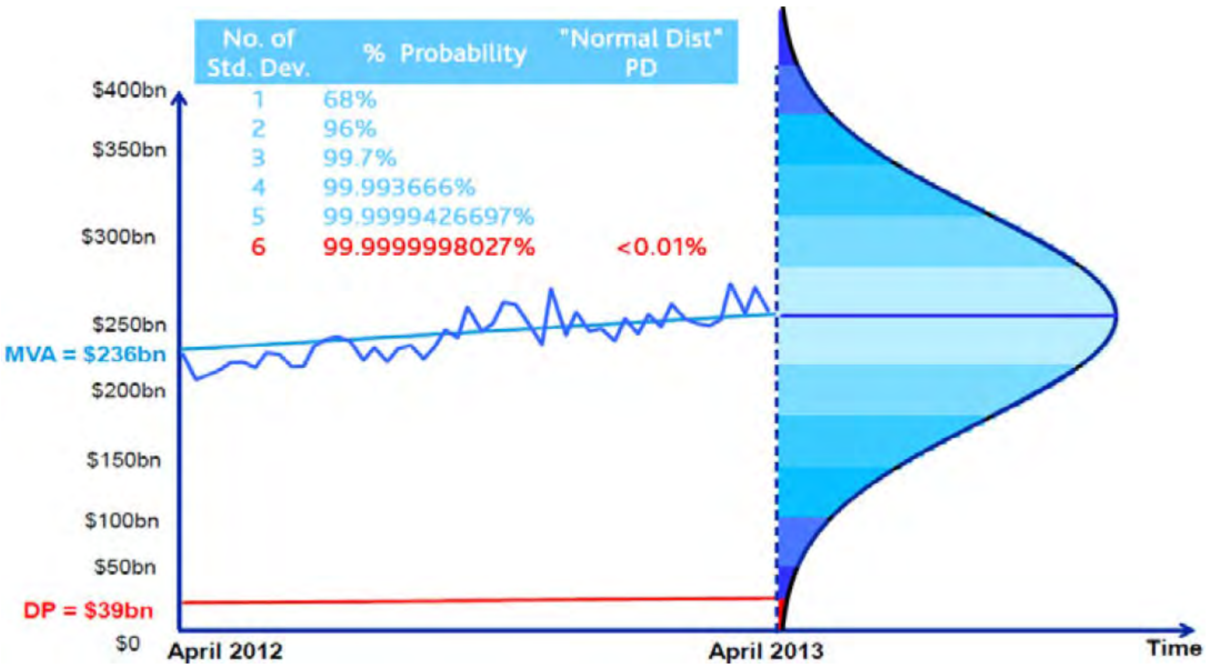


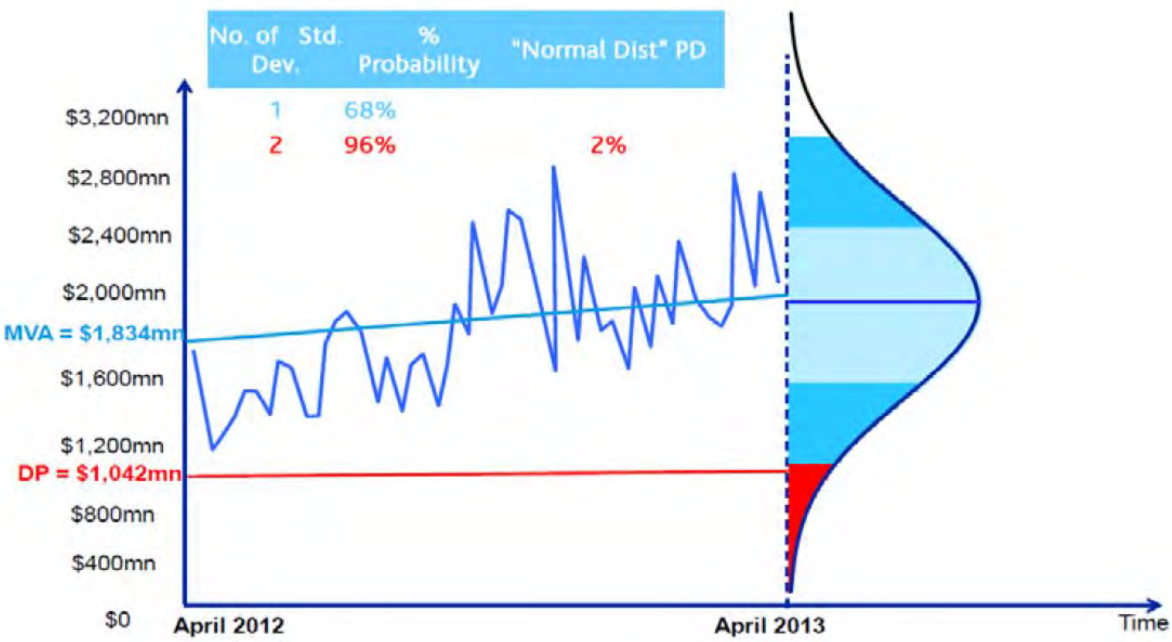
Source: Moody's Analytics

Based on the assumption that returns are normally distributed, the probability of default is defined as the area under the standard normal distribution (denoted Φ) as follows:

$$\text{Probability of Default} = \Pr(\text{MVA} < DP) = \Phi[\text{MVA} < DP]$$

As shown graphically above, it would take a six standard deviation move for the market value of Johnson & Johnson's assets to fall below their default point. Johnson & Johnson's Distance to Default (DD) would be classified as 6 under the EDF model. The probability attached to default over the next year would be essentially 0% or (1-99.9999998027%)/2.

The company's actual default probability would be a lot higher for two reasons (1) the DD has a long and fat right tail compared to the normal distribution i.e. a normal distribution of corporate default does not hold; and (2) since defaults are a rare occurrence for high credit quality companies, such as Johnson & Johnson (Aaa stable since 15 September 1987) it is difficult to calibrate and calculate an exact default rate beyond a certain DD level. This means that the normal distribution underestimates the probability of default especially for high-credit quality companies. This underestimation is adjusted by empirical mapping. This is achieved by using a distribution of corporate defaults reliant upon historical data.

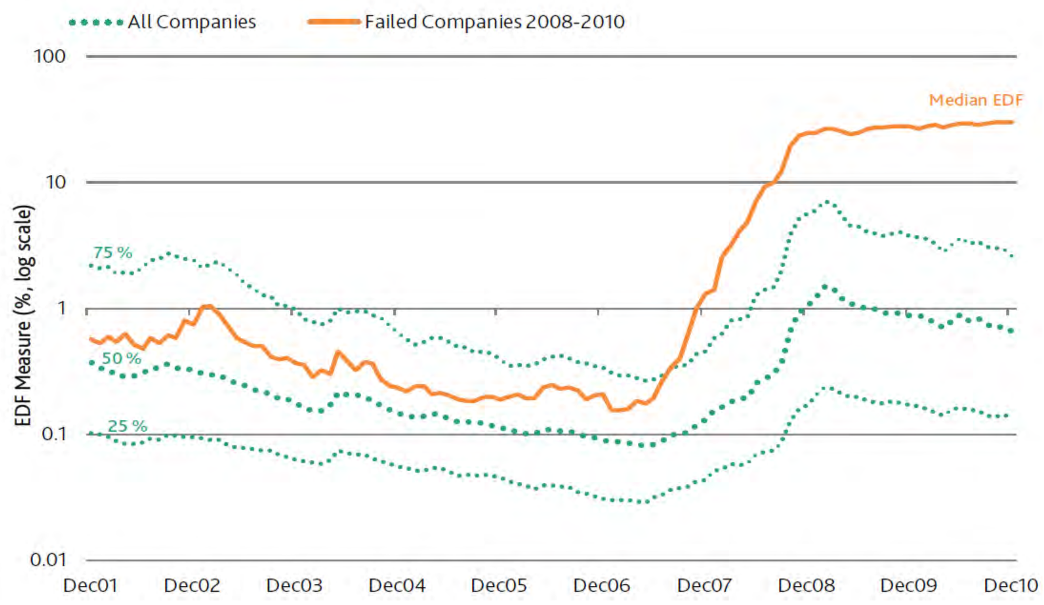


Source: Moody's Analytics

Considering companies with low credit quality such as RadioShack (In Default), the default risk between that of the EDF model (3.58%) and the normal distribution (2%) narrows. RadioShack has a DD of 2, driven by a narrow gap between the market value of assets and its default point.

Moody's Analytics' public company EDF™ model demonstrates strong empirical evidence of forecasting default in timely manner and providing sufficient advance warning:

<u>EDF Evolution of North American Corporates vs. Companies Defaulted 2008-2010</u>



Source: Moody's Analytics

As clearly shown above the EDF model demonstrates strong predictive power for signalling a default well in advance of its occurrence. The above chart compares the median EDF for North American Corporates and those that defaulted between 2008 and 2010 representing the first, second and third quartile of all observations in this sample.

As mentioned previously, EDF models are an extension of basic structural credit risk models that build upon those developed by Black and Scholes (1973) and Merton (1974). Although these models rely on assumptions, which are both unrealistic and problematic, they provide a good underpinning for basic theory to develop the EDF model.

The basic structural credit risk model assumes that the market value of a company's assets evolves according to the following stochastic process:

$$(1) \qquad dA = \mu A dt + \sigma_A A dW$$

where μ is the expected growth rate of the company's asset value, σA is the asset volatility, and W represents a standard Brownian motion mathematical model process based upon particle theory. For simplicity, a time horizon of one year is assumed. Annual log asset value is normally distributed as assumed by the geometric Brownian motion. Geometric Brownian motion is used to describe the change in asset values over time or dA. The drift term, μAd, describes the expected growth rate μ of asset value over a short time interval dt; the volatility term, σ_AAdW, describes the uncertainty associated with the path travelled by asset value – the "instantaneous" volatility of the asset return over the short interval dt is ${\sigma_A}^2$.

$$(2) \qquad \ln A_1 \sim N\left(\ln A_0 + \left(\frac{\mu - {\sigma_A}^2}{2}\right), {\sigma_A}^2\right)$$

A normal distribution of the market value of assets is assumed. It also implies that if the value of the necessary inputs is known then calculating the probability is a straightforward process. The Φ[x – E(y)] / σ(y)] expresses the probability that a normally distributed variable (y) falls below a given value, call it x, is exactly equal to where Φ is the cumulative standard normal distribution. The relevant value of x is the log of the default point, lnX, where the focus is on the likelihood that a company's asset value (A) falls below its default point in the next year, Pr ($\ln A_1 < \ln X$). This is determined from the company's book value of liabilities. Plugging these quantities into the cumulative normal distribution gives:

$$(3) \qquad \text{probability of default} = \Phi\left[-\frac{\ln\frac{A_0}{X} + (\mu - \frac{{\sigma_A}^2}{2})}{\sigma_A}\right]$$

The negative of the quantity inside the brackets is what is defined as the DD. The EDF model uses this term to express standard deviations. Using this definition the notation can be considerably simplified:

$$(4) \qquad \text{probability of default} = \Phi[-DD]$$

For ease of exposition, under some innocuous assumptions the second term can be ignored of the numerator of the DD definition to arrive at a simpler expression for DD

$$(5) \qquad DD = \frac{\ln A_0 - \ln X}{\sigma_A}$$

From the above it is evident that the DD is a count of standard deviations which encapsulates the aforementioned three key inputs (1) market value of assets; (2) default point; and (3) asset volatility. Put another way, the numerator of the DD captures the company's financial leverage whereas the denominator captures the business risk. Therefore, the DD for a firm is the difference between the expected asset value of a company and the default point, standardised by the company's business risk. DD combines all these inputs into a single stationary statistic, which provides a rank ordering of default risk. The area under the normal distribution below the default point is used to calculate the probability of default under the structural model approach.

Converting this into a structural credit risk model again requires some contextualisation. Going back to using capital markets to determine asset value, equity holders in companies are perceived to have a walk away option. If the value of the firm is lower than its liabilities, shareholders can walkway from the company. They have limited liability protection and can let the creditors assume ownership.

This is analogous to a home loan. The home is not owned until the loan is fully paid and the title transferred by the bank. This is similar to equity holder's option on a company with the addition of their limited liability protection. As the home loan is repaid, similar to that of the debt in a company, default risk reduces.

This is similar to a call option, where the debt owed by the company is the same as the strike price for equity holders. When a company is funded purely with equity and a zero coupon bond with a face value of X, this can then be incorporated under an application of the Black Scholes option pricing model. This connects an observable equity value to an unobservable asset value and asset volatility. Denoting E as the value of equity, expected growth rate of assets as μ and the time horizon as T, the following formula is arrived at:

$$(6) \qquad E = A_0\, \Phi(d_1) - e^{rT} X \Phi(d_2)$$

where:

$$(7) \qquad d_1 = \frac{\ln\left({A_0}/{X}\right) + \left(r + \frac{\sigma_A{}^2}{2}\right)T}{\sigma_A\sqrt{T}}, d_2 = d_1 - \sigma_A\sqrt{T}$$

This demonstrates that a company's equity value (E) is a factor of its asset value, directly, and its asset's $d_1$volatility, indirectly through a normal distribution. The twist in this application of the Black Scholes model comes in that the value of the underlying option, the equity value, is a known parameter. The unknown parameters are instead the asset value and its volatility. This can be solved for backwards using the known input, option price and volatility, to arrive at an implied asset value and its volatility. In addition to having related firm equity value to asset value in (6), Ito's lemma can then be used to relate a company's equity volatility σ_E to its asset volatility σ_A:

$$(8) \qquad \sigma_E = \frac{\partial E}{\partial A}\frac{A}{E}\sigma_A$$

These two functional relationships (6) and (8) allow for the determination of A and σ_A from the values of E and σ_E which are observable from the public firm's equity prices. Estimates of A and σ_A are then used in formula (5) which allows for the calculation of the probability of default under a basic structural credit risk model using a normal distribution's assumption of DD.

The EDF model transcends what some practitioners view as a summary of equity market movements. It transforms equity market data into credit relevant data (1) market leverage; and (2) asset volatility. Debt levels have a dual impact on the model through the calculation of the default point and how equity values and equity volatilities are translated into asset values and volatilities as demonstrated in formula's (6) and (8).

The correlation between equity values and firm credit quality weakens as credit quality strengthens. This is referred to as the "deleveraging process" as credit quality strengthens the equity value becomes less and less driven the by credit parameters of the EDF model. In other words default risk becomes less of a concern for investors where other drivers begin to weigh more prominently in moving equity valuations.

Sun, Munves and Hamilton (2012) note that dirms with better equity returns can exhibit higher default risk than firms with average equity returns. Firms with extremely poor equity performance do have higher EDFs and default rates. This shows that equity returns are not always consistent with EDFs. This is demonstrated through empirical data provided in the table below:

<u>EDFs and Default Rates of Portfolios' Sorted on Six-Month Stock Returns, North American Corporates, 2001-2009</u>

	Average Return %	**Average EDF %**	**Median EDF %**	**Default Rate %**
Lowest Return	-0.51	14.5	11.33	9.24
2	-0.26	5.16	2.04	2.07
3	-0.15	3.18	0.8	1.1
4	-0.07	2.25	0.42	0.66
5	-0.01	1.85	0.28	0.51
6	0.06	1.68	0.24	0.4
7	0.13	1.56	0.22	0.41
8	0.21	1.66	0.26	0.39
9	0.36	2.09	0.38	0.51
Highest Return	0.87	3.81	0.92	0.77

f) Multiple discriminant analysis

Multiple discriminant analysis is a statistical technique used to classify observations into a number of a priori groupings, which are dependent upon the individual characteristics associated with each observation in the samples of each grouping. Durbach (2008) explains that these groups are referred to as a priori in nature as their classification is already known prior to development of the multiple discriminant analysis model. Similarly these grouping are normally qualitative in nature i.e. male/female and failed/non failed.

The model will require specification or labelling of the groups upfront, which can consist of two or more groups. Once established, delineating characteristics, which are decided upon by the modeller, are then collected for each observation. As outlined by Tinsley and Steven (2000) and Rees (1995) multiple discriminant analysis attempts then to derive a linear formula applying a weighting to each characteristic allowing for the differentiation of each observation according to their respective grouping and therein maximizing the distinction between groups.

Multiple discriminant analysis considers the entire profile of characteristics associated with each observation as well as the interaction of these characteristics and in doing so decides which characteristics are the best discriminators. In addition, space dimensionality is reduced as result of the application of multiple discriminant analysis. This is defined as the number of independent variables of G-1 dimension(s), where G is the number of a priori groups.

Grimm and Yarnold, (1994) indicate that the independent variables are referred to as canonical variables. In the case of an a priori grouping comprising of failed and non-failed corporates the analysis is transformed into only one dimension. The resulting discriminant function is of the following form:

$$Z = v_1 x_{1+} v_2 x_{2+} v_3 x_{3+} \dots v_n x_n$$

$$where\ v_1, v_2, \dots v_{n=} discriminant\ coefficients$$

$$x_1, x_2, \dots x_{n=} independent\ coefficients$$

The resulting model will then define cut-off ranges, that depending on the range into which an observation falls, their grouping will be determined. This defined cut-off range in some cases will also include an area referred to as a ‘grey zone’ or a zone of ignorance where the observation does not necessarily conform to any particular grouping. In some cases the model will also specify a constant, but this is mostly dependent on the software modelling application used.

Tinsley and Stevens (2000) identify three conditions will need to be satisfied in order for the results of the multiple discriminant analysis models to be relied upon (1) independence of observations; (2) multivariate normality and (3) homogeneity of covariance matrices. In addition, Tinsley and Stevens (2000) concluded that any violation of these assumptions will lead to inflated Type I errors or incorrectly classifying failed companies as non-failed. Furthermore, Brown and Tinsley (1983) recommended that the minimum total sample size required should be equal to approximately ten times the number of variables used in the model. Tinsley and Stevens (2000) however were of the view that the sample multiple should be closer to twenty times the number of variables used in the model. Grimm and Yarnold (1994) through using a test derived by Box (1949) and applying this to Altman, Haldeman and Narayanan's (1977) ZETA® model demonstrated that this resulted in a different variance and covariance for the variables. In this instance Altman had transferred variables with skewed distributions. Grimm and Yarnold (1994) explain that this was done by applying natural logarithmic transformation through the analysis of their histograms while keeping variables of an approximately symmetric distribution in their original form.

Fisher (1936) was the first to apply multiple discriminant analysis in a practical setting. Since then multiple discriminant analysis has been extended to application in a number of fields, where its primary use was first towards biological and behavioural sciences. Its first application in the field of finance was to consumer credit evaluation by Durand (1941) and later Myers and Forgy (1963) as well as to investment classification by Walter (1959) and later Smith (1965). Altman, Eisenbeis and Sinkey (1981) further demonstrated multiple discriminant analysis' application to a number of financial areas.

Watson and Keasey (1991) identified a shortcoming of multiple discriminant analysis in its application to corporate failure. They identified that the relative costs associated with both types of misclassification errors, Type I errors (incorrectly classifying a failed company as healthy) and Type

II errors (incorrectly classifying a non-failed firm as being financially distressed), were treated as being equal.

In a real world setting this is unlikely to be the case where losses on loans to failed clients almost always exceed profits that are forgone on not making an identical loan amount to non-failed clients. Nevertheless, they did conclude that one of the greatest advantages of a multiple discriminant analysis model is that it does not focus on the significance of individual variables but rather the significance of the entire profile of individual variables. This enhances the predictive accuracy of the model.

Further shortcomings of multiple discriminant analysis were identified by Grice and Ingram (2001) who pointed out an upward bias in holdout sample accuracy rates relative to the initial 'training' sample. The initial sample theoretically would be expected to more likely result in higher accuracy rates as the model has been tailored to fit this original sample of observations.

Altman and Narayanan (1997) in their survey of corporate failure models studies identified multiple discriminant analysis as most popular statistical technique. This was based upon statistical techniques used by researchers spanning a number of difference countries. Multiple discriminant analysis was seen to be the de facto standard for comparison of distress prediction models. Where authors had opted for a different statistical technique these were almost always compared with the results under a multiple discriminant analysis approach. In all such cases multiple discriminant analysis results compared favourably when compared to other statistical techniques.

g) Accounting-based corporate failure prediction models versus market-based models

Mensah (1984) highlights the sample specific nature of accounting-specific models, where ratios and their corresponding weightings are derived. This requires periodic redevelopment to ensure that the ratios selected and the weightings attached remain relevant.

Agarwal and Taffler (2008) identify the following weaknesses in using accounting-based models:

» Future prediction ability is limited due to the reliance on historical backward looking data

» Market values of assets often differ starkly compared to reported accounting values

» Interpretive elements of financial accounting standards opens up numbers for manipulation

Market-based models counter these shortcomings through offering:

» Reliance on market information which ensures forward-looking information that considers an extensive universe of variables and considerations

» Market information is less likely to be manipulated

» Market information has a greater alignment with cash flows, where valuation is essentially the present value of future dividends and value of the firm, and therefore reflects cash generation ability

» Models are not sample dependent and do not need to be continuously recalibrated

However as Saunders and Allen (2002) point out, market models require a number of assumptions such as:

» Normality of stock returns

» All debt being seen as the same. There is no differentiation between different types of debt and the firm's debt is deemed to comprise a single zero coupon bond

» Measurement of asset value and volatility is required, both of which are unobservable

The empirical test of market models have received a mixed response. Kealhofer (2003) and Odera, Dacorogna, Jung (2002) suggest that such models outperform and are more timely than credit ratings. Hillegeist, Keating, Cram and Lundestedt (2004) conclude that market-based corporate failure models provide more information when compared to accounting-ratio-based models noting the latter's poor performance.

Juxtaposed to this Campbell, Hilsher, and Szilagyi (2006) see market-based models after controlling for other variables as offering little forecasting power. Reisz and Perlich (2007) found Altman's

(1969) Z-Score model to be marginally better over a one year period at predicting corporate failure when compared to more complex KMV-type barrier option models, which had better predictive abilities three to ten years out.

Barth, Beaver, Hand and Landsman (2005) found that equity values can be accurately predicted using financial statement data, both of a non-accrual i.e. cash flow data and accrual nature i.e. income statement data. This means that accounting-based models ostensibly are already including a market-based element which can be used to accurately assess credit risk and distance to default.

Agarwal and Taffler (2008) compared results using Taffler's (1984) Z-Score model against market-based models over a seventeen year period spanning 1985 to 2001 using Receiving-Operator-Characteristic curves and information content tests. The same framework as Stein (2005) was used along with that which was used by Blöchlinger and Leippold (2006). The study was however extended to consider differences in market share, revenues and profitability of banks using competing models and the error differences in misclassification costs.

The main conclusions from the study that were drawn are as follows:

» The Z-Score model was more accurate, but the resulting difference was not statistically significant

» Banks using a Z-Score model would realise significantly higher risk adjusted revenues, profits, return on capital employed and return on risk adjusted capital

» Both models provided significant information about failure, but with neither model subsuming the other

Traditional accounting-ratio based models were therefore shown to be better allocators of capital when it came to bank lending taking into account loan pricing and misclassification costs. It was further concluded that Hillegeist, Keating, Cram and Lundestedt (2004) findings were mainly as result of poor performing comparator models rather than the superior predictive capabilities of option-pricing models.

Agarwal and Taffler (2008) in summary observed that corporate failure does not occur abruptly and is normally a culmination of a number of years of deteriorating operating performance or balance sheet strength. Companies with strong balance sheets supported by profitable operations are unlikely to fail suddenly, without warning due to a change in operating conditions. It was also highlighted that loan covenants are based on accounting ratios and that their breach is normally the first indication of corporate failure. Furthermore, the Altman model included the market value of equity as one of the variables in determining the Z score.

h) South African research on corporate failure prediction

There have been numerous academic attempts to recalibrate Altman's Z score model to both a listed and unlisted universe of corporate failures. One of the potential shortcomings has been the dearth of large-scale South African corporate failures in a listed setting, which have lead many studies to focus on unlisted corporate failures. Public data for these unlisted corporates is limited and is not subject to the same level of scrutiny by investors and regulators compared to listed companies. This has narrowed the context of application of such models. This is predicated by there being a more focused sample, which is unlikely to see large-scale defaults of benchmark size typically which are defined as debt instruments in excess of US$500 million. This also limits sample focus to private and mainly bank placed debt, rather than listed debt.

A pioneering study by De la Rey (1981) using a similar approach to that of the Z Score model achieved a 96% classification rate in correctly classifying failed companies one year prior to failure. This model was based on twenty-six failed companies, with corporate failure occurring between 1972 and 1979. These were then paired with non-failed South African listed companies. The final model relied upon eight variables which were deemed to be significant from an initial set of twenty five variables.

Further applications using a multivariate approach included the commercially developed model by Clarke, Hamman and Van der Smit (1991) for privately owned industrial operations. Their model relied upon twenty-nine corporates that failed or experienced financial distress between 1985 and

1990 and forty-three non-failed corporates. Five variables from an initial thirteen variables were statistically significant. The model correctly classified 85% of failed companies correctly four years in advance of their failure. A hold out sample yielded a similar degree of accuracy with predictive accuracy for failed companies of 78%; 74%; 75% and 77% for years one; two; three; and four, respectively.

Court, Radloff and van der Walt (1999) instead of applying the common Bayes-Fisher discriminant analysis approach, opted for a two-stage model. Twenty-one failed and nineteen non-failed companies taken from 1974 to 1985 were used to develop a dichotomous model, which attempted to predict corporate failure one year and two years in advance of this occurring. The first stage used macroeconomic variables in an attempt to explain the variability of business failure using regression analysis. Total advances from the banking sector when lagged for two periods or months appeared to be an adequate discriminator. The second stage used twenty financial and non-financial variables along with a Bayes-Fisher discriminant analysis approach where six variables were decided upon for the dichotomous model. Using various cut-off scores the highest yielding classification rate led to 76% and 78% of failed and non-failed companies, respectively, being correctly predicted.

More recent studies included Bruwer and Hamman's (2006) study, which identified and addressed various shortcomings of previous South African studies along with applying international research techniques and learning from findings by researchers. There were a number of key observations that were made by the study.

The use of cash flow ratios along with certain accrual ratios and not simply a trial and error approach avoided brute empiricism. This is when independent variables are selected not based on a theoretical model underlying failure, but for reasons such as popularity as explained by Hossarri & Rahman (2005).

Furthermore, Bruwer and Hamman (2006) decided not to limit failure to bankruptcy but any condition where the company could not exist in the future which included delisting and major structural changes measured by four ratios: (1) total liabilities/equity; (2) total debt/cash; (3) accounts receivable/revenues; and (4) total assets/current assets.

Additionally, a grey area in between failed and non-failed companies was included in developing the model through inclusion of corporates that were not necessarily clearly confined to either of these two a priori groupings.

Contrary to many previous studies, an entire population was used rather than limiting the sample to sample of paired non-failed and failed corporates. This accounted for the different number of observations when it came to failed and non-failed companies. However, the sample was limited to industrial corporates listed between June 1997 to May 2002.

There was also a greater focus by the study on out of sample testing rather than the predictive accuracy when applied to the learning sample. This was supported by the view that this approach would provide a truer indication of model accuracy and applicability in a real world setting.

Lastly, consideration was given to economic cycles as suggested by Cybinski (2001) and Mensah (1984). This accommodated for growth and recessionary periods through using three distinct populations. These were based on where the majority of the months in the past financial year were ascribed to and grouped according to the following periods (1) recessionary and growth; (2) recession; and (3) growth.

Using the solutions above based on international studies a classification model was developed for the classification of failed and non-failed industrial companies listed on the Johannesburg Stock Exchange between 1995 and 2002. Three populations where used for failed and non-failed financial years from June 1997 to May 2002 including (1) both a recessionary and a growth phase; (2) a recession phase; and (3) a growth phase.

A different statistical approach was used. This model instead relied upon recursive partitioning or also known as decision or classification tree analysis. This was due to the classification being based on the ability to be graphically explained. Through using this approach more widely relevant outcomes were seen to result.

Fifteen independent variables were selected, where eleven of these variables demonstrated the ability to statistically significantly differentiate between failed and non-failed companies for both recessionary and growth phases. This was shown by using the Kruskal-Wallis test, given that the Lilliefors test indicated non normality of the independent variables. For the recession phase only five independent variables indicated a statistically significant difference and for the growth phase eight variables were identified.

Three credit statistics were found to be the best discriminators for prediction of corporate failure across all three populations (1) total assets; (2) cash flow from operating activities divided by sales for the last financial year end reporting period; and (3) cash flow from operating activities divided by sales from last financial year end reporting period as well as the cumulative three financial year end reporting periods preceding this.

Classification rates for the study were not as high as some previous South African studies that had been conducted. This study resulted in corporate failure prediction accuracy of 66% and classification accuracy of 70%. However, it is worth noting that many of the previous studies had numerous inherent shortcoming, as outlined earlier, which are likely to have contributed to inflated accuracy rates. These previous studies were not truly reflective of their model's potential in a 'real world' application. Classification rates were also below those on average for international studies:

Country	Authors (Year)	Statistical Technique	Classification Rate
Australia	Izan (1984)	Multiple discriminant analysis	100% one year prior to default; 70% two years prior to default; and 40% three years prior to default
Brazil	Altman, Baidya and Ribeiro-	Multiple discriminant analysis	88% one year prior to default; 84.2% two years prior to default; and 77.8%

Country	Authors (Year)	Statistical Technique	Classification Rate
	Dias (1979)		three years prior to default
Canada	Knight (1979)	Multiple discriminant analysis	54% one year prior to default
Canada	Altman and Lavallee (1981)	Multiple discriminant analysis	83.3% one year prior to default
England	Taffler (1976)	Linear discriminant analysis	96% one year prior to default; 70% two years prior to default; 61% three years prior to default; and 35% four years prior to default
England	Taffler and Tisshaw (1977)	Linear discriminant analysis	97% one year prior to default
England	Èarl and Marais (1982)	Multiple discriminant analysis	93% one year prior to default; 87% two years prior to default; and 84% three years prior to default
England	Taffler (1983)	Multiple discriminant analysis	0% one year prior to default due to time period anomalies
Finland	Suominen (1988)	Multiple discriminant analysis	Model 1/Model 2: 73-75/65-70% one year prior to default; 60-67/57-65% two years prior to default; and 50-52% three years prior to default
France	Bontemps (1981)	Linear discriminant analysis	87% one year prior to default
Germany	Beermann	Linear discriminant	91.5% one year prior to default; 81.0%

Country	Authors (Year)	Statistical Technique	Classification Rate
	(1976)	analysis	two years prior to default; 71.4% three years prior to default; and 61.9% four years prior to default
Germany	Weinrich (1978)	Linear discriminant analysis	89.0% two years prior to default; 84.3% three years prior to default; and 78.1% four years prior to default
Germany	Von Stein and Ziegler (1984)	Fix/Hodges non parametric model	88.9% one year prior to default; 82.2% two years prior to default; 75.6% three years prior to default; and 73.3% four years prior to default
Greece	Gloubos and Grammatikos (1988)	Linear probability model; probit analysis; logit analysis and multiple discriminant analysis	Linear probability model 91.7%; probit analysis 85%; logit analysis 86.7% and multiple discriminant analysis 91.7%.
Italy	Altman, Marco, Varetto (1994)	Multiple discriminant analysis and neural networks	Multiple discriminant analysis/neural networks: 96.5/95.3% one year prior to default; and 86.4/86.2% three years prior to default
Japan	Ko (1982)	Discriminant model using factor analysis	82.9% one year prior to default
Korea	Altman, Kim and Eom (1995)	Multiple discriminant analysis	Model 1/Model 2: 97.1/96.6% one year prior to default; 88.2/85.2% two years prior to default; 69.7/71.4% three years

Country	Authors (Year)	Statistical Technique	Classification Rate
			prior to default; 50/40% four years prior to default ; and 68.8/75% five years prior to default
Netherlands	Bilderbeek (1979)	Multiple discriminant analysis	70% to 80% one year prior to default
Singapore	Ta and Seah (1981)	Multiple discriminant analysis	86.2% one year prior to default; and 79.3%
Spain	Fernández (1988)	Multiple discriminant analysis	84% one year prior to default
Spain	Briones, Marín, Cuerto (1988)	Linear & multiple discriminant analysis	Linear/multiple discriminant analysis: 90/80% one years prior to default; 75/80% two years prior to default; 75/75% three years prior to default; 75/75% four years prior to default; and 80/75% five years prior to default
USA	Altman (1968)	Multiple discriminant analysis	Z Score Model: 96% one year prior to default; and 79% two years prior to default
USA	Edmister (1972)	Multiple discriminant analysis	90%
USA	Deakin (1972)	Multiple discriminant analysis	86% one year prior to default; 90% two years prior to default; and 81% three years prior to default
USA	Blum (1974)	Multiple discriminant	93-95% one year prior to default; 80%

Country	Authors (Year)	Statistical Technique	Classification Rate
		analysis	two years prior to default; and 70% three -five years prior to default
USA	Altman (1977)	Multiple discriminant analysis	Zeta Model: >90% one year prior to default; 70% five years prior to default
USA	Dambolena and Khoury (1980)	Multiple discriminant analysis	87% one year prior to default; 85% two years prior to default; and 78% three years prior to default
USA	Altman (2000)	Multiple discriminant analysis	Revised Z Score Model: 90.9% one year prior to default

Muller, Steyn-Bruwer and Hamman (2009), built on the approach of Bruwer and Hamman, but instead subdivided their data according to years before failure rather than economic phases. In addition, the concept of Normalised Cost of Failure (NCF) was introduced to adequately capture the effect of the number of Type I errors (incorrectly classifying a failed company as healthy) and Type II errors (incorrectly classifying a non-failed firm as being financially distressed). NCF is calculated by adding an additional weighting to the number of Type I errors and then adding this to the number of Type II errors as follows:

$$NCF = W_1 X \left(\sum (Type\ I\ Errors)\right) + \sum (Type\ II\ Errors)$$

Zavgren (1985) attempted to quantify this weighting to accurately depict the loss that a lending institution would occur in the case of a Type I error. This was established relative to a Type II error where the lending institution would forgo the profit, which would have been generated from making the loan. The appropriate weighting or cost ratio of Type I to Type II errors was calculated as being in the range of 20:1 to 38:1. Altman, Haldeman and Narayanan (1977) in their analysis of small regional banks in the United States found that the cost ratio of Type I errors was thirty-five times greater than

Type II errors. Muller, Steyn-Bruwer and Hamman used the upper limit of this weighting of 38:1 given the severe implications for an economy arising from misplaced loan activity.

Various predictive statistical techniques were considered such as (1) multiple discriminant analysis; (2) recursive partitioning; (3) logit analysis and (4) neural networks. Application of each predictive statistical technique yielded different results. Multiple discriminant analysis and recursive partitioning were shown to have the lowest NCF but also the lowest classification accuracies. Logit analysis and neural networks had the highest classification rates but also the highest NCF. The table below summarises the outcome for each predicative technique examined in the study:

Predictive technique applied	**Classification rate (Averaged over 4 Years)**	**NCF (Lower scores more favourable)**
Multiple discriminant analysis	68.0%	1042.5
Recursive partitioning	83.5%	1232.5
Logit analysis	83.5%	1503.3
Neural networks	84.8%	1361

Multiple discriminant analysis had the highest classification rate for correctly predicting failed companies at 35.9%. The study's recursive partitioning model resulted in a higher classification rate of 77.1% when compared to the Bruwer and Hamman (2006) combined model's 65.9%. However, the model was not as effective at predicting failed companies at 20.5% compared to Bruwer and Hamman (2006) combined model's 66.9%. This could suggest that perhaps the former models use of economic phases was better suited to corporate failure prediction than the traditional subdivision of the data into years before failure as shown in the table on the next page:

	MDA	LA	RP	NN(Ff)
	N	N	N	N
Failed correctly predicted	14,5	1,0	8,8	2,0
Type I error	26,0	39,5	31,8	35,8
Type II error	54,5	2,3	26,0	2,5
Non-failed correctly predicted	156,3	208,5	184,8	211,0
Total	251,3	251,3	251,3	251,3
Incorrectly predicted in total	80,5	41,8	57,8	38,3
Correctly predicted in total	170,8	209,5	193,5	213,0
NCF (38:1)	1042.5	1503,3	1232,5	1 361,0
	%	%	%	%
% of failed companies correctly predicted	35.9	2,6	20,5	4,6
% of non-failed companies correctly predicted	74,1	98,9	87,7	98,8
% of total incorrectly predicted	32,0	16,5	22,9	15,2
% of total correctly predicted	68,0	83.5	77,1	84.8

However, when NCF was introduced into the Bruwer and Hamman (2006) model it was found that the NCF per observation was higher at 4.9 versus this model's 5.2. Therefore it was concluded that subdivision of data into years before failure was deemed to result in a better quality model as opposed to by economic phase. This is illustrated in the table on the next page for average predictive accuracy for each different technique:

	This study	Steyn-Bruwer & Hamman		
	Average RP N	Combined N	Recession N	Growth N
Failed correctly predicted	8,8	95	48	36
Type I error	31,8	47	31	27
Type II error	26,0	75	24	28
Non-failed correctly predicted	184,8	141	88	76
Total	251,3	358	191	167
Incorrectly predicted in total	57,8	122	55	55
Correctly predicted in total	193,5	236	136	112
Proportion of “failed” to “non-failed” (%)	16,1	39,7	41,4	37,7
NCF (38:1)	1 232,5	1 861,0	1 202,0	1 054,0
NCF per observation	4,9	5,2	6,3	6,3
% of failed companies correctly predicted	20,5	66,9	60,8	57,1
% of non-failed companies correctly predicted	87,7	65,3	78,6	73,1
% of total incorrectly predicted	22,9	34,1	28,8	32,9
% of total correctly predicted	77,1	65,9	71,2	67,1

Correia (2010) applied both the Z-score and revised Z'' (Emerging Market) models to South Africa's Alternative Exchange (AltX) listed companies in 2009.

The AltX is a subsection of the Johannesburg Stock Exchange (JSE) and was introduced as an alternative market for small to medium size companies that did not meet the qualifying criteria for a JSE mainboard listing. This also means that companies that list themselves on the AltX are subject to less onerous listing requirements.

In obtaining an AltX listing a company must have (1) share capital of at least ZAR2 million; (2) a public shareholder holding of a minimum of 10% of each class of equity security and public shareholders numbering at least 100; (3) directors having completed the AltX Directors Induction Programme or make arrangements to the satisfaction of the JSE to complete it; (4) an executive financial director appointed and satisfaction of the audit committee of the applicant issuer with submission confirmation in writing to the JSE that the financial director has the appropriate expertise and experience to fulfil his/her role; and (4) was required to produce a profit forecast for the remainder of the financial year during which the company will list and one full financial year thereafter; (5) auditors or attorneys holding 50% of the shareholding of each director and the Designated Adviser in trust in such applicant issuer from the date of listing, and a certificate to that effect lodged with the JSE by the issuers auditors or attorneys; and (6) at least 3 directors, or 25% of the directors being non-executive.

Companies wishing to list on the JSE mainboard must have a subscribed capital of at least ZAR25 million; (2) not less than 25 million equity shares in issue; and (3) 20% of each class of equity securities shall be held by the public.

Additional requirements also include a satisfactory audited profit history for the preceding three financial years, the last of which reported an audited profit of at least ZAR8 million before taxation and after taking account of the headline earnings adjustment on a pre-tax basis. The company must also be carrying on as its main activity independent business which is supported by its historic revenue earning history. This can be carried out either by itself or through one or more of its subsidiaries, where it has control over a majority of its assets. Furthermore, if it is a company with a majority of its assets invested in securities of other companies listed on the JSE it must satisfy the criteria for listing for investment entities.

Lastly a JSE mainboard listing also requires that the number of the public shareholders in respect of listed securities shall number at least (1) 300 for equity securities; (2) fifty for preference shares; or twenty-five for debentures. Investment entities, mineral companies and property companies that are listed on the Main Board have certain modified criteria for listing.

Correia (2010) concluded that there were significant differences that resulted from the application of the Z-score and Z'' models to companies listed on the AltX. The Z'' model indicated that 78% of companies on the AltX exhibited low default characteristics, where only 11% indicated signs of financial distress in the next few years. The Z-score model presented a different picture where only 51% of companies exhibited low default characteristics, and where 19% indicated signs of financial distress in the next few years.

A revision was made whereby the market value of equity replaced the book value of equity by using market values three months after the financial year-end reporting date of each company. This resulted in 74% of AltX companies exhibiting low default characteristics, where only 6% showed signs of financial distress in the next few years. This pointed to a possible overreaction of the market during the financial crisis between 2008 and 2009. AltX companies were also shown to demonstrate low levels of financial leverage. It was also noted that a significant depreciation in equity values, which often can force a delisting, is not always a sure sign of impending corporate failure.

Coelho (2014) extended this study to include companies listed on the Alt-X for the period from 2008 to 2012 through application of both Altman's (1968) Z-Score model and Altman's (2005) Emerging Market Scoring (EMS) Model using Altman's (1993) Z″ model. It was found that Altman's Z-Score was better at predicting corporate failure when compared to Altman's Z″ model. Altman's Z-Score's provided classification rates of 60% and 50%, one and two year's prior to corporate failure, respectively. Whereas, Altman's Z″ model only classified corporate failure correctly with 17% for both one year and two years prior to this occurring.

This was unexpected given that Altman's Z'' model had been specifically adapted for use in emerging markets. This was attributed to the omission of market value of equity in the variables used where book value of equity to book value of debt was used instead. The rationale behind this was that Altman (1993) was of the view that market value could be skewed given the lack of liquidity in many emerging stock exchanges. This meant that equity prices were often detached from the fundamental value of a company given that they were not as actively traded.

Earnings before interest and taxation over total assets explained most of the decline in solvency for Alt X listed corporates. Similarly to Correia (2009) it was concluded that these corporates had low levels of financial leverage and consequently were not subject to a high likelihood of failure. This was supported by positive contributions to both Altman's Z-Score and Altman's Z″ model by the market value of equity to debt and book value of equity to debt variables, respectively.

EMS bond equivalent ratings calculated for these Alt X corporates showed that 76% mapped to investment grade equivalent ratings in 2008 compared to only 52% in 2012. At the same time in 2008 approximately 30% of these companies would have mapped to AAA bond equivalent ratings compared to 15% in 2012. What was not mentioned was that this showed yet another shortcoming in the EMS model. None of these corporates in real world setting would have achieved AAA ratings due the sovereign foreign and local currency ceiling considerations. Lastly, companies mapping to D had increased from 5% to 10 % over the period.

The study omitted Moody's Investors Service ratings on the basis that the bond ratings were fundamentally comparable; with only Standard & Poor's bond ratings being used instead. This is not the case as technically the ratings between these agencies differ on an ideological basis. Fitch and Standard & Poor's ratings only reflect probability of default in their assessment of credit risk. Moody's Investors Service's ratings on the other hand reflect loss given default. This is calculated as the probability of default multiplied by the expected loss.

The study also went further to examine the financial strength of those companies that had delisted over the period. One year prior to delisting as result of either being privatised or acquired, 33% of these companies had a high probability of corporate failure.

Commercial focused studies in South African corporate failure by Moody's Analytics, a subsidiary of Moody's Corporation, led to the development of a South African version of its RiskCalc™ application. The application relies upon the EDF™ model as discussed previously in *Chapter 3 | e) Market-based models for corporate failure prediction for international markets*. Dwyer and Wang (2010) adapted the EDF™ model to measure default risk for South African private companies, which was developed using a sample comprising financial statements and defaults for local companies. Their derivation of the model also made certain exclusions with regards to specific companies.

Small companies were excluded. This was defined as companies with net sales less than ZAR250 000, adjusted for inflation using a 2000 base year. Finance was often seen to be linked to the finances of key individuals, which were deemed not to be reflective of middle market models. This also omitted the impact of the provision of personal sureties, which if included, would lead to debt ratios being higher.

Financial institutions were also excluded given that they exhibited higher leverage than a typical company and were also subject to different regulation and capital requirements.

Public sector and not for profit institutions were excluded on the basis that government run institutions are influenced by the state or municipalities willingness to allow them to fail, where financial results are also not comparable to private companies. Financial reporting for non-profit companies differs from the financial reporting of traditional companies thus meaning that financial ratios are not comparable.

Lastly start-up companies were also excluded due to the volatility of their financial results during early year's resulting in a poor reflection of the underlying creditworthiness of the company.

This led to sample data comprising over 51 000 companies, 1000 defaults and 16 200 financial reports from 1997 to 2009. Variable selection commenced with a long list of potential variables that could be employed with nine variables included in the final model by adhering to the five criteria. This included (1) availability of the variable; (2) clear definition of inputs with no ambiguity; (3) variable being intuitive; (4) variable being able to predict default; and (5) uncorrelated with other variables.

These variables were then transformed into interim probabilities of defaults using non-parametric techniques. A probit model was then used to estimate the weightings of the financial statement variables, which were also combined with industry variables. A non-parametric final transformation was created to convert the probit model score into an actual EDF credit measure.

This led to inclusion of the following nine variables with the associated weightings per category:

Category		Variable (Ratio)
Activity	21.79%	» $\frac{\text{Inventories}}{\text{Cost of Goods Sold}}$ » $\frac{\text{Accounts Receivable(t)} / \text{Accounts Receivable(t−1)}}{\text{Sales}}$
Debt Coverage	7.90%	» $\frac{\text{Cash Flow}}{\text{Financial Charges}}$
Growth	8.87%	» $\frac{\text{Sales(t)}}{\text{Sales(t−1)}} - 1$
Leverage	14.36%	» $\frac{\text{[Current Liabilities+Long Term Debt]}}{\text{Tangible Assets}}$
Liquidity	26.36%	» $\frac{\text{Cash}}{\text{Total Assets}}$ » $\frac{\text{[Current Assets+Current Liabilities]}}{\text{Tangible Liabilties}}$
Profitability	16.74%	» $\frac{\text{Net Income(t−1)}}{\text{Total Assets(t−1)}}$
Size	3.98%	» Real Total Assets

The model also introduced credit cycle adjustment, which accounted for systemic risk namely the general credit cycle in the economy. This was designed to factor the current position of the credit cycle into the estimate of default for a company. This was specifically selected as being a forward-looking indicator of default risk. In order to quantify this systemic risk Moody's Analytics uses Distance to Default or DD. This was discussed in detail in *Chapter 3 | e)*. These signals are extracted from the stock market performance of individual public companies. The application is then extended to private companies by comparing the outcomes of public companies in the industry versus the historical average for the industry. If the DD exceeds the average, the EDF for the private company is adjusted upwards. If the DD is below the average, the EDF model for the private company is adjusted downwards. In the case where a private company does not conform to a particular industry represented by the universe of South African public companies, then an aggregation of all South African public companies is resorted to. In addition it was found that the DD factor increases with Annual GDP Growth in South Africa.

The study's predictive capacity was separated into two sets of results (1) Financial Statement Only (FSO) mode which excluded the systemic credit cycle adjustment factor; and (2) Credit Cycle Adjustment (CCA) mode which combined the FSO mode with the systemic credit cycle adjustment factor. The five year model accuracy ratio for the FSO mode was 41.64%, whereas the CCA mode was 45.83%. This compared favourably with the Z-score accuracy ratio of only 27.59% over the same period. All results were significant at a 95% confidence level. Making certain industry adjustments improved accuracy further with the FSO mode improving to 48.21% from 46.93% based on a one year model accuracy ratio. This also resulted in the aforementioned 41.64% accuracy over a five year period.

Similarly, on an industry by industry basis, the CCA mode generally resulted in lower EDF where EDF's were lower for (1) Agriculture; (2) Construction; (3) Mining, Transportation, Utilities and Natural Resources (4) Services; (5) Trade; and (6) Miscellaneous. This points to the FSO mode perhaps being too aggressive in terms of its quantification of EDF. The impact of this could lead to certain creditworthy companies not being offered credit. This would lead to lending institutions forgoing profit through interest income, which could be generated from a loan being made to the company.

Over a one-year time horizon the model was shown to be most accurate at predicting failure in the Consumer Products category (55.6%) and least accurate at predicting failure in the Communication Hi Tech (33.32%) category. Over a five-year time horizon, the model was most accurate at predicting failure in the Trade industry (45.12%) and least accurate at predicting failure in the Construction industry (27.62%). Also worth noting is that over a one year horizon as company size increased, so predictive power increased in a linear fashion. This relationship was not evident when relating company size to predictive power over a five-year time horizon.

Holman, Van Breeda and Correia (2011) applied the Merton (1974) model to calculate default probabilities for the top 42 non-financial firms listed on the JSE. The model was developed by using Moody's KMV model white papers as a guide. Theoretical default probabilities were determined under a base-case and a worst-case scenario. It was found that South African companies on the whole had low default probabilities. This was attributed to the low inherent financial leverage of South African corporates.

At the same time the paper suggested a weak correlation between Merton's default probabilities and ratings issued by rating agencies. However there was a fundamental error made in this analysis. A differentiation between national scale ratings and global scale ratings was missed. This meant that for some companies, national scale ratings were used, whilst for other companies global scale ratings were used. The risk assessment for these two ratings table can differ widely depending on the country.

National Scale Ratings are a rank ordering of credit risk on a domestic basis. This means that in this assessment of credit risk, ratings factor risk relative to the sovereign rating, which normally will carry a Aaa rating given that it is supposed to have the lowest credit risk. This is explained by the notion that a sovereign should under most circumstances have the highest credit quality and be the last to default under any set of conditions. This is because the sovereign has the ability to raise taxes or nationalise assets in order to raise funds to meet its debt commitments. National scale ratings are mapped across from Global Scale Ratings (see appendix D). This will mean that a National Scale Rating will in most cases differ to that of their Global Scale Rating as per the rating agencies methodology with regards to mapping.

Freedman (2015) explains further that a change in a National Scale Rating does not indicate a difference in credit risk, but rather a change in the unit of measurement. He likened this to moving from Fahrenheit to Celsius. It was further explained that National Scale Ratings are used to also provide a greater degree of differentiation than may be available under Global Scale Ratings. This is particularly apparent in countries with low Global Scale Ratings. Low local and foreign currency sovereign ceilings or sovereign ratings often can result in compression of ratings for domestic issuers. This is eliminated through increasing the rank ordering of domestic issuer's credit risk using a country specific scale from Aaa down, where the sovereign for reasons explained earlier will always be rated at this level as having the strongest domestic creditworthiness.

Global Scale Ratings, on the other hand are, as the name suggests, globally comparable. This credit assessment not only takes into account the credit profile of an issuer on an individual basis but also how it compares to the global universe of rated issuers. Therefore this allows for a globally consistent comparison of credit risk for all issuers.

Holman, Van Breda and Correia (2011) however used a combination of Nation Scale Ratings and Global Scale Ratings in their comparison of default probabilities under Merton's (1974) model and ratings assigned by Moody's Investors Service or Fitch. This meant that under this analysis National Scale Ratings were deemed to be equivalent to Global Scale Ratings in their assessment of credit risk. As explained earlier, this is not the case in practice. A parallel could be drawn by viewing Fahrenheit and Celsius as equivalent on a temperature scale. This meant that some of the conclusions drawn between the linkages between default probabilities under Merton's (1974) model and ratings assigned by either Moody's Investors Service or Fitch are not technically correct.

However, in defence of the findings by Holman, Van Breda and Correia (2011), Merton's (1974) model becomes less accurate at differentiating between risk the further way a company moves away from default expressed by an increasing distance to default. This in many respect is explained by the same relationship observed by Sun, Munves and Hamilton (2012) with respect to default rates and the EDF model, which is based upon Merton's (1974) model.

Furthermore, as with Coelho's (2014) study the same technical error was made in the assumption that Fitch and Moody's Investors Service ratings were equivalent. Fitch's rating scale, like that of Standard and Poor's only assesses probability of default. Moody's Investors Service's rating scale however reflects loss given default or the probability of default multiplied by the expected loss given default.

Chapter 4 | Analysis of key data and the methodological approach

This chapter will start with the definition of corporate failure that will be applied to non-financial South African corporates in this study. This then leads into how the sample of those non-financial South African corporates will be collected through applying this filter for defining corporate failure.

Following sample construction, credit statistics or independent variables are then identified for use in the model. This process is based upon their prevalence in Moody's Investors Service's sixty-three non-financial corporate rating methodologies. This is also expanded to include market-based metrics seen to be useful for the prediction of corporate failure.

The process for collecting data required for credit statistics for each observation included in the initial sample is then discussed.

The chapter concludes with a discussion of the final sample selection, model design and application of the multiple discriminant analysis.

a) Definition of corporate failure

The considerations applied in screening the universe of listed non-financial South African corporates for an event of financial distress resulting in ultimate failure required the satisfaction of three primary criteria. Firstly, non-financial South African corporate failure by definition was deemed to include an application made for business rescue under Chapter 6 of the South African Companies Act no.71 of 2008 or where there was a specific resolution issued by a corporate to begin liquidation proceedings due to financial distress or insolvency. Secondly, defined corporate failure was extended to South African non-financial corporates which had experienced a creditor enforcing security interests by legal right. This included where there was formal recognition and confirmation of a default on interest or principal payments, without remediation. Lastly, any form of debt restructuring event whereby a creditor received a diminished financial obligation relative to the original obligation or was economically disadvantaged, was construed as corporate failure.

Instances where there was an occurrence of a rights issue or other shareholder capital injection event, such as a shareholder loan, to avoid impeding corporate failure where reviewed. It was concluded that this would not be treated as a credit event given that creditors were not negatively impacted. The likelihood of occurrence of corporate failure should be considered in the broader context of the financial strength of shareholders or a parent against long term value potential of a corporate. Recent examples of such occurrence include Super Group Limited, where a rights issue was orchestrated by fund manager Allan Gray, one of the largest shareholders in the company, to protect equity value long-term. Similarly, state pension fund custodian, the Public Investment Corporation, was the key supporter of Lonmin Plc's rights issue. This was done with an aim to safeguard miners' jobs and the contribution of platinum production to South Africa's overall gross domestic product. In both cases rights issues avoided impending financial failure for corporates. The value proposition and the strategic nature of a company to its shareholders should therefore not be overlooked as part of any corporate failure analysis exercise.

b) Identification of South African non-financial corporate failures

Only listed corporates were considered given the need for access to public and independently audited financial information coupled with the preference for the inclusion of equity market data as outlined in *Chapter 1 | b) iii)*. A combined approach was applied to the detection of failed non-financial South African corporates.

The first data source comprised all delisted and suspended corporates from the JSE. Stock Exchange News Service announcements together with financial filings were then reviewed for each delisted or suspended corporate seeking any mention or reference to the aforementioned criteria for corporate failure.

Secondly, a search of the Johannesburg Stock Exchange's Stock Exchange News Service was undertaken for announcements containing any reference to business rescue, liquidation, restructuring, default or the qualification of an audit opinion on the basis of a corporates inability to continue as a going concern. This then allowed for the incorporation of corporates that remained listed despite having fulfilled the criteria for corporate failure. Such examples could have included an early resolution amongst creditors and the corporate, which then allowed for a corporate to continue as a listed going concern. Similarly, there could be instances where the corporate continues as a listed entity under business rescue protection. This would occur when the business rescue practitioners appointed view the benefits of maintaining a listing as outweighing the associated listing costs.

Lastly, and for the same reasons mentioned earlier for widening the sample to include all firms regardless of their listing status, the same search string was run through reputable news providers for both current and past Johannesburg listed entities available via a Bloomberg terminal, Reuters, Dow Jones and Google News. At the same time, financial corporates such as Saambou Holdings Ltd were excluded, for the reasons mentioned in *Chapter 1 | b) i)*. This resulted in a sample comprising eighty failed firms with the approximate date of corporate failure by definition spanning from April 2007 to December 2015. A full listing of this initial sample of failed firms is provided in *Appendix L*.

The sample of failed South African non-financial corporates collected were then paired with corporates with similar business profiles and where practicable, scale of operations. This process involved using a Bloomberg terminal and through the company information tab comparing each company to peers provided and filtered to South Africa only. Certain non-Johannesburg Stock Exchange peers were included by Bloomberg on the basis of material operational exposure to South Africa. Examples included non-financial corporates such as Petra Diamond Limited, a peer initially identified for Afgem Ltd which also was a South African focused diamond miner. Petra generates most of its cash flow from its Finsch and Cullinan diamond mines in South Africa, but is listed on the London Stock Exchange. These non-financial corporates were not included as peers given the preference to limit the sample to only those corporates listed on the Johannesburg Stock Exchange. This at the same time ensured consistency of comparison when it came to the use of equity price data and the need for uniformity. Often certain broad drivers, which influence listings on the Johannesburg Stock Exchange would not have the same impact on those corporates listed on the London Stock Exchange. This approach avoided any nuanced effects possibly skewing equity price data that was used.

c) Credit statistic selection

The entire distribution of quantitative ratios was collected for all Moody's Investors Service non-financial corporate rating methodologies, which span sixty-three sectors. Moody's Investors Service non-financial corporate rating methodologies comprise both quantitative and qualitative inputs, which together result in an overall score providing what is referred to as a grid indicated rating. This is used as a guide by rating analysts in their determination of a non-financial corporate's overall rating. This is considered whilst amongst other factors, most notably liquidity, forward-looking expectations, sovereign credit risk exposures, legal priority of claim with regards to the debt structure and regulatory and litigation risk to which a non-financial corporate is exposed. By way of example, Moody's Investors Service's Building Materials Industry Rating Methodology (2014) grid has been provided on the next page:

Factors	Sub-Factor	Weight	Aaa	Aa	A	Baa	Ba	B	Caa	Ca
		Score	1	3	6	9	12	15	18	20
SCALE	**Revenue ($bn)**	5%	>=$40	$20 - $40	$10 - $20	$3 - $10	$1.25 - $3	$0.25 - $1.25	$0.1 - $0.25	<$0.1
BUSINESS PROFILE	**Business Profile**	15%	Excellent geographic diversity with leading market positions (generally Top 1 or sometimes Top 2 positions) in emerging and developed countries on several continents. Operations include several independent: profitable and very well balanced product lines with exposure to the entire product spectrum of the industry.	Very good geographic diversity with leading market positions (Top 2 positions) in emerging and developed countries on several continents. Operations include several independent: profitable and well balanced product lines with exposure to most of the product spectrum of the industry.	Good geographic diversity in emerging and developed countries on at least two continents and with leading market positions (Top 3 positions). Operations include at least three independent and profitable business lines with exposure to some parts of the product spectrum of the industry.	Sound geographic diversity in emerging and developed countries preferably on two or more continents and with good market shares (Top 4). Operations include at least three independent business lines that vary in profitability with a focus on specific parts of the product spectrum of the industry.	Moderate geographic diversity mainly focused on several selected countries where it is at least among the top 5 players. Operations include more than one product line but with a focus on one segment: which is reasonably cash-flow generative.	Low geographic diversity mainly focused on some selected countries where it is at least among the top 10 players. Operations include more than one product line but with a strong focus on one segment: which is cash-flow generative.	Regional or niche player with very limited geographic diversification. Operations are focused on one product with break-even cash-flow generation in varied economic conditions.	Regional or niche player with extremely limited geographic diversification. Operations are focused on one product with unsustainable cash-flow generation even in healthy economic conditions.
PROFITABILITY AND EFFICIENCY	**Operating Margin**	10%	>=30%	24% - 30%	18% - 24%	12.5% - 18%	7.5% - 12.5%	2.5% - 7.5%	1% - 2.5%	<1%
	Operating Margin Volatility	10%	<2.5%	2.5% - 5%	5% - 10%	10% - 17.5%	17.5% - 25%	25% - 40%	40% - 50%	>=50%
	EBIT / Avg. Assets	10%	>=25%	16% - 25%	11% - 16%	7% - 11%	4% - 7%	2% - 4%	1% - 2%	<1%
LEVERAGE AND COVERAGE	**Debt / Book Capitalization**	10%	<15%	15% - 20%	20% - 30%	30% - 45%	45% - 65%	65% - 80%	80% - 100%	>=100%
	Debt / EBITDA	10%	<1x	1x - 1.75x	1.75x - 2.5x	2.5x - 3.5x	3.5x - 4.5x	4.5x - 6x	6x - 7x	>=7x
	EBIT / Int.	10%	>=16x	10x - 16x	7x - 10x	4x - 7x	2x - 4x	1x - 2x	0.5x - 1x	<0.5x
	RCF / Net Debt	10%	>=70%	50% - 70%	35% - 50%	20% - 35%	10% - 20%	5% - 10%	2.5% - 5%	<2.5%
FINANCIAL POLICY	**Financial Policy**	10%	Expected to have extremely conservative financial policies; very stable metrics; public commitment to very strong credit profile over the long term.	Expected to have very stable and conservative financial policies; stable metrics; minimal event risk that would cause a rating transition; public commitment to strong credit profile over the long term.	Expected to have predictable financial policies that preserve creditor interests. Although modest event risk exists: the effect on leverage is likely to be small and temporary; strong commitment to a solid credit profile.	Expected to have financial policies that balance the interest of creditors and shareholders; some risk that debt funded acquisitions or shareholder distributions could lead to a weaker credit profile.	Expected to have financial policies that tend to favour shareholders over creditors; above average financial risk resulting from shareholder distributions: acquisitions or other significant capital structure changes.	Expected to have financial policies that favour shareholders over creditors; high financial risk resulting from shareholder distributions: acquisitions or other significant capital structure changes.	Expected to have financial policies that create elevated risk of debt restructuring in varied economic environments.	Expected to have financial policies that create elevated risk of debt restructuring even in healthy economic environments.

In selecting financial ratios, or what Moody's Investors Service refers to as credit statistics, the entire universe of quantitative ratios used in Moody's Investors Service sixty-three non-financial corporate rating methodologies were surveyed and counted for their frequency of usage. A frequency or count cut-off of ten (representing around 10% of total ratios used and therefore deemed material) was applied resulting in an initial sample of nine credit statistics set out below that would be considered for usage in the multiple discriminant analysis model:

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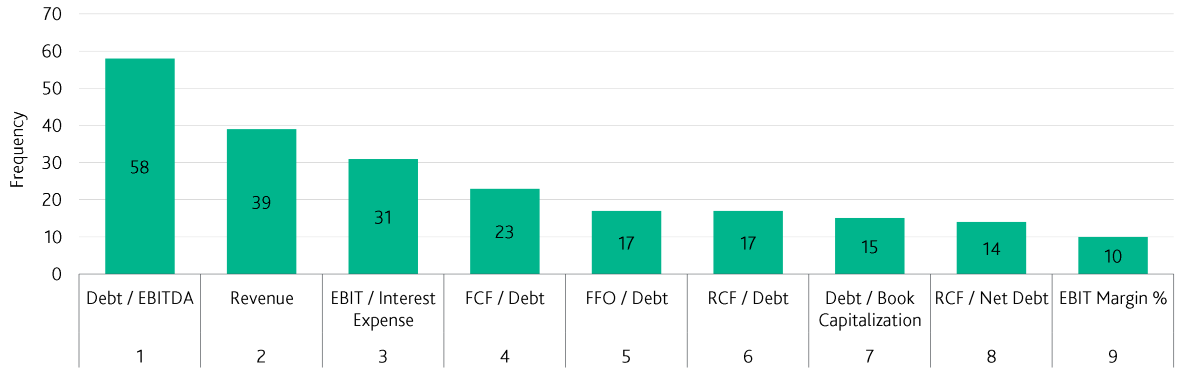


Debt to Earnings before Interest Tax Depreciation and Amortisation (EBITDA) is the most common credit statistic, which Moody's Investors Service uses in their assessment of relative creditworthiness of non-financial corporates. This is not surprising given the wide use of this financial risk metric by the credit community. Based on first-hand experience as a credit analyst it has been observed that most banks notably include debt to EBITDA in most of their maintenance covenant compliance tests contained in loan agreements. This is the same for EBIT/ Interest Expense.

Most lenders have two essential considerations when extending loans to non-financial corporates. Short-term, the focus is on interest coverage and the ability to provide a return on loans advanced by lenders represented by EBIT/Interest Expense and long term, the focus is on financial leverage and the ability to ultimately repay principal, gauged through Debt to EBITDA.

The remaining credit statistics ostensibly assess the same, but with a greater focus on cash flow based metrics from the cash flow statement rather than accrual based metrics from the income statement.

The latter often is more easily manipulated through a misguided interpretation of IFRS accounting standards.

In addition, and in line with the aforementioned rationale in *Chapter 1 | b) iii),* debt/ market capitalisation was added to provide linkage of the model to that of market-based models. Furthermore, the percentage change in equity price over the prior year reporting period was added to reflect financial risk dimensioned by the equity capital markets.

Although intended as a consideration with regards to liquidity analysis (*Chapter 1 | b) iv)*) and incorporation of forward-looking expectations (*Chapter 2* | d)), both were ultimately excluded on the basis of non-uniform disclosure across the non-financial corporates surveyed in the sample outlined in *section c of this chapter*.

Only a handful of failed non-financial corporates provided information on available committed bank facilities. This therefore limited the ability to form an accurate view on liquidity sources at their disposal. At the same time there was also limited information if any at all on bank covenants to which that the corporates were subjected to. This constrained the ability to assess the robustness of bank facility availability.

When it came to forward-looking statements made by the company which could be used in assessing the future operating cash flow generation capacity, there was limited information provided in most cases which was largely qualitative in nature. Only certain companies in certain sectors provided such disclosure, such as miners.

On the liquidity side there was also limited disclosure. There was limited delineation when it came to debt maturity profiles. The same applied to sufficiency of information required for forecast financial year capital expenditure spend along with any other expected cash outflows for the corporates. This therefore inhibited the ability to undertake a liquidity uses and sources analysis exercise.

At the same time this also limited the ability to attempt to generate forward-looking expectations for independent credit statistic variables. However, it is hoped through the inclusion of equity price information, forward-looking expectations to some degree will be factored in the model.

However, what was observed is that forward-looking statements seem to be improving with regards to the granularity of detail provided by a number of corporates.

i) Debt / EBITDA

This is an indicator of debt serviceability and leverage and is commonly used as a proxy for comparative financial strength. EBITDA comprises Pretax Income + Interest + Amortization of Intangibles + Depreciation + Non-Recurring Expenses/(Gains). In line with the approach outlined in *Chapter 2 | c)* income from equity accounted entities was excluded. Exceptions were made if equity accounted income was attributed to equity accounted entities considered to be an integral part of the company's income generating operations and sufficiently backed by cash distributions closely approximating that of equity accounted income levels. In instances where equity accounted entities were regular dividend payers, but paid out a low proportion of net income, equity accounted income was replaced with dividends received.

Debt is classified using the balance sheet as Short-term Debt + Current portion of Long-term Debt + Long-term Debt, net of its current portion, + any resulting liabilities for capital leases, if not already included in Debt, as per the approach outlined in *Chapter 2 | b)* with respect to the capitalisation of operating leases. Gross debt is generally preferred in assessing 'debt capacity' or the ability to repay and service debt levels. Although cash balances, should not be ignored, there is often a certain proportion which should be attributed to keeping a corporate's day to day operations going or what sometime is referred to as 'keeping the lights on'. Therefore it cannot be assumed that the entire amount of cash balances can be deployed to debt reduction. It is difficult to estimate without insight from the company what level of cash, with a degree of safety margin, is required to meet the day-to-day cash flow needs of the company. It is expected that most companies will try to optimise cash levels as much as they possibly can. This reduces negative carry or the loss of earnings due to lower interest income on cash balances relative to higher interest charges on debt balances. Therefore it is fair to assume that in most instances, where there are certain exceptions such as prefunding of capital expenditure, debt will be reduced with surplus cash balances as far as is reasonably possible. Taking this into account, looking at debt serviceability through net debt as opposed to gross debt, is in the most part viewed sceptically, as this is not deemed to be representative of the 'true' financial leverage of a company.

This ratio serves as a useful proxy for a non-financial corporate's inherent financial strength.

ii) Revenue

Revenue provides useful information content on a number of credit characteristic traits for non-financial corporates. Scale of revenue often will capture geographical and operational diversification along with financial resources available to the corporate entity. The larger the firm, the broader the extent of its operations and locations along with its access to financing both from the equity and credit markets, where it is likely to be seen as being more reputable and recognisable. A larger scale of revenue often can also reflect a more extensive customer base, along with potentially purchasing power and price leadership, which are often linked to market share.

Scale of revenue can also often be seen as a representation of the age of the firm including the number of business cycles it has successfully navigated and learnt from in the process, therein also demonstrating resilience.

Revenue was converted into US dollars using the average translation rate over the reporting period. This is in line with the approach that Moody's Investors Service uses on a global basis, to ensure comparability of scale. This also at the same time introduced a currency effect for consideration by the Multiple Discriminant Analysis model. This is an import consideration in the context of non-financial corporate failure prediction in a South African context, where the inherent volatility of the South African rand can in itself have a part to play in the propensity for financial distress.

Import or export businesses, or business reliant on inputs that are denominated in foreign currency, can often find themselves under pressure if the South African rand moves the wrong direction for the company. Such examples include industrial companies and miners, where their businesses become less competitive in a global context if the South African rand appreciates relative to key currency exposures, as their cost bases are no longer globally competitive. Similarly, businesses reliant upon inputs denominated in foreign currency, such as domestically focused airlines that have not entered into any foreign currency hedging arrangements on their jet fuel, can face financial pressure if the South African rand depreciates. These non-financial corporates may not be able to pass on cost push inflation experienced from inputs by the businesses, such as jet fuel, to end customers, in this case passengers.

iii) EBIT / Interest Expense

The same approach that was applied to EBITDA for equity accounted income from equity accounted entities is also applied to Earnings Before Interest and Tax (EBIT). EBIT is calculated as Pretax Income+ Interest + Non-Recurring Expenses/(Gains). Interest Expense is defined as Gross Interest Expense per the Income Statement. This provides an indication of a company's ability to pay interest.

iv) FCF / Debt

Through using the Consolidated Statement of Cash Flow, Free cash flow is calculated as follows: Cash Flow From Operations (CFO) − Capital Expenditures − Common Dividends − Preferred Dividends − Minority Dividends. Debt is per the definition provided under Debt/EBITDA.

v) FFO / Debt

By using the Consolidated Statement of Cash Flow, Funds From Operations (FFO) is defined as follows: Cash flow from operations before changes in working capital and changes in other short-term and long-term operating assets and liabilities. Debt is as per the classification given under Debt/EBITDA.

vi) RCF / Debt

Retained Cash Flow (RCF) is calculated using the Consolidated Statement of Cash Flow as follows: FFO, as defined above, − Common Dividends − Preferred Dividends − Minority Dividends. Debt is calculated in line with the definition for Debt/EBITDA.

vii) Debt / Book Equity

Book Capitalisation is defined by Moody's Investors Service from the balance sheet as follows: Short-term Debt + Gross Long-term Debt, + Deferred Taxes + Minority Interest + Book Equity. This is seen to be an extension of Capital Employed. Debt is as per the definition provided in Debt/EBITDA.

Due to Deferred Taxes not being disclosed as a separate line item for some corporates, it was decided that Book Equity instead of Book Capitalisation would be used.

viii) RCF / Net Debt

RCF is as defined under RCF to Debt, whereas Net Debt is Debt, as defined under Debt/EBITDA, less unrestricted cash balances.

ix) Percentage EBIT Margin

The EBIT margin is calculated by dividing earnings before interest, and taxes by net sales. This provides an indication of a non-financial corporate's profitability.

x) Debt/ Market Capitalisation

Debt is as per the definition provided in Debt/EBITDA. Market capitalisation is defined as # of Shares x Market Price at the financial reporting date. Debt/Market Capitalisation brings market model theory in terms of distance to default as explained in *Chapter 3 | e)* for consideration in application in the multiple discriminant analysis model.

xi) Equity price return over the prior year

Market Price at the financial reporting date divided by the Market Price at the financial reporting date minus 1. Data should be screened for volatility attributed to share splits or share buy backs which could mask the rationale for share movements. The impact of dividends on share price should not be removed as they ultimately also have a liquidity impact that is attached to the company which should be considered in overall credit analysis.

d) Independent variable data collection

Data required for calculation of the eleven variables to be used in the Multiple Discriminant Analysis Model was sourced from a combination of annual reports, sourced from financial filings, and financial information provided through a Bloomberg terminal. This was then cross compared through adjusted financial data sourced from FactSet, a proprietary software application used by Moody's Investors Service, which provides both financial statement and market data. Data was collected on an annual reporting basis, given that some firms had not prepared interim reports. Financial data obtained from interim financial statements was deemed to have a lower degree of integrity and reliability of information provided. This was predicated by their review by independent auditors. This is different too annual financial statements, which are audited and subject to a comprehensive review process. Hence, only financial information provided on an annual basis was used.

Financial data was collected for two data points for each paired failed and non-failed South African non-financial corporates. The first data point included the latest financial data that was provided by the failed South African non-financial corporate, ahead of its corporate failure as defined in *section b of this chapter*. This was then matched to the same accompanying data point for the non-failed firm. This allowed for the comparability of failed and non-failed South African non-financial corporates on a like for like basis. This at the same time then gave due consideration to the same economic cycles and business conditions that corporates with an overlapping business profile would experience.

Bruwer and Hamman (2006), attempted to control for economic cycles. However in the case of this study, variables of each paired failed and non-failed South African non-financial corporate would ostensibly capture the impact of economic cycles. As such, to factor economic cycles would be double accounting given that this would already be incorporated in the information content of the independent variables. Similarly, controlling for economic cycles would in effect be removing the differentiating power offered through the independent variables.

Furthermore, considering economic cycles could also be counter intuitive for some sectors. Performance for some corporates may prove stronger in recessionary economic cycles when compared to growth economic cycles. Examples of these could be retailers with lower price points and low cost airlines, where both generally benefit in a weaker economic climate as consumers are forced to down trade when it comes to their consumer expenditure patterns. Therefore, controlling for economic cycles would be not be representative of credit fundamentals, where credit metrics could be either weakened or strengthened, depending on the corporate, in either up or down economic cycle.

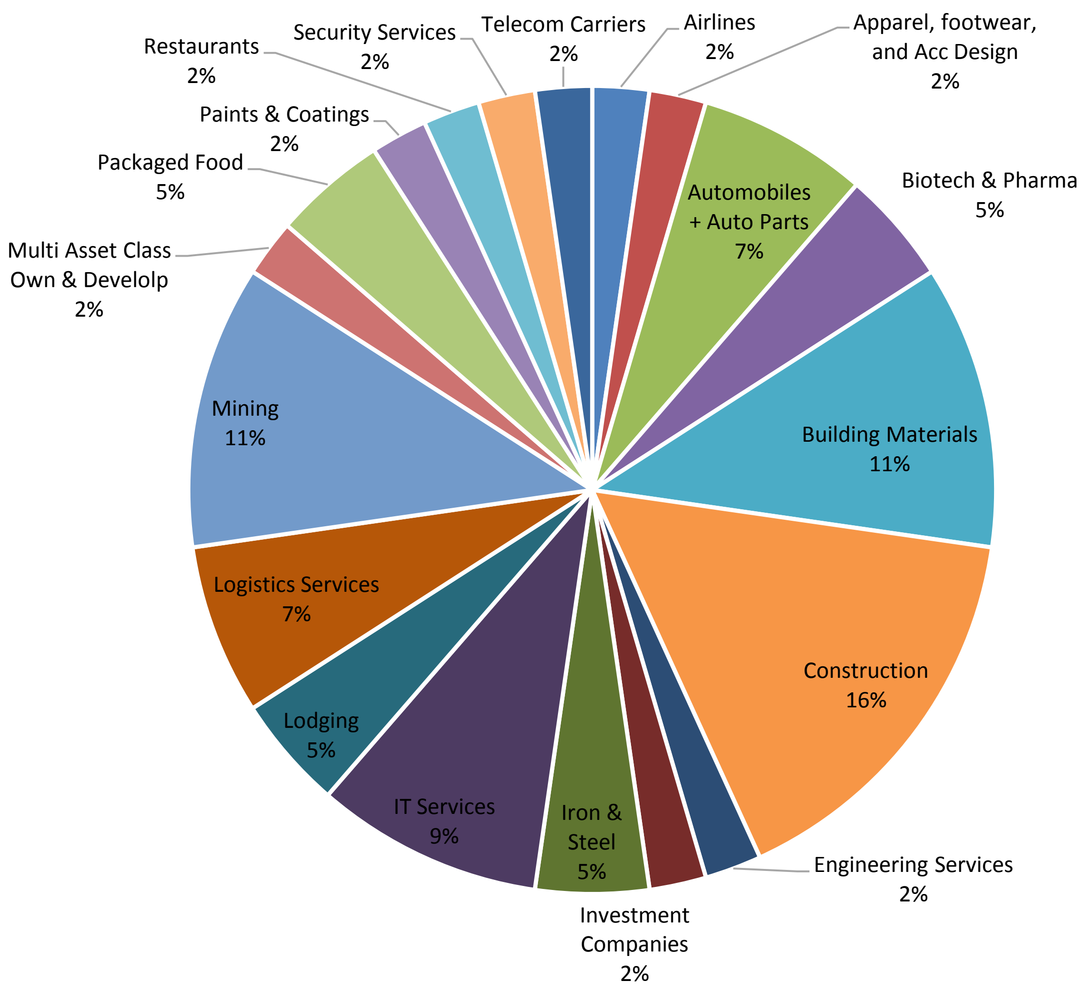
Ultimately, the discriminant function derived from the multiple discriminant analysis model should instead focus on prediction based on credit metric movements, rather than economic cycles. Credit metrics would in any case take this into account, no matter what sector or economic environment a corporate finds itself in.

The second data point was the financial information provided a year prior to the first data point.

e) Sample selection of failed South African non-financial corporates

From the initial sample of eighty failed South African non-financial corporates this was reduced to forty-four corporates through application of the research design. Firstly data, as discussed in *Chapter 1 | b) i)*, from South African non-financial corporates that met the definition of corporate failure were only included if their annual financial reporting had been prepared under IFRS. This resulted in a reduction of the initial sample to sixty-one failed South African non-financial corporates. A second round of exclusion was based upon the inclusion of only those firms where there was sufficient financial disclosure to make necessary adjustments as were outlined *Chapter 2 | b)*. This should be used to realign financial metrics to provide the necessary information required for a true obligation reflection and assessment in their credit metrics. This led to a final sample of forty-four failed South African non-financial corporates paired with their appropriate non-failed peer.

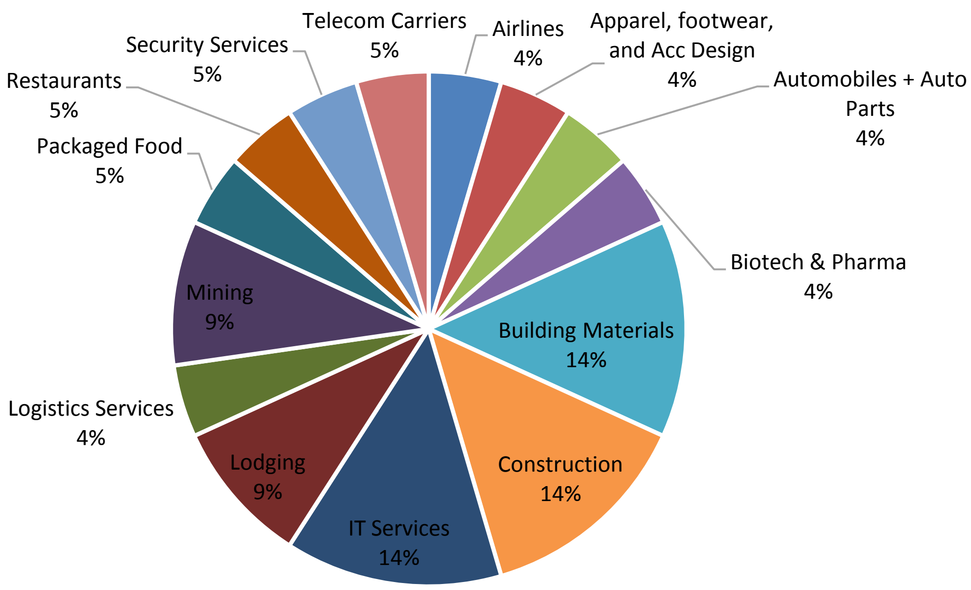
The greatest concentration of South African non-financial corporates failures in the sample data comprised construction companies followed jointly by building materials and mining companies. This can in part most likely be explained by the slowdown in construction following the financial crisis. This followed from reduced bank lending for property developments and the tapering off of FIFA World Cup 2010 linked infrastructure spending. Mining related failure was in part explained by a softening of commodity prices, specifically gold and platinum prices, followed subsequently by a decline in base metals prices.



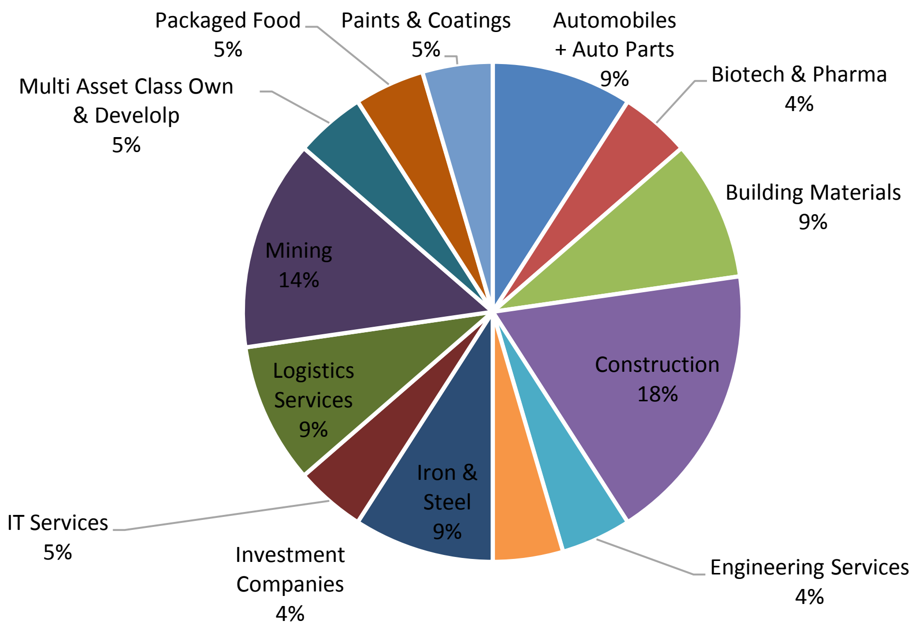
The inherent shortcoming of applying the research design constraints to the original sample is a reduction in the sample size. This will therefore limit the possibility of out of sample testing.

Although this will still be attempted through a halving of the sample, the applicability of such testing may be lowered to some extent given that the relatively small sample size comprising only twenty-two failed firms paired with twenty-two non-failed firms. This split will also be varied through considering the first twenty-two failed firms for the learning sample, with the remaining twenty-two failed firms used for the test sample, and vice versa.

The sector distribution for the first twenty-two failed firms was as follows with Building Materials, Construction and IT Service sectors evenly weighted with highest corporate failure observations:



The sector distribution for the first twenty-two failed firms was as follows with the Construction sector showing the highest number of corporate failure observations:



Another limitation will be the reliability of financial information, which is open to accounting manipulation or fraudulent activity, which cannot be controlled for in the model. The hope though is that in some instances, where such activity has occurred that this could potentially be reflected through movements in equity prices. Some market participants are likely to have picked up on such activity in advance of it being formally announced to the market. They would then reflect such information in their valuation and in turn, in the equity price of the corporate.

Through using a second data point, which preceded the prior year data point, some firms were further excluded in the interest of consistency of cross sampling, on the basis of either not having adopted IFRS or not having sufficient disclosure necessary to make the necessary adjustments as were outlined in *Chapter 2 | b)*.

Therefore in the interests of maintaining a sufficient sample size, only the latest financial data point provided before failure was used. This aligns with the general credit rule that most corporate failure should be identified and navigated twelve months out in line with Moody's Investors Service (2016) ratings' time horizons and the focus on twelve-month default rates. This was also seen by Taffler (1976) to be an adequate period to divest or limit loan losses. In most cases the latest financial data point still gave more time than twelve months from the date non-financial South African corporates met the definition of corporate failure as discussed earlier in *section a) of this chapter*. This is in line with a Moody's Investors Service credit policy post mortem assessment for default prediction, where ratings should signal a high probability of default one year in advance of a default occurring.

f) Multiple discriminant analysis model design and inputs

StatSoft, Inc's Statistica data analysis software system Version 12 was used to run the discriminant analysis model. All data comprising eighty-eight combined and unique peer-matched failed and non-failed South African non-financial corporates along with their corresponding financial data that had been gathered for each of the eleven variables identified in *section c of this chapter* were imported into Statistica. This resulted in twelve columns of data, including a final column identifying the South African non-financial corporates as either failed or non-failed, and eighty-eight rows. Statistica automatically incorporates column labels in a separate non-counted row at the top of the sheet.

The failed/non-failed column was selected as the grouping variable with the eleven independent credit statistic variables selected to be included in the independent variable list. Stepwise analysis was selected, with a forward stepwise analysis specified.

The model had a critical cut-off score of zero i.e. a score above zero indicated non-failure, a score below, failure.

The limitation of multiple discriminant analysis and the sample that it will use in developing a discriminant function, is that the results are completely sample dependent. It is worth noting that this may influence the outcomes of this study in a number of ways.

Firstly, there may be a degree of distortion with regards to observations that occurred during the financial crisis in 2008 and 2009. This may lead to the discriminant function being distorted to some extent for increase financial risks that are remote, but not impossible. This may prove to be beneficial in structuring the model towards being more conservative in its assessment of risk and its consideration for the occurrence of outlying events.

Secondly, the period that followed the financial crisis reflects the effects of easing monetary policy leading to a positively skewed risk distribution. With the longer term view of removing quantitative easing this may result in consequences that may not be fully factored by a discriminant function developed for different economic conditions.

This change in economic conditions is already apparent with the growing degree of volatility witnessed in financial markets and corporate fundamentals as the world economy moves from the 'new normal' to the 'new abnormal'. This new era is expected to be characterised by an expectation of negative short term interest rates in many economies and depressed asset valuations.

g) Treatment of outliers

Both Bruwer and Hamman's (2006) and Sun, Munves and Hamilton (2012) highlighted that the nature of financial data often means that it does not conform to a normal distribution. This is as a result of a higher than expected concentration of outliers or extreme events. Under a normal distribution the probability of outlying financial data is low, but in reality this is often a lot higher.

This leads to fatter tails due to a greater number of outlying observations resulting, which more closely aligns with that of a Student's t-distribution of observations which accommodates for a higher propensity for the occurrence of extreme observations.

There is a general preference for excluding outliers in a sample before running a multiple discriminant analysis. In the case of this sample an attempt will be made to not to exclude paired-firms on the basis of any one independent credit statistic variable observation being considered to be an outlier.

The exclusion of outliers in essence would be a decoupling of the model from real world possibilities, where extreme financial data can exist for anyone of a number of reasons, excluding no debt, a low interest expense, negative equity or relatively high debt or low EBIT generation. It can be expected that there will be a greater number of extreme observations for independent credit statistic variables when it comes to failed firms. This can be expected as volatility of financial data often represents an elevated level of financial risk providing early indication for the increased propensity for corporate failure. This often not only indicative of financial leverage but in many cases operating leverage too.

To overlook this consideration would not be reflective of the true ingredients that often can lead to corporate failure. Adjusting the sample for a cleaner and perhaps more palatable picture of independent credit statistic variables would not be respecting the proposed research design outlined to meet the research objectives. This could be seen as making the sample fit the modelling rather than attempting to see if the modelling itself can fit the sample which ultimately is the research objective.

By attempting to run the multiple discriminant model on a sample comprising a range of different observations it is hoped that the resulting discriminant function will be more robust when it comes to the classification of corporate failure.

Chapter 5 | Empirical findings of the study and a discussion of the results

This chapter will commence with an examination of the descriptive statistics relating to the sample used in the multiple discriminant analysis. This will include reviewing the correlation between the various independent credit statistic variables used for discrimination of the data used in the sample. Any intercorrelation existing between any two independent credit statistic variables will also be identified. At the same time this will be extended to a graphical analysis to include scatter plots to demonstrate any pre-existing linear relationships between two independent credit statistic variables. This will then be followed by a review of the sample means to assess which independent credit statistic variables appear to show the greatest degree of variation between failed and non-failed firms.

This analysis of variation will be extended to the generation of both histograms and box and whisker plots. At the same time these will also provide insights into any outlying data points as well as the distribution of data and how closely they conform to a normal distribution.

There is consideration given to outliers in some observations for independent credit statistic variables in the sample and how these should be addressed and their implications for multiple discriminant analysis.

This will flow into a review of the multiple discriminant analysis outputs. Firstly, independent credit statistic variables not included in the model will be discussed along with the potential motivations for their exclusion. This will entail examination of the resulting discriminant function, its ability to classify corporate failure, and its application to the initial sample. Additionally, an attempt will be made to refine the model, if possible.

Lastly, the multiple discriminant analysis will extend to a splitting of the initial sample. This will done firstly by splitting into a learning sample, comprising the first forty-four paired non-failed and failed non-financial South African corporates. The resulting discriminant function will then be applied to a test sample comprising the remaining forty-four paired non-failed and failed non-financial South

African corporates. This therefore provides the ability for the applicability of the discriminant function to accurately predict corporate failure on a hold out sample.

This will also be performed the other way around where the last forty-four paired non-failed and failed non-financial South African corporates will become the learning sample. The resulting discriminant function is applied to a test sample comprising the first forty-four paired non-failed and failed non-financial South African corporates.

After having completed this analysis, all discriminant functions will be assessed and their classification rates compared a multiple discriminant analysis model run on a sample comprising financial data that has been prepared under both IFRS and SA GAAP. This will allow for a conclusion to be drawn on whether IFRS only financial information results in improved accuracy for the prediction of corporate failure. At the same time a determination can also then be made on whether by using an expanded sample of failed firms this will improve upon classification rates.

a) Analysis of descriptive statistics

i) Pooled within group correlations

The correlation matrix sets out below the correlation coefficients for all variables included in the model compared themselves and other variables.

	Pooled Within-Groups Correlations (Test Sample)										
Variable	**Debt/ EBITDA**	**Rev.**	**EBIT /Int**	**FCF/ Debt**	**RCF /Debt**	**FFO/ Debt**	**Debt/ B.E.**	**RCF/ Net debt**	**EBIT Margin**	**Debt/ M Cap**	**1 Year Equity Price Return**
Debt/ EBITDA	**1**	-0.05	0.06	-0.03	-0.11	-0.12	-0.05	0.06	0.08	0.06	-0.01
Rev.	-0.05	**1**	0	0.01	0.06	0.11	-0.02	0.15	0.01	-0.03	-0.06
EBIT/Int	0.06	0	**1**	0.05	0.04	-0.12	0.02	-0.02	-0.02	0.08	-0.02
FCF/Debt	-0.03	0.01	0.05	**1**	**0.79**	**0.78**	-0.01	-0.1	0.03	-0.01	-0.05
RCF/Debt	-0.11	0.06	0.04	**0.79**	**1**	**0.97**	-0.04	-0.14	-0.09	-0.12	0.18
FFO/Debt	-0.12	0.11	-0.12	**0.78**	**0.97**	**1**	-0.02	-0.15	0.03	-0.13	0.18
Debt/ B Cap	-0.05	-0.02	0.02	-0.01	-0.04	-0.02	**1**	0.01	0.09	0.08	-0.04
RCF/Net debt	0.06	0.15	-0.02	-0.1	-0.14	-0.15	0.01	**1**	-0.17	0.02	-0.22
EBIT Margin	0.08	0.01	-0.02	0.03	-0.09	0.03	0.09	-0.17	**1**	0.09	0.06
Debt/ M Cap	0.06	-0.03	0.08	-0.01	-0.12	-0.13	0.08	0.02	0.09	**1**	-0.11
1 Year Equity Price Return	-0.01	-0.06	-0.02	-0.05	0.18	0.18	-0.04	-0.22	0.06	-0.11	**1**

The correlation matrix demonstrated a strong intergroup correlation (>0.75x<-0.75) shown between FFO/Debt, RCF/Debt and FCF/Debt. This is to be expected given that all three credit statistics rely upon FFO as a starting point. RCF then reduces this by dividends paid with FCF factoring movements in short term and long term operating assets and liabilities, movements in working capital and capital expenditure.

Therefore, in an additional enhanced model test only one of these should be included, therein reducing the number of independent credit statistic variables to eight from eleven. It would be recommended that FCF be used given that it is more representative for debt serviceability capacity as it most accurately demonstrates residual cash flow generation ability to meet debt repayments. This additional information content offered is further supported by a lower intergroup correlation between the three cash flow metrics of 0.78.

ii) Samples means

Analysing the means of the independent credit statistic variables will allow for an assessment of variation between observations for failed and non-failed firms. In addition this will also allow for an analysis of some key differences between observed means for failed and non-failed firms.

	Means (Test Sample)											
Failed / Non-failed	**Debt/ EBITDA**	**Rev.**	**EBIT/ Int**	**FCF/ Debt**	**RCF/ Debt**	**FFO/ Debt**	**Debt/ B.E.**	**RCF/ Net debt**	**EBIT Margin**	**Debt/ M Cap**	**1 Year Equity Price Return**	**N**
Failed	9.18x	$97.49mn	-332.28x	8%	102%	115%	1470%	-74%	-323%	193%	-22%	44
Non-Failed	1.63x	$1,291.01mn	23.87x	43%	108%	138%	225%	84%	25%	31%	7%	44
All Grps	5.41x	$694.25mn	-154.20x	26%	105%	127%	847%	5%	-149%	112%	-7%	88

It is worth noting that in the table of means above that some of the independent credit statistic variables were skewed due to the presence of some outlying observations. Although these outlying observations are correctly specified, their presence does result in a material impact on some of the means for the independent credit statistic variables.

	Medians (Test Sample)											
Failed / Non-failed	**Debt/ EBITDA**	**Rev.**	**EBIT/ Int**	**FCF/ Debt**	**RCF/ Debt**	**FFO/ Debt**	**Debt/ B.E.**	**RCF/ Net debt**	**EBIT Margin**	**Debt/ M Cap**	**1 Year Equity Price Return**	**N**
Failed	2.94x	$22.75mn	-2.96x	-23%	-19%	-13%	27%	-25%	-9%	63%	-47%	44
Non-Failed	1.42x	$517.63mn	4.31x	13%	43%	59%	34%	38%	6%	24%	2%	44
All Grps	1.76x	$91.47mn	1.80x	-2%	19%	28%	31%	5%	3%	38%	-16%	88

The presence and impact of outliers for independent credit statistic variable observations is even more clearly evident when substituting means for medians. Medians can be seen to be more representative of typically what would be seen for observed financial data for the independent credit statistic variables in most failed and non-failed South African non-financial corporates. Again, this does not take into the account for possibility of extreme values where their occurrence is higher than would be commonly expected.

The most notable outliers in the independent credit statistic variable observations were explained by some observations having a very low to negative EBITDA with a relatively high debt level in the case of debt/ EBITDA and a very low Interest Expense with a relatively large EBIT loss in the case of EBIT/ Interest Expense. Similarly, an extremely low Book Value of Equity or Market Capitalisation, tied to a relatively high debt level, impacted Debt/ Book Value of Equity and Debt/ Market Capitalisation, respectively.

The independent credit statistic variable observation outliers were primarily related to failed firms. As explained previously in *Chapter 4 | G*, this is to be expected given the nature of some of the business conditions that resulted in ultimate corporate failure and reflected in the extreme volatility and swings in the financial data.

By excluding outliers the sample would reduce to thirty-three failed firms combined with thirty-three non-failed firms with the means provided below for both.

	Means (Test Sample)											
Failed / Non-failed	**Debt/ EBITDA**	**Rev.**	**EBIT/ Int**	**FCF/ Debt**	**RCF/ Debt**	**FFO/ Debt**	**Debt/ B.E.**	**RCF/ Net debt**	**EBIT Margin**	**Debt/ M Cap**	**1 Year Equity Price Return**	**N**
Failed	6.26x	$122.77mn	-3.28x	-69%	15%	25%	173%	-113%	-32%	235%	-14%	33
Non-Failed	1.65x	$1,380.56mn	7.93x	21%	75%	120%	35%	55%	29%	30%	9%	33
All Grps	3.96x	$751.66mn	2.32x	-24%	45%	72%	104%	-29%	-2%	133%	-3%	66

The impact of using the sample without outliers on the discriminant function is discussed in detail in *section c) iv) of this chapter*.

The expressed intention outlined in *Chapter 4 | G* is to respect the research objectives and to fit the model to the data, rather than the other way around. As such, the discussion of the means will focus on the original sample and the initial table of means presented at the beginning of this section, despite the occurrence of outlying data points.

The multiple discriminant analysis on the original sample indicated that the most notable material differences in the means occurred between failed and non-failed South African non-financial corporates for Debt/EBITDA and Revenue. Also worth mentioning, is that these two credit metrics are most frequently used by Moody's Investors Service in their corporate rating methodologies as outlined in *Chapter 4 | C*.

There also appears to be material differences between the means for failed and non-failed corporates when it comes to EBIT/ Interest Expense, Debt/ Book Equity, FCF/Debt, RCF/Net Debt, EBIT Margin and Debt/ Market Capitalisation. The mean of the grouping of failed firms also exhibited that they were significantly loss making relative to their interest burden.

Notable exceptions where means did not demonstrate material variances between failed and non-failed were; FFO/ Debt, RCF/ Debt and Equity price return over the prior year. The first two can be explained by these metrics not being reflective of debt servicing capacity and liquidity, where this additional consideration was shown to add value through considering cash balances against debt in RCF/Net Debt.

Equity price return over the prior year return may be driven more from a systemic risk perspective, rather than a firm risk perspective when it comes to variation in equity price returns. This could be expressed that concerns often expressed through equity price returns are often not unique to a corporate but rather a sector or the economy at large.

However, those corporates carrying more debt are likely to be seen to be more at risk in such instance and therefore more likely to see a sharper decline in their equity price. The value however was shown when it came to considering these equity price movements against the amount of debt carried by the corporate, therein factoring a distance to default characteristic which provides the theoretical underpinnings for market-based models as described in *Chapter 3 | e)*.

The preference to first pair failed with non-failed firms by sector and then by scale of operations could skew the explanatory power of the multiple discriminant analysis given the inclusions of non-failed firms with revenues significantly exceeding that of their pair failed firm. Although with this said, and in line with arguments presented in *Chapter 4 | C)ii)*, this may still represent the substance of corporate failure prediction.

Often firms with larger scale revenue, as measured in this study in millions of US dollars, may resemble characteristics of having greater diversity of operations across business units and geographies. This consideration provides natural risk mitigation, which can reduce the propensity for corporate failure. The research design was also not deemed to be misplaced given that when it came to inclusion of the two equity price linked independent credit statistic variables it wouldn't have made sense to pair two firms from different sectors together even if this meant a better alignment of scale/revenue. This approach then allowed for comparison of the unique financial risk differences between the failed and non-failed corporate rather than financial risks that were endemic to the sector within which it operated.

It is also worth reiterating the point that any exercise attempting a perfect pairing of non-failed and failed non-financial South African firms also faces the limitation of a smaller sample of corporates to select from when compared to larger equity markets in the United States and the United Kingdom.

The concentration of outliers mainly related to that of the failed firms, however there were some unique instances where outliers existed for certain independent credit statistic variable observations.

iii) Histograms of independent credit statistic variables

1. Combined for failed and non-failed South African non-financial corporates

With reference to *Appendix E*, only a few of the independent credit statistic variables used in the sample appeared to conform to a normal distribution. These only included EBIT/ Interest Expense and RCF/Net Debt. The remainder of the credit statistic variables were characterised by non-normal distribution of data with outliers either resulting in left tailed or right tailed distributions of data. However, in the large part, most of the data appeared to be concentrated around the mean with the exception of debt/EBITDA and Revenue, however this was expected given the greater degree of variability in the data, for failed and non-failed South African non-financial corporates. It is worth noting that there were no instances of multi-modal distribution of observations.

2. Grouped by failed or non-failed South African non-financial corporates

Independent credit statistic variables data for non-failed South African non-financial corporates consistently showed a normal distribution of observations with the exception of revenue. This is to be expected given the inherent financial stability of their businesses, and hence why they did not find themselves in financial distress as opposed to their failed peers.

At the same time the distribution of observations for failed corporates showed a greater degree of volatility and non-normality. This again is not surprising given that volatility of both financial and equity market linked data points are often indicative of impending pressures that these corporates will face. In the case of these corporates the pressure of these challenges proved overwhelming, ultimately leading to failure.

However, in both the failed and non-failed grouping of South African non-financial corporates there were no instances of multi-modal distribution of observations, although there was evidence of fat tailing to both the left and right with regard to the distribution of observations. This however is an observed characteristic of most financial data.

iv) Box and whisker plot of independent credit statistic variables

1. Combined for failed and non-failed South African non-financial corporates

Given scaling, specifically for Revenue and EBIT/Interest Expense followed by debt/EBITDA, Debt/Book Equity and EBIT margin, the initial box and whisker plot of all variables had to be split into a further two box and whisker plots in order to be visibility interpretable. The resulting three box and whisker plots are provided in *Appendix F*. As highlighted earlier in *section iii) of this chapter*, the data is characterised by outliers although there appears to be an equal concentration of observations either side of the mean for most independent credit statistic variables. Outliers are representative of an increased likelihood of the occurrence of extreme left or right tailed event, where both should be given consideration in any credit analysis.

2. By failed or non-failed South African non-financial corporate groupings

With reference to *Appendix F*, non-failed South African non-financial corporates have lower variability across all independent credit statistic variables, with the exception of revenue. At the same time, all independent credit statistic variables for non-failed corporates were characterised by lower variability, positive concentration and were skewed positively. Across all independent credit statistic variables non-failed corporates were also shown to be more favourably positioned based upon appropriate interpretation of the unit of measurement. Revenue was higher, Debt/EBITDA and debt/ market capitalisation lower for the spectrum of non-failed corporates.

The converse of all of the above mentioned for non-failed corporates, was true of failed corporates.

v) Scatter plot of correlations between sample of independent credit statistic variables

Appendix G graphically demonstrates the interrelationship demonstrated by upward trending linear curves shown between FFO/Debt, RCF/Debt and FCF/Debt. As discussed in *section c of this chapter* it would be advisable to undertake a rerun of the data under an enhanced approach to exclude FFO/Debt and RCF/Debt, whilst only including FCF/Debt for the aforementioned reason.

b) Analysis of multiple discriminant function

This section will examine the outputs generated in Statistica through running a multiple discriminant analysis. The analysis will result in a discriminant function with coefficients provided for each independent credit statistic variable and a constant. These are derived from the canonical scores of the raw coefficients that the model generates. Through inputting the various observations for each non-failed and failed non-financial South African corporate and including the constant, a discriminant or z-score can be calculated. If the z-score<0, then the firm is classified as having failed. If the z-score>0 then the firm is deemed to be non-failed. Classification rates are determined by calculating the number of firms correctly classified by the discriminant function and dividing these by the total number of observations in the sample.

The statistical significance of the discriminatory power of the multiple discriminant analysis model is assessed through using Wilks' lambda. The values range from 1, indicating no discriminatory power, to 0 indicating perfect discriminatory power. Each value provided indicates the cumulative discriminatory power the variables have in combination up until the point of their inclusion.

The Partial Wilk's Lamda provides the unique contribution of the respective variable to the discrimination between groups. The same measurement scale applied to Wilks' lambda applies, where 0.0 indicates perfect discriminatory power and 1 no discriminatory power.

i) Variables not included in the model

	Variables currently not in the model (Test Sample) Df for all F-tests: 1,79					
N=88	**Wilks' Lambda**	**Partial Lambda**	**F to enter**	**p-value**	**Toler.**	**1-Toler. (R-Sqr.)**
FCF/Debt	0.62216	0.998205	0.142069	0.707243	0.980396	0.019604
RCF/Debt	0.619684	0.994232	0.458316	0.50039	0.919944	0.080056
FFO/Debt	0.619248	0.993533	0.514213	0.475436	0.906059	0.093942
Debt/BV	0.620289	0.995203	0.380831	0.538934	0.980406	0.019594

With reference to the above table, FCF/Debt, RCF/Debt, FFO/Debt and Debt// BV were excluded due to their high Partial Wilks' Lambda, where all three independent credit statistic variables were above 0.99, where 1.0 is indicative of no discriminatory power, and 0 is indicative of perfect discriminatory power. Partial Wilks' Lambda is the unique contribution of the respective variable to the discrimination between groups.

P values for these variables were excessively high ranging from 0.47 to 0.7, where a cut-off of 0.05 or 5% implies a 95% confidence level, which is applied for most statistical techniques. Notable, was that the highest p-value was FCF/Debt which would therefore refute its inclusion in an enhanced sampling model as suggested in *section a)i of this chapter*.

Tolerance is 1 minus R-Square or the multiple correlation often referred to as the percentage of variation explained by an independent variable. Therefore, each variable in isolation explained less than 10% of variation in discriminating between non-failed and failed South African non-financial corporates, with the lowest percentage of variation being explained by Debt/Book Equity at 1.9594% followed by FCF/Debt at 1.9604%.

The exclusion of these variables could be explained by cash flow information not factoring some of the accrual elements, which may provide useful information content with regards to the propensity for corporate failure. At the same time book equity may prove meaningless as an input given that it is often seen to be an out-dated measure of firm value.

ii) Variables included in the model

	Discriminant Function Analysis Summary (Test Sample) Step 7, N of vars in model: 7; Grouping: Failed / Non-failed (2 grps) Wilks' Lambda: .62328 approx. F (7,80)=6.9076 p< .0000					
N=88	**Wilks' Lambda**	**Partial Lambda**	**F-remove (1,80)**	**p-value**	**Toler.**	**1-Toler. (R-Sqr.)**
Rev.	0.715336	0.87131	11.81581	0.000935	0.969098	0.030902
Debt/M Cap	0.667387	0.933909	5.66142	0.019724	0.965815	0.034185
Debt/EBITDA	0.661253	0.942573	4.87411	0.030126	0.97932	0.02068
1 Year Equity Price Return	0.646549	0.964009	2.98676	0.087806	0.93767	0.06233
RCF/Net debt	0.647921	0.961967	3.1629	0.079129	0.902392	0.097608
EBIT Margin	0.639825	0.97414	2.12376	0.148945	0.952334	0.047666
EBIT/Int	0.63565	0.980539	1.58781	0.211303	0.987847	0.012153

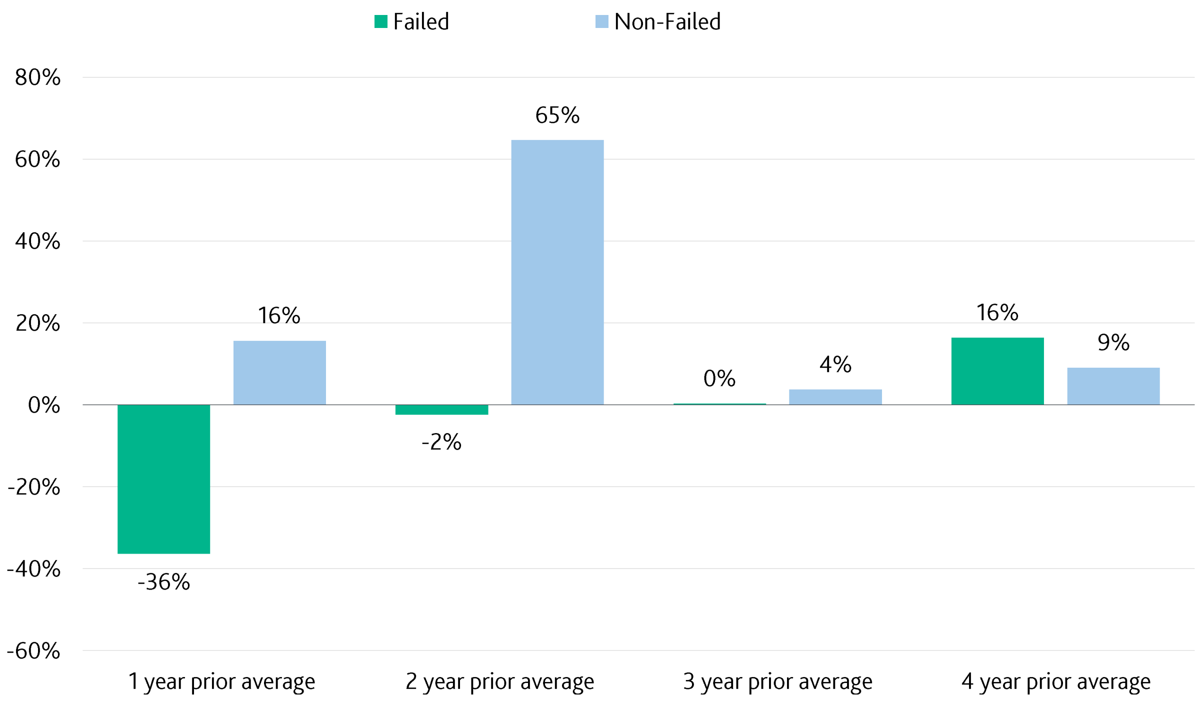
As evidenced in the table above, the Revenue independent credit statistic variable contributes the most when it comes to discriminating between independent credit statistic variables, given that it has the lowest Partial Wilks' Lambda of 0.871310. This is followed by Debt/ Market Capitalisation and then Debt/EBITDA. All three independent credit statistic variables have a p-value below 0.05 or 5% at a 95% confidence level cut-off. Low R-squares are not a concern given they ignore the impact of the ability to explain variation through a combination of variables.

From the initial eleven independent credit statistic variables that were specified for inclusion in the multiple discriminant analysis model, only seven independent credit statistic variables were seen together in their combination to provide a statistically significant differentiation between the sample of failed and non-failed corporates. In order of inclusion based on level of differentiation and addition to the Revenue, Debt/ Market Capitalisation and Debt/EBITDA, these included, 1 year equity price return, RCF/Net Debt, percentage EBIT margin and EBIT/Interest Expense.

This is not surprising given the prior mention in the preamble in *section b of this chapter* where there has been a continued focus of the credit community on leverage as measured by Debt/EBITDA and interest coverage, as measured by EBIT/ Interest Expense, in assessing the propensity for corporate failure. EBIT/ Interest Expense was included despite its high p-value as its addition was seen to improve the overall discriminatory power of the discriminant function by Statistica.

However, what was not expected was the inclusion of a RCF/Net Debt given the prior discussion in *section b of this chapter* around debt being viewed net of cash balances, where cash balances are often seen to be transitory in some respects. This could also in part be explained by the historical preference of the South African non-financial corporate management community to rely more heavily on surplus cash balances rather than committed bank facilities, more commonly seen in the US and Europe, to provide liquidity buffers.

Also to be highlighted are the inclusion of two market-based metrics namely, Debt/ Market Capitalisation followed by Equity price return over the prior year. Debt/Market Capitalisation brings market model theory in terms of distance to default as explained in *Chapter 3 | e)* for consideration in application in this multiple discriminant analysis model. Equity price return over the prior year also provides useful insights into how the equity market is calibrating the residual value of a company in the context of prevailing business conditions. This is presented in the chart below, which shows elevated downside risk for failed-firms when compared to their non-failed matched peers:



Revenue, as the strongest differentiator out of the initial eleven independent credit statistic variables identified for the model is also not surprising. The usefulness of revenue as a credit failure predictor was discussed in *Chapter 4 | c) ii* where it was also highlighted in the preamble that it is the second most common credit metric used by Moody's Investors Service in its rating methodologies used for ranking relative credit risk by sector for non-financial corporates.

iii) Canonical analysis

This is used in assessing the ability of the independent credit statistic variables included in the discriminant function to discriminate between non-failed and failed non-financial South African corporates. The multiple discriminant analysis will attempt to create independent or orthogonal discriminant functions, with each function contributing less to overall discriminatory power in line with the forward stepwise applied in running the multiple discriminant analysis model. The maximum number of discriminant functions that will result will either be the number of independent variables or the number of groups minus one, where the smaller of two is selected. In this case given that there are only two groups, failed and failed non-financial South African corporates, this will be the smaller number and only one discriminant function will result.

Roots Removed	Chi-Square Tests with Successive Roots Removed (Test Sample)					
	Eigen-value	Canonicl R	Wilks' Lambda	Chi-Sqr.	df	p-value
0	0.604417	0.613776	0.623279	39.00276	7	0.000002

As indicated in the table above only one discriminant function/canonical root was derived for differentiating between non-failed and failed South African non-financial corporates. The singular discriminant function that resulted is deemed to be statistically significant in its differentiation of failed and non-failed firms evidenced through a p-value of 0.000002 or 0.0002% where a result below 0.05 or 5% which would have been deemed to be statistically significant at a 95% confidence threshold level.

iv) Discriminant function coefficients

	Raw Coefficients (Test Sample) for Canonical Variables
Variable	**Root 1**
Rev.	0.000504
Debt/M Cap	-0.18426
Debt/EBITDA	-0.03193
1 Year Equity Price Return	0.449887
RCF/Net debt	0.088777
EBIT Margin	0.019311
EBIT/Int	0.000151
Constant	0.109247
Eigenval	0.604417
Cum.Prop	1

By using the table above and the discriminant function coefficients provided the discriminant function derived from the multiple discriminant analysis model is as follows:

$$Z = 0.109247 + 0.000504(X_1) - 0.18426(X_2) - 0.03193(X_3) + 0.449887(X_4) + 0.088777(X_5) + 0.019311(X_6) + 0.000151(X_7)$$

$where\ (X_1)\ is\ Revenue\ measured\ millions\ of\ US\ dollars$

$(X_2)\ is\ \frac{Debt}{Market\ Capitalisation}\ measured\ in\ percent\ in\ decimal\ form$

$(X_3)\ is\ \frac{Debt}{EBITDA}\ measured\ in\ times\ cover$

$(X_4)\ is\ Equity\ price\ return\ over\ the\ prior\ year\ measured\ in\ percent\ in\ decimal\ form$

$(X_5)\ is\ \frac{RCF}{Net\ Debt}\ measured\ in\ percent\ in\ decimal\ form$

$(X_6)\ is\ \frac{EBIT}{Revenue}\ or\ EBIT\ margin\ measured\ in\ percent\ in\ decimal\ form$

$(X_7)\ is\ \frac{EBIT}{Interest\ Expense}\ measured\ in\ times\ cover$

By means of illustration of the application of this discriminant function it will be applied to 1Time Holdings Limited. The company announced on 21 August 2012 that it was placing its subsidiaries, 1Time (Pty) Limited and Jetworx Aircraft Services (Pty) Limited, under business rescues as a result of their being in financial distress:

$$Z = 0.109247 + 0.000504(177.1) - 0.18426(1.8) - 0.03193(5.9) + 0.449887(-0.7) \\ + 0.088777(-0.9) + 0.019311(-0.1) + 0.000151(-4.5)$$

$$Z = -0.72$$

The discriminant function has correctly classified 1Time Holdings Limited as having failed. This is concluded as Z<0, indicating failure as per the model. Had Z>0, then the firm would have been classified as a non-failed firm.

The assessment of the unique discriminatory power of each independent credit statistic variable on the overall discriminant function should not be limited in its extent to the magnitude of impact on the final z-score. Such an assessment does not apply in the context of the mechanics of multiple discriminant analysis. This relies upon the discrimination functioning as a whole, taking into account both additive and subtractive elements for calculation of the discriminant score or Z-score, across observations for entire sample.

Through a typical statistical standardisation process using $z = \frac{x-\mu}{\sigma}$, standardised coefficients allow for an easier interpretation of the variables on a comparable scale. The influence of each independent credit statistic variable on the overall discriminant function and its unique discriminatory power is also then made observable as presented below:

	Standardized Coefficients (Test Sample) for Canonical Variables
Variable	**Root 1**
Rev.	0.593717
Debt/M Cap	-0.4262
Debt/EBITDA	-0.39454
1 Year Equity Price Return	0.319198
RCF/Net debt	0.33448
EBIT Margin	0.268481
EBIT/Int	0.228682
Eigenval	0.604417
Cum.Prop	1

As shown through the cumulative proportion figure of 1, 100% of variance or 100% of all discriminatory power is explained by the above function. In line with in *section b) iii of this chapter* only one root or discriminant function was provided based upon discriminatory power. By standardising the coefficients as shown in the table above, the coefficients are weighted according to their discriminatory power as already discussed in *section b) ii of this chapter*, with Revenue having the highest weighting and EBIT/Interest Expense the lowest weighting, and therefore the lowest discriminating contribution, out of the seven independent credit statistic variables selected by the model.

v) Factor structure coefficients

	Factor Structure Matrix (Test Sample) Correlations Variables - Canonical Roots (Pooled-within-groups correlations)
Variable	**Root 1**
Rev.	0.659662
Debt/M Cap	-0.45609
Debt/EBITDA	-0.39752
1 Year Equity Price Return	0.272286
RCF/Net debt	0.27377
EBIT Margin	0.162483
EBIT/Int	0.153128

As shown in the table above, no single independent credit statistic variables was shown to have a strong correlation (>0.75x<-0.75) with the resulting discriminant function. The combination of the seven independent credit statistic variables selected for the discriminant function resulted in greater discriminatory power between failed and non-failed South African non-financial corporates.

However, the significant singular discriminating power of Revenue should not be overlooked. This was moderately correlated (>0.65x<-0.65) with that of the overall discriminant function indicating that by itself it almost had a similar degree of discriminating power of that of the discriminant function, however not sufficient enough to allow for its consideration in a univariate discriminant analysis function.

vi) Means of canonical variables

	Means of Canonical Variables (Test Sample)
Group	**Root 1**
Failed	-0.76856
Non-Failed	0.768558

Given that that the means of canonical variables provided in the table above are equivalent, it can be said that the discriminant should differentiate equally between failed and non-failed South African non-financial corporates.

vii) Classification Matrix

	Classification Matrix (Test Sample) Rows: Observed classifications Columns: Predicted classifications		
Group	**Percent Correct**	**Failed p=.50000**	**Non-Failed p=.50000**
Failed	79.54546	35	9
Non-Failed	86.36364	6	38
Total	**82.95454**	41	47

With reference to the table above, the discriminant function demonstrated a high overall accuracy rate of 82.95% for discriminating between failed and non-failed South African non-financial corporates. This exceeds that of all prior corporate failure prediction models developed in academia to date as outlined in *Chapter 3 | g) South African research on corporate failure prediction* with the exception of De la Rey (1981). Although, De la Rey's model relied on a much smaller sample of twenty-six failed corporates and on financial data from corporates experiencing failure between 1972 and 1979 where accounting standards would not be viewed to be as sophisticated compared to the current IFRS framework. Therefore De la Rey's finding may not be directly comparable to this model's findings given marked differences in the underlying data used.

It worth noting the positive bias of the discriminant function, which was weighted towards the classification of South African non-financial corporates as non-failed. Forty-seven out of the total eighty-eight or 53% of corporates included in the sample were classified as non-failed.

This is of concern in the context of the *Chapter 3 | g) South African research on corporate failure prediction* where Muller, Steyn-Bruwer and Hamman (2009) outlined considerations for Normalised Cost of Failure (NCF). In effect the preference would always be for discriminant functions derived for corporate failure prediction to be more biased towards a higher classification rate for failed firms rather than non-failed firms.

The classification function, which allows for classifications independently based on the highest achieved score has been provided in Appendix H. Appendix K includes a model output including all classification of cases.

Appendix J provides the Mahalanobis distances and posterior probabilities. Mahalanobis distances provides a measure of each case from the centre of the group or the group centroid, where the groups are defined as either failed or non-failed South African non-financial corporates. The shorter the distance between case and the centroid of either failed or a non-failed grouping, the greater the confidence that can be attached to a case belonging to this particular group. Posterior probabilities are the probability that an observation will fall into a particular group before the characteristics associated with the observation are considered.

c) Model enhancement considerations

This section will attempt to improve and test the robustness of the initial multiple discriminant analysis model.

Firstly, the number of independent credit statistic variables will be reduced to those seen to be the most statistically significant at a 95% confidence threshold level or a p-value of 0.05 or 5%. This also then aligned with the recommended number of independent variables relative to the sample size as outlined in *Chapter 3 | h) Multiple discriminant analysis*. Although Brown and Tinsley (1983) recommended the sample should equate to at least ten times the number of independent variables, Tinsley and Stevens (2000) recommended a factor of twenty. This will be reduced to three independent credit statistic variables comprising a sample of eight-eight paired failed and non-failed firms. This will therefore satisfy the more conservative of the two recommendations, which would only require a sample of sixty observations.

Secondly, the initial sample will be split into two samples comprising twenty-two failed firms. This will allow for in sample and out of sample testing. This will be done using both samples independently to generate a discriminant function, which will then be run on the other sample. The combination of paired failed and non-failed firms have been included in each sample on a randomness basis. However, by reversing the learning and testing sample, this will allow for any unique peculiarities such as potential sector concentration or exposure to a greater number of outliers to be tested.

Thirdly, a multiple discriminant analysis model will be run to generate a discriminant function which excludes independent credit statistic variable observation outliers. The implications for overall discriminating ability will also be discussed in length.

Lastly, a final sample comprising independent credit statistic variable reliant upon both IFRS and SA GAAP financial date will be subjected to multiple discriminant analysis. The resulting discriminant function and classification rates are then discussed in detail in relation to the initial research objective in this regard.

i) Revenue, Debt/EBITDA and Debt/ Market Capitalisation only model

Group	Classification Matrix (IFRS 1 Year) Rows: Observed classifications Columns: Predicted classifications		
	Percent Correct	Failed p=.50000	Non-Failed p=.50000
Failed	**93.18182**	41	3
Non-Failed	68.18182	14	30
Total	**80.68182**	55	33

With reference to the table above, by limiting the independent credit statistic variables to the three variables, which demonstrated the greatest degree of discriminating power in the initial model, namely Revenue, Debt/EBITDA and Debt/ Market Capitalisation, classification accuracy still remained high at 80.68%.

However, what was of even greater interest was the shift in the classification bias of the model towards conservatism, where 63% of the firms overall were classified as having failed. This brought about a better alignment of NCF consideration as discuss previously in *section b) vii of this chapter*.

Therefore this model overall would be deemed to be preferable to the initial model for predicting South African non-financial corporate failure given that it would result in a lower NCF but still be backed by high classification expectations. Also, an additional benefit to this discriminant function would be the lower statistical complexity and easier interpretation, given that it only includes three strongly statistically significant independent credit statistic variables versus the initial model's seven, where some of their p-values exceeded 0.05 or 5%.

Put another way, the preference is always to have a model that is more accurate at classifying failed firms as opposed to non-failed firms. The economic consequences of lending to a firm that will fail are far more severe than not lending to a firm that will not fail. Therefore Type I errors (incorrectly classifying a failed company as healthy) and Type II errors (incorrectly classifying a non-failed firm as being financially distressed) are not seen to be asymmetric in there implications on economic decision for the credit community.

In the case of this model ability to correctly forecast failure has increased to 93% from 79% even though the overall accuracy has fallen from 82.95454% to 80.68182%. Of the forty-four firms that actually failed the model was able to accurately classify forty-one firms that failed and so would not lend to these firms. Conversely, of the forty-four firms that did not fail, the model was able to classify thirty of these firms correctly. However, this should not be viewed negatively as the implication would be that lenders would have forgone interest income only from fourteen firms but avoided far greater loan losses on only three firms.

	Discriminant Function Analysis Summary (IFRS 1 Year) Step 3, N of vars in model: 3; Grouping: Failed / Non-failed (2 grps) Wilks' Lambda: .69099 approx. F (3,84)=12.522 p< .0000					
N=88	**Wilks' Lambda**	**Partial Lambda**	**F-remove (1,84)**	**p-value**	**Toler.**	**1-Toler. (R-Sqr.)**
Revenue	0.827438	0.835091	16.58791	0.000105	0.99682	0.00318
Debt/Mkt Cap	0.743749	0.929057	6.4143	0.01318	0.995199	0.004802
Debt/EBITDA	0.726445	0.951187	4.31068	0.040931	0.994248	0.005752

At the same time, as shown above all p-values were below 0.05 or 5 % which would have been deemed to be statistically significant at a 95% confidence threshold level.

Variable	Raw Coefficients (IFRS 1 Year) for Canonical Variables Root 1
Revenue	0.000622
Debt/Mkt Cap	-0.207647
Debt/EBITDA	-0.032260
Constant	-0.025141
Eigenval	0.447209
Cum.Prop	1.000000

Using the table above and the discriminant function coefficients provided, the discriminant function derived from the multiple discriminant analysis model is as follows:

$$Z = -0.025141 + 0.000622(X_1) - 0.207647(X_2) - 0.032260(X_3)$$

$where\ (X_1)\ is\ Revenue\ measured\ in\ millions\ of\ US\ dollars$

$$(X_2)\ is\ \frac{Debt}{Market\ Capitalisation}\ measured\ in\ percent\ in\ decimal\ form$$

$$(X_3)\ is\ \frac{Debt}{EBITDA}\ measured\ in\ times\ cover$$

The application of the model has been included in Appendix I.

ii) Splitting the sample in half to create a learning sample and a testing sample

1. First forty-four observations for a learning sample

Group	Classification Matrix (Test Sample- In) Rows: Observed classifications Columns: Predicted classifications		
	Percent Correct	**Failed p=.50000**	Non-Failed p=.50000
Failed	86.36364	19	3
Non-Failed	95.45454	1	21
Total	**90.90909**	20	24

Through using the first forty-four observations for the learning sample the multiple discriminant analysis model demonstrated the highest classification rate of 90.90909%, as shown in the table above. The increase in classification rate could possibly be explained by the independent credit statistic variables included being better differentiators when it came to predicting corporate failure in the sectors that were included in the reduced testing sample.

Means (Test Sample- In)											
Failed / Non-failed	**Debt/ EBITDA**	**Revenue**	**EBIT /Int**	**FCF/ Debt**	**RCF/ Debt**	**FFO/ Debt**	**Debt/ B.E.**	**RCF/ Net debt**	**EBIT Margin**	**Debt/ Mkt Cap**	**1 Year Equity Price Return**
Failed	12.74x	$23.56mn	-652.63x	-95%	-25%	11%	293%	-73%	-50%	172%	-22%
Non-Failed	1.30x	$1,180.81mn	38.85x	58%	104%	131%	30.5%	54%	40%	30%	7%
All Grps	7.02x	$602.18mn	-306.89x	-19%	40%	71%	162%	-9%	-5%	101%	-8%

Although this may be due to sampling bias to some extent given greater sector concentrations. This often results in better differentiating power being accorded to certain independent credit statistic variables which are more sector specific. This sample showed a greater degree of differentiation against some of the independent credit statistic variables when compared to the initial sample of eighty-eight observations as illustrated in the table above.

Outliers remain a feature of the significant variation and skewness of some of the independent credit statistic variable observation. Again, and in line with the what was communicated in *Chapter 4 | G* and *section a) ii of this chapter*, these have been left in the sample to ensure that the model fits sample rather than the other way around.

Pooled Within-Groups Correlations (Test Sample- In)											
Variable	**Debt/ EBITDA**	**Revenue**	**EBIT /Int**	**FCF/ Debt**	**RCF/ Debt**	**FFO /Debt**	**Debt/ BV**	**RCF/Net debt**	**EBIT Margin**	**Debt/Mkt Cap**	**1 Year Equity Price Return**
Debt/EBITDA	**1**	0	0.1	0.12	-0.01	-0.06	-0.09	0.08	0.08	-0.1	0.02
Revenue	0	**1**	-0.01	-0.07	-0.11	-0.11	-0.01	0.16	-0.06	0	0.01
EBIT/Int	0.1	-0.01	**1**	0.03	0.01	-0.39	0.05	-0.03	-0.03	0.13	-0.04
FCF/Debt	0.12	-0.07	0.03	**1**	0.55	0.49	0.05	-0.1	**0.64**	0.17	0.02
RCF/Debt	-0.01	-0.11	0.01	0.55	**1**	**0.89**	0.01	-0.01	0.09	-0.01	-0.04
FFO/Debt	-0.06	-0.11	-0.39	0.49	**0.89**	**1**	0.01	0	0.02	-0.09	-0.04
Debt/B.E.	-0.09	-0.01	0.05	0.05	0.01	0.01	**1**	0.04	0.07	0.16	-0.06
RCF/Net debt	0.08	0.16	-0.03	-0.1	-0.01	0	0.04	**1**	0.03	0.07	0.11
EBIT Margin	0.08	-0.06	-0.03	**0.64**	0.09	0.02	0.07	0.03	**1**	0.12	0.16
Debt/Mkt Cap	-0.1	0	0.13	0.17	-0.01	-0.09	0.16	0.07	0.12	**1**	0.05
1 Year Equity Price Return	0.02	0.01	-0.04	0.02	-0.04	-0.04	-0.06	0.11	0.16	0.05	**1**

At the same time as shown in the correlation matrix with the exception of RCF/Debt and FCF/Debt there are no strong statistical relationships (>0.75x<-0.75) existing between the independent variables. The rationale for the relationship between these two variables is for the same reasons as discussed earlier in this *section in a)i)*. Worth noting is the relationship between EBIT margin and FFO/Debt which showed a moderate degree of correlation (>0.65x<-0.65). This relationship most likely can be explained to some extent by the degree of linkage between cash flow from operations, the starting point for the calculation of FCF, and EBIT.

Although this may be due to sampling bias to some extent, this sample showed a greater degree of differentiation against some of the independent credit statistic variables when compared to the initial sample of eighty-eight observations.

	Discriminant Function Analysis Summary (Test Sample- In) Step 7, N of vars in model: 7; Grouping: Failed / Non-failed (2 grps) Wilks' Lambda: .49055 approx. F (7,36)=5.3410 p< .0003					
N=44	**Wilks' Lambda**	**Partial Lambda**	**F-remove (1,36)**	**p-value**	**Toler.**	1-Toler. (R-Sqr.)
Revenue	0.564503	0.868993	5.427285	0.025549	0.970261	0.029739
Debt/Mkt Cap	0.587660	0.834750	7.126685	0.011322	0.924224	0.075776
Debt/EBITDA	0.566908	0.865307	5.603744	0.023418	0.946544	0.053456
FCF/Debt	0.555629	0.882872	4.776027	0.035447	0.933712	0.066288
RCF/Net debt	0.509228	0.963318	1.370823	0.249362	0.933310	0.066690
EBIT/Int	0.513285	0.955705	1.668523	0.204688	0.965914	0.034086
1 Year Equity Price Return	0.504291	0.972749	1.008515	0.321962	0.983299	0.016701

In line with the initial model, only seven variable are included in the model base on their statistical significance whereas the remaining four variable deemed not be statistically significant were excluded. Revenue, Debt/Market Capitalisation and Debt/ EBITDA featured most prominently as measured by the Partial Wilks' lambda or the unique contribution of the respective variable to the discrimination between groups. In addition, the multiple discriminant analysis model also included FCF/Debt, RCF/ Net Debt, EBIT/ Interest Expense and One Year Equity Price Return as independent credit statistic variables. The initial model also included RCF/ Net Debt, EBIT/ Interest Expense and 1 Year Equity Price Return for differentiating between failed and non-failed South African non-financial corporates. Therefore, the inclusion of FCF/Debt as an independent credit statistic variable, was unique to this model.

Variable	Raw Coefficients (Test Sample- In) for Canonical Variables
	Root 1
Revenue	0.000469
Debt/Mkt Cap	-0.320661
Debt/EBITDA	-0.032632
FCF/Debt	0.183754
RCF/Net debt	0.106732
EBIT/Int	0.000140
1 Year Equity Price Return	0.363845
Constant	0.384024
Eigenval	1.038533
Cum.Prop	1.000000

The discriminant function coefficients provided in the table above resulted in the discriminant function derived from the multiple discriminant analysis model as follows:

$$Z = 0.384024 + 0.000469(X_1) - 0.320661(X_2) - 0.032632(X_3) + 0.183754(X_4) + 0.106732(X_5) + 0.000140(X_6) + 0.363845(X_7)$$

$where\ (X_1)\ is\ Revenue\ measured\ in\ millions\ of\ US\ dollars$

$(X_2)\ is\ \frac{Debt}{Market\ Capitalisation}\ measured\ in\ percent\ in\ decimal\ form$

$(X_3)\ is\ \frac{Debt}{EBITDA}\ measured\ in\ times\ cover$

$(X_4)\ \ is\ \frac{FCF}{Debt}\ measured\ in\ percent\ in\ decimal\ form$

$(X_5)\ is\ \frac{RCF}{Net\ Debt}\ measured\ in\ percent\ in\ decimal\ form$

$(X_6)\ is\ \frac{EBIT}{Interest\ Expense}\ measured\ in\ times\ cover$

$(X_7)\ is\ Equity\ price\ return\ over\ the\ prior\ year\ measured\ in\ percent$

It is worth highlighting that the ordering of the coefficients for the independent credit statistic variables is based upon their discriminatory power. The first independent credit statistic variable will always have the greatest discriminatory power, the second independent credit statistic variable, the second most discriminatory power and so on. The standard approach for writing out the discriminating function is to include the independent variables in order of their discriminatory power, as is the case in this study.

By applying this multiple discriminant analysis model's coefficients to the test sample or hold out sample of the remaining forty-four failed and non-failed South African non-financial corporates in the original sample resulted in a 77.27273% overall classification rate.

2. First forty-four observations for a learning sample with four variables

Group	Classification Matrix (Test Sample- In) Rows: Observed classifications Columns: Predicted classifications		
	Percent Correct	**Failed p=.50000**	**Non-Failed p=.50000**
Failed	90.90909	20	2
Non-Failed	95.45454	1	21
Total	**93.18182**	21	23

As shown above by refining the model based on assessing the initial learning sample of only forty-four South African non-financial corporates to the most statistically significant (p-value <0.05 or 5%) independent credit statistic variables, the classification rate improved further to 93.18182%. This was done for the same reasons as outlined earlier *section a) ii of this chapter*. This again could possibly be explained by these independent credit statistic variables being more applicable to the sectors that were included in this carve out sample.

N=44	Discriminant Function Analysis Summary (Test Sample- In) Step 4, N of vars in model: 4; Grouping: Failed / Non-failed (2 grps) Wilks' Lambda: .55044 approx. F (4,39)=7.9632 p< .0001					
	Wilks' Lambda	**Partial Lambda**	**F-remove (1,39)**	**p-value**	**Toler.**	1-Toler. (R-Sqr.)
Revenue	0.668903	0.822896	8.393598	0.006146	0.995402	0.004598
Debt/Mkt Cap	0.640900	0.858851	6.409498	0.015492	0.957221	0.042779
Debt/EBITDA	0.624085	0.881992	5.218108	0.027878	0.969691	0.030309
FCF/Debt	0.622607	0.884085	5.113414	0.029395	0.948622	0.051378

All p-values were below 0.05 or 5 % which would have been deemed to be statistically significant at a 95% confidence threshold level, with FCF/Debt demonstrating the highest unique contribution. This was to be expected though given how this model was specified from the beginning.

	Raw Coefficients (Test Sample- In) for Canonical Variables
Variable	**Root 1**
Revenue	0.000573
Debt/Mkt Cap	-0.309994
Debt/EBITDA	-0.032125
FCF/Debt	0.193060
Constant	0.228234
Eigenval	0.816737
Cum.Prop	1.000000

Using the table above and the discriminant function coefficients provided the discriminant function derived from the multiple discriminant analysis model is as follows:

$$Z = 0.228234 + 0.000573(X_1) - 0.309994(X_2) - 0.032125(X_3) + 0.193060(X_4)$$

$where\ (X_1)\ is\ Revenue\ measured\ in\ millions\ of\ US\ dollars$

$$(X_2)\ is \frac{Debt}{Market\ Capitalisation}\ measured\ in\ percent\ in\ decimal\ form$$

$$(X_3)\ is \frac{Debt}{EBITDA}\ measured\ in\ times\ cover$$

$$(X_4)\ \ is \frac{FCF}{Debt}\ measured\ in\ percent\ in\ decimal\ form$$

Through application of this multiple discriminant analysis model's coefficients to the test sample or hold out sample of the remaining forty-four failed and non-failed South African non-financial corporates in the original sample resulted in a 75% overall classification rate.

3. Last forty-four observations for a learning sample

The use in the multiple discriminant model of the two split samples will now be reversed. The last forty-four observations will be used for the learning sample or the in sample testing. The first forty-four observations will in turn then be used for the testing or hold out sample. This will allow for conclusions to be drawn on any unique observed characteristics relating to the sample in relation the multiple linear regression model.

In using these last forty-four observations in the sample to develop a South African non-financial corporate failure prediction model, a classification rate of 79.54546% was achieved as shown below.

Group	Classification Matrix (Test Sample- LSL44) Rows: Observed classifications Columns: Predicted classifications		
	Percent Correct	Failed p=.50000	Non-Failed p=.50000
Failed	81.81818	18	4
Non-Failed	77.27273	5	17
Total	79.54546	23	21

The model, like the initial model using the full sample of observations, included Revenue, Debt/ Market Capitalisation, One Year Equity Price Return and RCF/Net Debt. Inclusion of FCF/Debt and RCF/Debt were unique to this model.

N=44	Discriminant Function Analysis Summary (Test Sample- LSL44) Step 6, N of vars in model: 6; Grouping: Failed / Non-failed (2 grps) Wilks' Lambda: .62546 approx. F (6,37)=3.6928 p< .0056					
	Wilks' Lambda	Partial Lambda	F-remove (1,37)	p-value	Toler.	1-Toler. (R-Sqr.)
Revenue	0.782077	0.799739	9.265107	0.004284	0.892521	0.107479
Debt/Mkt Cap	0.654082	0.956237	1.693333	0.201207	0.929292	0.070708
RCF/Debt	0.694912	0.900053	4.108714	0.049914	0.147663	0.852337
1 Year Equity Price Return	0.713806	0.876228	5.226462	0.028068	0.464784	0.535216
FCF/Debt	0.670736	0.932494	2.678561	0.110187	0.158594	0.841406
RCF/Net debt	0.649239	0.963370	1.406864	0.243139	0.819396	0.180604

Variable	Raw Coefficients (Test Sample- LSL44) for Canonical Variables
	Root 1
Revenue	0.00061
Debt/Mkt Cap	-0.12952
RCF/Debt	-0.21998
1 Year Equity Price Return	+1.07102
FCF/Debt	+0.23254
RCF/Net debt	+0.07332
Constant	-0.04416
Eigenval	0.59883
Cum.Prop	1.00000

The discriminant function coefficients provided in the table above resulted in the discriminant function derived from the multiple discriminant analysis model as follows:

$$Z = -0.04416 + 0.00061(X_1) - 0.12952(X_2) - 0.21998(X_3) + 1.07102(X_4) + 0.23254(X_5) + 0.07332(X_6)$$

$where\ (X_1)\ is\ Revenue\ measured\ in\ millions\ of\ US\ dollars$

$(X_2)\ is\ \frac{Debt}{Market\ Capitalisation}\ measured\ in\ percent\ in\ decimal\ form$

$(X_3)\ is\ \frac{RCF}{Debt}\ measured\ in\ percent\ in\ decimal\ form$

$(X_4)\ is\ Equity\ price\ return\ over\ the\ prior\ year\ measured\ in\ percent$

$(X_5)\ \ is\ \frac{FCF}{Debt}\ measured\ in\ percent\ in\ decimal\ form$

$(X_6)\ is\ \frac{RCF}{Net\ Debt}\ measured\ in\ percent\ in\ decimal\ form$

The application of this multiple discriminant analysis model's coefficients were applied to the test sample of the first forty-four failed and non-failed South African non-financial corporates in the original sample resulted in a 81.81818% overall classification rate.

4. Last forty-four observations for a learning sample with three variables

Group	Classification Matrix (Test Sample- LSL44) Rows: Observed classifications Columns: Predicted classifications		
	Percent Correct	Failed p=.50000	Non-Failed p=.50000
Failed	90.90909	20	2
Non-Failed	59.09091	9	13
Total	**75.00000**	29	15

Through refining the model design to only assess the initial learning sample of only forty-four South African non-financial corporates using the most statistically significant (p-value <0.05 or 5%) independent credit statistic variables, the classification rate reduced to 75%. This was done for the same reasons as outlined earlier *section a) ii of this chapter*.

N=44	Discriminant Function Analysis Summary (Test Sample- LSL44) Step 3, N of vars in model: 3; Grouping: Failed / Non-failed (2 grps) Wilks' Lambda: .73229 approx. F (3,40)=4.8744 p< .0056					
	Wilks' Lambda	Partial Lambda	F-remove (1,40)	p-value	Toler.	1-Toler. (R-Sqr.)
Revenue	0.941867	0.777487	11.44780	0.001613	0.964094	0.035906
1 Year Equity Price Return	0.787971	0.929335	3.04152	0.088842	0.909674	0.090326
RCF/Debt	0.762940	0.959825	1.67426	0.203110	0.911140	0.088860

Despite an attempt to refine this model using only those independent credit statistic variables seen to statistically significant at a 95% confidence threshold level or having a p-value below 0.05 or 5%, only Revenue demonstrated statistical significance. This was to be expected though given how this model was specified from the beginning due to less variables in combination offering a lower propensity to explain variation uniquely on their own.

Variable	Raw Coefficients (Test Sample- LSL44) for Canonical Variables
	Root 1
Revenue	0.000731
1 Year Equity Price Return	0.684207
RCF/Debt	-0.066409
Constant	-0.412438
Eigenval	0.365581
Cum.Prop	1.000000

Using the discriminant function coefficients provided in the table above resulted in the discriminant function derived from the multiple discriminant analysis model as follows:

$$Z = -0.412438 + 0.000731(X_1) + 0.684207(X_2) - 0.066409(X_3)$$

$where\ (X_1)\ is\ Revenue\ measured\ in\ millions\ of\ US\ dollars$

$(X_2)\ is\ Equity\ price\ return\ over\ the\ prior\ year\ measured\ in\ percent\ in\ decimal\ form$

$(X_3)\ \ is \frac{RCF}{Debt}\ measured\ in\ percent\ in\ decimal\ form$

This multiple discriminant analysis model's coefficients when applied to the test sample of the first forty-four failed and non-failed South African non-financial corporates in the original sample resulted in a 77.27273% overall classification rate.

iii) Using combined IFRS and non-IFRS data

Through removing the filter of IFRS only data that was applied to the sample this expanded the initial sample from forty-four failed firms to fifty-six failed firms with the approximate date of failure occurring between February 2000 to December 2015. The addition of a further twelve failed firms matched to non-failed firms with both reporting under SA GAAP at the time of failure decreased the classification accuracy for corporate failure using a multiple discriminant analysis model on this sample.

Group	Classification Matrix (Test Sample 2) Rows: Observed classifications Columns: Predicted classifications		
	Percent Correct	Failed p=.50000	Non-Failed p=.50000
Failed	75.00000	42	14
Non-Failed	73.21429	15	41
Total	74.10714	57	55

As shown above the complete IFRS sample resulted in a higher classification rate of 82.95454% versus 74. 10714% using both IFRS and non-IFRS financial data.

Also worth noting is that this was also below all classification rates of 90.90909% and 77.27273%, for the learning sample and test sample, respectively, for the split sample using the first forty-four observations. This was also below the refined four variable model using this sample selection which yielded classification rates of 93.18182% for the learning sample and 75% for the test sample.

Similarly the classification rate of 74% achieved by using both IFRS and non IFRS prepared financial data in the sample was below that of the split sample where the last forty-four observations were used. In this instance, the discriminant function resulted in a 79.54546% classification rate for the learning sample and 81.81818% for the test sample. Through an attempted refinement of the model to use only the three statistically significant independent credit statistic variables from the initial model this reduced to a classification rate of 75% for the leaning sample and 77.27273% for the test sample, both still above that achieved by discriminant function classification rate of 74% for the IFRS and non IFRS prepared financial data sample.

This was despite the sample comprising IFRS and non-IFRS prepared financial data sample benefiting from a larger sample size of fifty-six failed non-financial South African corporates versus the IFRS only prepared financial data sample of forty-four non-financial South African corporates.

Variable Enter/Remove	Summary of Stepwise Analysis (Test Sample 2)										
	Step	F to entr/rem	df 1	df 2	p-value	No. of vars. in	Lambda	F-value	df 1	df 2	p-value
Rev.	1	22.16992	1	110	0.000007	1.000000	0.832262	22.16992	1	110	0.000007
Debt/M Cap	2	8.69160	1	109	0.003912	2.000000	0.770799	16.20587	2	109	0.000001
Debt/EBITDA	3	5.01148	1	108	0.027230	3.000000	0.736618	12.87201	3	108	0.000000
FCF/Debt	4	2.83776	1	107	0.094987	4.000000	0.717587	10.52773	4	107	0.000000
RCF/Net debt	5	2.45413	1	106	0.120197	5.000000	0.701349	9.02746	5	106	0.000000
EBIT Margin	6	3.58588	1	105	0.061025	6.000000	0.678188	8.30406	6	105	0.000000
1 Year Equity Price Return	7	2.72198	1	104	0.101993	7.000000	0.660891	7.62335	7	104	0.000000
EBIT/Int-(E)	8	1.43570	1	103	0.233587	8.000000	0.651805	6.87784	8	103	0.000000

It is worth noting as shown in the table above, that there were differences from the original IFRS only prepared financial data sample when it came to both the relative ordering of discriminating power and inclusion of independent credit statistic variables.

iv) Excluding outliers from the sample

As previously discussed in *section a) ii of this chapter*, outliers were excluded to assess the impact on the resulting discriminant function and classification rates. The occurrence of outliers had a material impact on the means of the independent credit statistic variables. Through removing these outliers the means were subject to a lower degree of skewness and were seen to be more in line with what would have normally been expected for observations for independent credit statistic variables for non-failed and failed firms. However through the exclusion of outlying observations the effect of extreme events was removed and the ability for the discriminant function to consider their occurrence.

Group	Classification Matrix (Test Sample- In) Rows: Observed classifications Columns: Predicted classifications		
	Percent Correct	Failed p=.50000	Non-Failed p=.50000
Failed	72.72727	24	9
Non-Failed	90.90909	3	30
Total	**81.81818**	27	39

Through excluding the outliers the sample was reduced to thirty-three failed firms that were paired with thirty-three non-failed peers. The discriminant analysis model demonstrated a slightly lower classification rate of 81.81818% when compared to the 82.95454% resulting from the sample including the outliers. This could in part be explained by a sample that had twenty-two less observations with model fit proving to be more challenging for the multiple discriminant analysis model.

It was concerning that there was a marked decrease in the ability to classify failed firms by about seven percentage points as result of excluding outliers. This in essence showed that by manipulating the sample to exclude outliers, the ability to forecast extreme events, primarily attributed to failed firms, was lowered. This is supportive of the rationale behind original approach adopted by the research design to not modify the sample for outliers, so that the discriminant function is built upon their occurrence, however remote.

The ability to classify non-failed firm correctly, was four percentage point higher in this model compared to the initial model, as would be expected with reduced consideration for outlying observations.

Revenue again demonstrated the greatest degree of variability, followed by debt/ Market Capitalisation and then EBIT Margin. Although the means were seen to have been normalised to some extent they may not be reflective in reality of what observations could result for independent credit statistic variables, in particular for failed firms which tend to exhibit a greater propensity for extreme data points.

	Pooled Within-Groups Correlations (Sample(WithoutOutliers)5)										
Variable	**Debt/ EBITDA**	**Reve nue**	**EBIT/ Int**	**FCF/ Debt**	**RCF/ Debt**	**FFO/ Debt**	**Debt/ B.E.**	**RCF/Net debt**	**EBIT Margin**	**Debt/Mkt Cap**	**1 Year Equity Price Return**
Debt/EBITDA	**1.00**	-0.08	-0.11	0.10	-0.10	-0.14	-0.14	0.13	0.05	0.29	0.01
Revenue	-0.08	**1.00**	0.41	0.10	0.21	0.28	-0.01	0.14	-0.03	-0.05	-0.09
EBIT/Int	-0.11	0.41	**1.00**	0.57	0.64	0.72	0.01	0.13	0.23	-0.10	0.20
FCF/Debt	0.10	0.10	0.57	**1.00**	0.26	0.27	0.05	0.00	0.66	0.12	0.11
RCF/Debt	-0.10	0.21	0.64	0.26	**1.00**	**0.97**	-0.08	-0.12	0.12	-0.10	0.54
FFO/Debt	-0.14	0.28	0.72	0.27	**0.97**	**1.00**	-0.09	-0.09	0.06	-0.10	0.49
Debt/BV	-0.14	-0.01	0.01	0.05	-0.08	-0.09	**1.00**	-0.00	0.05	-0.02	0.02
RCF/Net debt	0.13	0.14	0.13	0.00	-0.12	-0.09	-0.00	**1.00**	0.03	0.07	-0.24
EBIT Margin	0.05	-0.03	0.23	0.66	0.12	0.06	0.05	0.03	**1.00**	0.07	0.14
Debt/Mkt Cap	0.29	-0.05	-0.10	0.12	-0.10	-0.10	-0.02	0.07	0.07	**1.00**	-0.15
1 Year Equity Price Return	0.01	-0.09	0.20	0.11	0.54	0.49	0.02	-0.24	0.14	-0.15	**1.00**

At the same time as shown in the correlation matrix with the exception of RCF/Debt and FFO/Debt there are no strong statistical relationships (>0.75x<-0.75) existing between the independent variables. The rationale for the relationship between this two variables is for the same reasons as discussed earlier in this *section in a)i)*. Worth noting is the relationship between EBIT/ Interest Expense and FFO/Debt which showed a moderate degree of correlation (>0.65x<-0.65). This relationship most likely can be explained to some extent by the degree of linkage between cash flow from operations, the starting point for the calculation of FCF, and EBIT.

N=66	**Discriminant Function Analysis Summary (Sample(WithoutOutliers)5) Step 6, N of vars in model: 6; Grouping: Failed / Non-failed (2 grps) Wilks' Lambda: .60552 approx. F (6,59)=6.4061 p< .0000**					
	Wilks' Lambda	**Partial Lambda**	**F-remove (1,59)**	**p-value**	**Toler.**	**1-Toler. (R-Sqr.)**
Revenue	0.687457	0.880817	7.983244	0.006433	0.968056	0.031944
Debt/Mkt Cap	0.643673	0.940732	3.717117	0.058675	0.910802	0.089198
EBIT Margin	0.641266	0.944263	3.482569	0.066991	0.988954	0.011046
Debt/EBITDA	0.64184	0.943419	3.538498	0.064897	0.875531	0.124469
Debt/B.E.	0.628628	0.963247	2.25115	0.138848	0.974687	0.025313
RCF/Net debt	0.619718	0.977096	1.382988	0.244316	0.95777	0.04223

Only six variables are included here based on their statistical significance. Revenue, Debt/Market Capitalisation and EBIT margin featured most prominently as measured by the Partial Wilks’ lambda or the unique contribution of the respective variable to the discrimination between groups. It is worth noting that only Revenue was statistically significant at a 95% confidence threshold level or having a p-value below 0.05 or 5%.

In addition, the multiple discriminant analysis model also included Debt/EBITDA, Debt/ Book Equity and RCF/Net debt as independent credit statistic variables. This overlapped with respect to the initial model’s inclusion of Revenue, Debt/Market Capitalisation, Debt/EBITDA, RCF/Net debt and EBIT Margin. The notable inclusion in this model was debt/Book Equity. This could be explained by the removal of outliers increasing its discriminatory power.

Variable	Raw Coefficients (Test Sample- In) for Canonical Variables Root 1
Revenue	0.000451
Debt/Mkt Cap	-0.157554
EBIT Margin	0.298266
Debt/EBITDA	-0.065908
Debt/BV	-0.081173
RCF/Net debt	0.060045
Constant	0.237619
Eigenval	0.651463
Cum.Prop	1.000000
Revenue	0.000451

The discriminant function coefficients provided in the table above resulted in the discriminant function derived from the multiple discriminant analysis model as follows:

$$Z = 0.237619 + 0.000451(X_1) - 0.157554(X_2) + 0.298266(X_3) - 0.065908(X_4) - 0.081173(X_5) + 0.060045(X_6)$$

$where\ (X_1)\ is\ Revenue\ measured\ in\ millions\ of\ US\ dollars$

$$(X_2)\ is \frac{Debt}{Market\ Capitalisation}\ measured\ in\ percent\ in\ decimal\ form$$

$$(X_3)\ is \frac{EBIT}{Revenue}\ or\ EBIT\ margin\ measured\ in\ percent\ in\ decimal\ form$$

$$(X_4)\ is \frac{Debt}{EBITDA}\ measured\ in\ times\ cover$$

$$(X_5)\ is \frac{Debt}{Book\ Equity}\ measured\ in\ percent\ in\ decimal\ form$$

$$(X_6)\ is \frac{RCF}{Net\ Debt}\ measured\ in\ percent\ in\ decimal\ form$$

By applying this multiple discriminant analysis model’s coefficients to the original sample of non-failed and failed South African non-financial corporates with outliers included in the observations resulted in a 78.41% overall classification rate. This was lower than the original model’s 82.95% classification rate.

d) Summary

The initial corporate failure model that was developed demonstrated a high classification rate of 82.95454%. This was not diminished through the refinement of the model to three independent credit statistic variables comprising: Revenue, Debt/EBITDA and Debt/ Market Capitalisation. Accuracy only reduced slightly to 80.68182%. However, through only using three independent credit statistic variables the degree of complexity in interpreting and applying the model was reduced significantly. This also sharply reduced the incidence of Type I errors, or classification of failed firm as non-failed, to 6.82% from 20.45%. The revised model was shown to be a lot more accurate at classifying failed firms. This meant that in using this model, lenders would be less likely to incur loan losses but at the expense of forgoing interest income on loans not made to non-failed firms. However, this is preferable given that loan losses will, in most cases depending on interest rates levels and the size of a loan, exceed that of interest income.

The analysis further demonstrated the prevalence of the discriminatory power offered by Revenue and Debt/ Market Capitalisation through splitting the initial sample into two, allowing for a learning sample and a hold out or testing sample. Classification rates remained above 75% throughout where using the first forty-four observations for the testing sample and limiting the independent credit statistic variables to Revenue, Debt/Market Capitalisation, Debt/EBITDA and FCF/Debt resulted in the highest classification rate in this study of 93.18182%. This was deemed to be a result of these independent credit statistic variables having a greater degree of differentiating power for the sectors which featured in the sample of non-failed and failed non-financial South African corporates.

The results of all multiple discriminant analysis models run until this point had relied solely on financial information prepared under IFRS. The classification rates achieved were then compared to that of multiple discriminant analysis model run using financial information prepared under both IFRS and SA GAAP. The accuracy achieved by this model was lower than that achieved in multiple discriminant analysis models that had been run using financial information prepared under IFRS only.

These provided answers to three of the salient research objectives. The classification of non-failed and failed non-financial South African corporates was improved by using an updated sample of failed firms, adjusting their financial statements to better align with the requirements of credit analysis, and using more uniform financial information prepared under IFRS.

By excluding outliers there were two noticeable impacts. Firstly, the ability to classify type I errors or failed firms as non-failed failed reduced, which was concerning for the economic consequence mentioned earlier relating to loan losses. This was attributed to the removal of outliers. Secondly, means moved to what would be more customarily observed for independent credit statistic variables for non-failed and failed South African non-financial corporates. The overall classification rate was not materially impacted.

Chapter 6 | Conclusion

The study focused on four main research objectives in developing a corporate failure model for non-financial South African corporates using multiple discriminant analysis. This included using a more up to date sample of failed non-financial South African corporates reporting under IFRS, and using Moody's Investors Service best practices, which are public knowledge, for assessing South African corporate credit risk. In addition the model included credit statistics using equity market price movements and liquidity strength as forward-looking predictors of default.

a) Advantages of updated IFRS data, adjustments to credit statistics and including outliers

The classification rates in themselves are indicative of the advantages that have been afforded to this multiple discriminant analysis model compared to that of previous studies that have been conducted on South African corporate failure prediction. There was only one study surveyed in the literature that offered higher classification rates, that being the De la Rey (1981) multiple discriminant analysis model.

Therefore it appears, through the accuracy rates achieved, that future studies on corporate failure prediction will benefit from improved classification as result of the better quality and the more uniform nature in the preparation of financial information. This study added to a growing sample of listed failed non-financial South African corporates. The sample is expected to grow as South Africa enters what appears to be another recession following the previous recession in 2009.

Furthermore, it is recommended that future studies consider making credit related financial adjustments to data as outlined in *Chapter 2 | b)* and in line with Moody's Investors Service best practices, which are public knowledge, so that financial information is more reflective of the credit risk exposures of non-financial South African corporates. It is also recommended that further examination should, at all times, decouple non-financial and financial corporates given the unique credit profiles of financial corporates which often can sustain higher leverage and where their systemic importance to the broader South African economy which often underlines a degree of implicit Reserve Bank support cannot be overlooked.

Penultimately the emphasis, of the use of uniform financial data which is broadly comparable across financial periods is also an important consideration. There should be due consideration for using financial data prepared under different sets of accounting standards as this can affect the accuracy of corporate failure prediction models developed which could be subject to a split sampling effect. As new IFRS standards are adopted there should also be an examination on the potential consequences when it comes to comparing financial data across time periods and sectors.

Lastly, the implications of removing outlying data points was considered. The impact of their inclusion or exclusion did not appear to have a meaningful difference on the overall classification of rate, however it did reduce the ability to classify failure. The ability to classify non-failed firms was improved. This was not seen as an ideal trade-off in the model's classification accuracy. The preference being for any corporate failure prediction model to be biased towards the classification of failed firms. This is due to the asymmetric nature of loans made to failed firms versus loans not made to non-failed firms, as loans losses made on bad loans almost always will exceed interest income forgone in not making a loan.

b) Liquidity analysis as an additional forward-looking predictor of default

Given the inconsistencies in the financial disclosures provided by the sample of failed South African non-financial corporates, this was excluded from the final model. However, as disclosure improves, especially when it comes to committed bank facility availability and forward-looking information, this should most certainly be considered. The ability for a non-financial corporate's forecast cash resources to support its uses is still seen to be one of the strongest determinants of corporate failure. It is suggested that as financial disclosures improve a recommended approach would be to consider this through $\frac{Forecast\ cash\ sources}{Forecast\ cash\ uses}$ where this should never be below one and always have a margin of safety factored in providing cushioning above one.

c) Applicability of equity market data and market model theory

Equity market price data should be considered in any analysis of corporate failure prediction. The applicability of this data was demonstrated in this study given the discriminatory power of debt/ Market Capitalisation which is a starting point for the theoretical underpinnings of market-based models as was detailed in *Chapter 3 | e)*. Equity markets introduced forward-looking characteristics for corporate failure prediction along with the capacity of a non-financial corporate to navigate prevailing business conditions versus their debt levels.

d) Avenues for further research

With the increasing accountability and transparency that firms are subject to, there appears to be improving disclosure around non-financial corporate liquidity positions and the resilience indicated by such disclosures. Through combining this with guidance around expectations for operating performance in the coming financial year a rough estimate of operating cash flow generation should be able to be derived. Liquidity sources through the combination of unrestricted cash balances, committed banking facility availability while factoring in covenant headroom to ensure that they are there when needed should be assessed against liquidity uses. This could be expressed as a ratio where there should always be a minimum coverage ratio exceeding one at all times.

At the same time future studies, could also consider using improved forward-looking guidance through an attempt to generate forecasts of credit metrics to be considered by employing multiple discriminant models as a forward-looking indicator of corporate failure.

There is scope for further analysis of the quality and consistency of financial information and ultimately how this affects the accuracy and reliability of corporate failure prediction. This will become increasingly important when it comes to the adoption of bellwether accounting standards such as IFRS 16 and its lease accounting framework, where its formal adoption will take place starting 1 January 2019. This will result in an adjustment (referred to in this study) no longer being required as all leases, including currently defined operating leases, will be capitalised and reflected on balance sheets.

Another consideration, would be comparing potential value that could be added in including a greater frequency of provision of financial information though comparing the impact of corporate failure prediction models that rely only on annual information versus those that rely upon both on interim and annual financial information.

Also of interest would be corporate failure prediction models developed that controls for sector of operations, where certain sectors are often deemed to be more inherently risky than others. Although it should also be noted that this is often characterised through greater volatility of historic credit metrics, but these may not be readily available for newly established or combined entities. At the same time, through combining failed firms with non-failed peers this introduces sector considerations. Although successfully matching firms with overlapping business profiles and a similar scale of operations can be challenging given the relatively small corporate universe in South Africa.

Currency volatility also often has a significant part to play when it comes to corporate failure prediction. This study only touched the tip of this by converting Rand revenue streams into US Dollars. This undoubtedly is an area worth exploring and its interlinkage with corporate failure prediction in a South African context.

Similarly, the volatile nature of credit statistics for failed firms often mean that there are both left and right tailed outliers across the spectrum of data that is collected. It is worth considering in detail the implications of these outliers in developing corporate failure models and what it means for the accuracy of predicting further corporate failure events.

Going concern qualifications expressed by auditors could also be worth incorporating into multiple discriminant analysis, although these have not always been present in the context of corporate failure. This is a challenging consideration for auditors, where the decision to qualify an audit opinion on the basis of a going concern assumption cannot be taken lightly, and can often lead to self-fulfilment of the financial failure of a corporate.

This study could also be further extended to examine the implications of applying backward versus forward stepwise analysis when it comes to developing a corporate failure prediction model using multiple discriminant analysis. At the same time an added consideration for further study, which was only touched upon in this study, is the concept of Normalised Cost of Failure (NCF) which was discussed in detail by Muller, Steyn-Bruwer and Hamman (2009).

Appendix A

<u>Application of equity credit methodology for non-convertible hybrids issued by investment-grade</u>

		#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12
Coupon Skip	Mandatory Weak[1]												
	Restricted Optional[2]		X										
	Optional	X			X	X		X	X			X	
	Optional & Mandatory[3]						X			X			X[4]
Settlement	Cumulative	X	X	X	X	X	X	X		X			
	Non-Cumulative								X		X	X	X
Ranking	Subordinated	X	X	X	X	X	X						
	Preferred							X	X	X	X	X	X
	Equity												
Maturity	< 30 years	X											
	30 – 59 years				X				X				
	>= 60 years		X	X		X	X	X		X	X	X	X
	Irredeemable												
Basket for Non-Financial Corporates		A	B	B	B	B	B	C	C	C	C	C	D

1 Mandatory Weak Triggers include minimum regulatory capital ratios set at low levels.
2 Restricted Optional is when the issuer has to stop payment on parity or junior securities for more than 6 months before being able to skip hybrid coupons.
3 Optional and Mandatory Strong Triggers includes both optional coupon skip mechanisms and strong or 'meaningful' triggers such as triggers that would be breached well in advance of a company-wide default.
4 The mandatory coupon suspension is non-cumulative;the optional coupon suspension can either be cumulative or non-cumulative.

Appendix B

Application of Moody's equity credit methodology for convertible securities issued by investment- grade non-banks

Host Security

Instrument Type	Maturity	Coupon Skip/ Settlement	Ranking	Timing to Conversion/ Write-down	Underlying Security	Conversion Ratio or Principal Write Down	Basket
US Common Units	5 to 10 years	None	Senior debt	3 years	Equity	Fixed # shares	A
Contingent Capital Securities	5 to 10 years	None	Subordinated debt	Depends on where trigger level is set	Equity or principal write-down	Varies	B
US Common Units[8]	5 years	Cum/ACSM	Junior sub debt	3 years	Equity	Fixed # shares	B
US Preferred Units[9]	> 10 years	Cum/ACSM	Junior sub debt	Earlier of 5 years or breach of reg cap trigger	Non-cum preferred	Par	B
Contingent Capital Securities	Perpetual	Non- cumulative	Preferred stock	Depends on where trigger level is set	Equity or principal write-down	Varies	C
European Mandatory Convertible Securities	≤3 years	Cum	Equity10	Earlier of insolvency or maturity	Equity	Fixed # shares	E
US Mandatory Convertible Preferred	3 years	Cum	Preferred	Maturity	Equity	Fixed # shares	E

Appendix C

Operating Lease Sector Multiples

Sector	Lease Multiple
Aerospace & Defense	3
Alcoholic Beverage	3
Apparel	4
Asset Managers	6
Automobile Manufacturer	3
Automotive Supplier	3
Broadcast & Advertising	4
Related Building Materials	3
Business Services	3
Chemical	3
Communications Equipment	3
Communications Infrastructure	5
Construction	3
Consumer Durables	3
Consumer Electronics	3
Consumer Services	4
Distribution & Supply Chain Services	3
Electric Generation & Transmission Cooperatives	3
Environmental Services & Waste Management	3
Equipment & Transportation Rental	3
Finance Companies	3
Gaming	4
Generic Project Finance	6
Government Owned Rail Network	3
Healthcare Service Providers	4
Homebuilding & Property Development	3
Independent Exploration & Production	4
Insurance Brokers & Service Companies	4
Insurers	4
Integrated Oil & Gas	3
Investment Holding Companies	3
Large Global Diversified Media	4
Lodging & Cruise	5
Manufacturing	3
Medical Product & Device	3
Midstream Energy	3
Mining	3
Natural Gas Pipelines	6
Oilfield Services	3

Sector	Lease Multiple
Packaged Goods	3
Packaging Manufacturers	3
Paper & Forest Products	3
Passenger Airlines	5
Passenger Railway	3
Pay TV-Cable & Direct-to-Home Satellite Operators	3
Pharmaceutical	3
Postal & Express Delivery	3
Privately Managed Airports & Related Issuers	6
Privately Managed Port Companies	6
Privately Managed Toll Roads	3
Protein & Agriculture	3
Publishing	4
Refining & Marketing	3
Regulated Electric & Gas Networks	4
Regulated Electric & Gas Utilities	4
Regulated Water Utilities	3
REITs & Other Commercial Property Firms	4
Restaurant	6
Retail	5
Securities Firms	5
Semiconductor	3
Shipping	3
Soft Beverage	3
Software	3
Steel	3
Surface Transportation & Logistics	3
Technology Hardware	3
Technology Services	3
Telecommunications	3
Tobacco	3
Trading Companies	3
Unregulated Power Companies	6
Unregulated Utilities	6

Appendix D

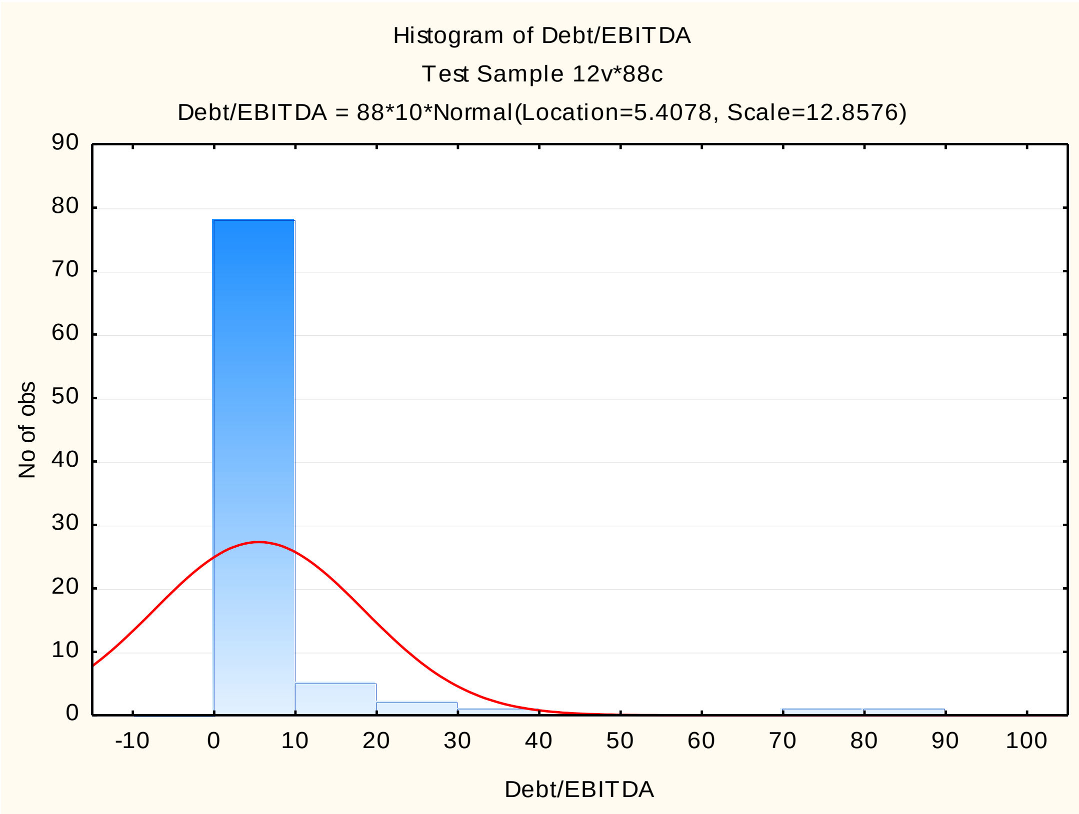
Moody's Investors Service National Scale Mapping Table for South Africa

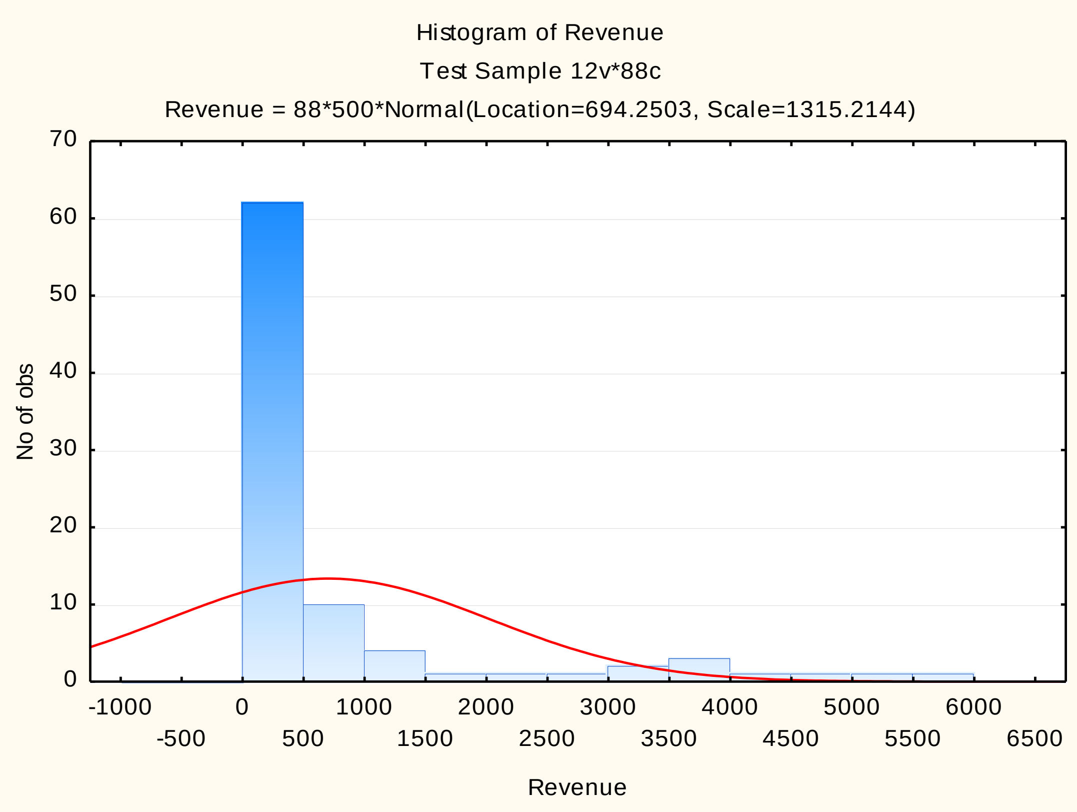
Global Scale Rating	National Scale Rating
A1	Aaa.za
A2	Aaa.za
A3	Aaa.za
Baa1	Aaa.za
Baa2	Aa1.za to Aa2.za
Baa3	Aa3.za to A1.za
Ba1	A2.za to A3.za
Ba2	Baa1.za
Ba3	Baa2.za
B1	Baa3.za
B2	Ba1.za to Ba2.za
B3	Ba3.za to B1.za
Caa1	B2.za to B3.za
Caa2	Caa1.za to Caa2.za
Caa3	Caa3.za
Ca	Ca.za
C	C.za

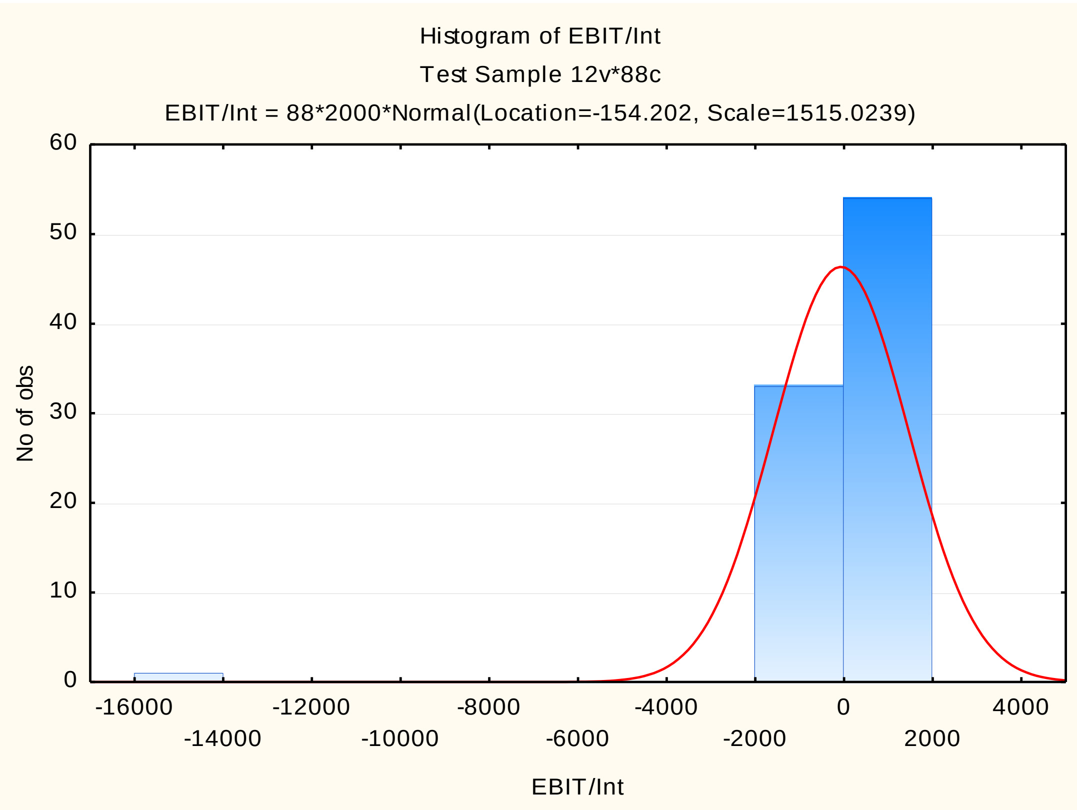
Appendix E

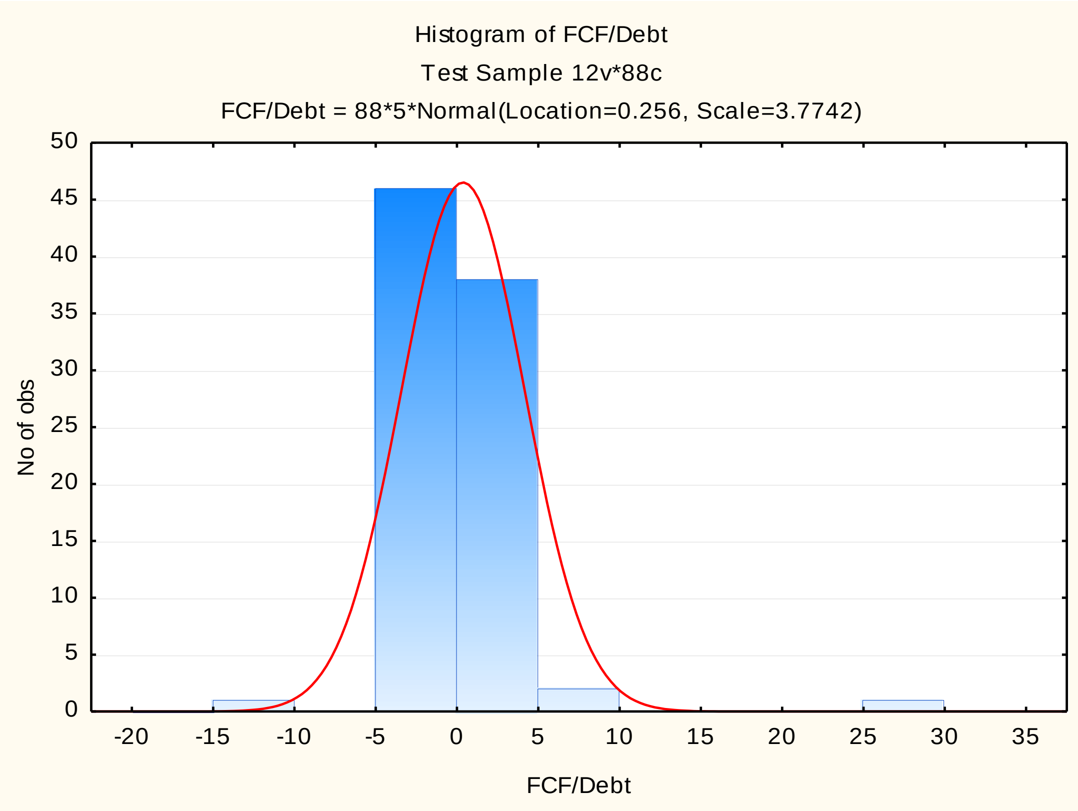
Normal fit histograms for South African non-financial corporates independent variables sample

1. **Combined for failed and non-failed South African non-financial corporates**

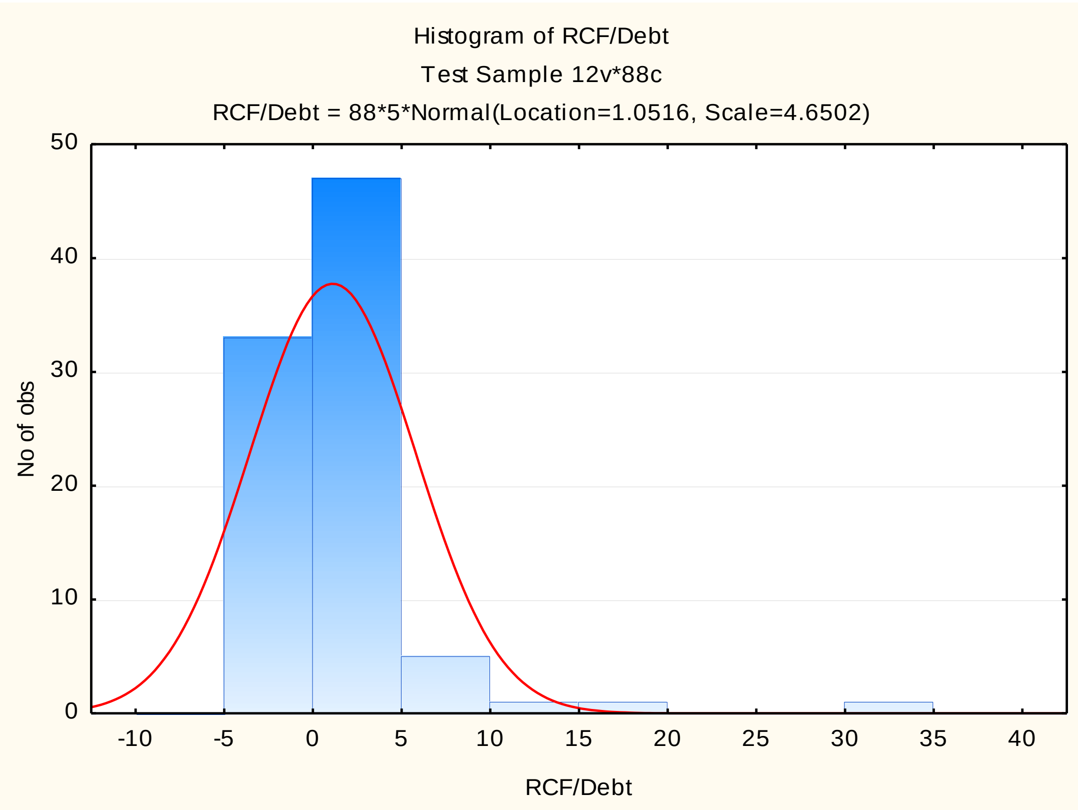



Histogram of Revenue
Test Sample 12v*88c
Revenue = 88*500*Normal(Location=694.2503, Scale=1315.2144)
No of obs
Revenue

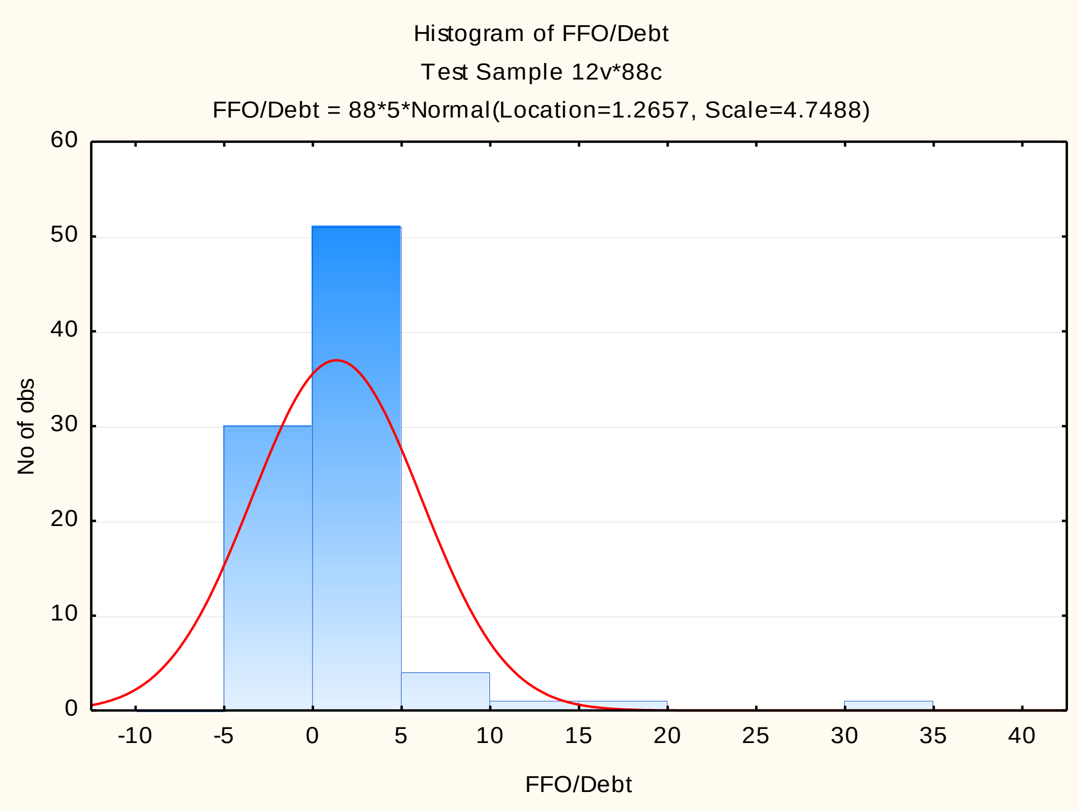

Histogram of EBIT/Int
Test Sample 12v*88c
EBIT/Int = 88*2000*Normal(Location=-154.202, Scale=1515.0239)
No of obs
EBIT/Int

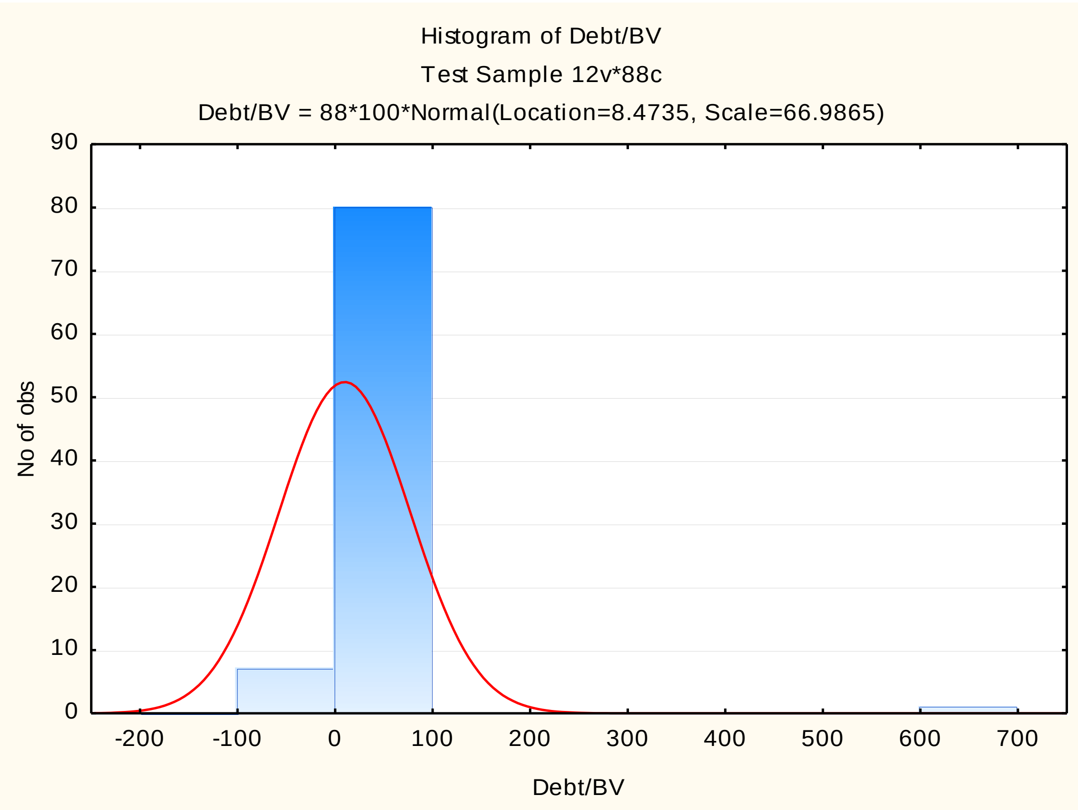


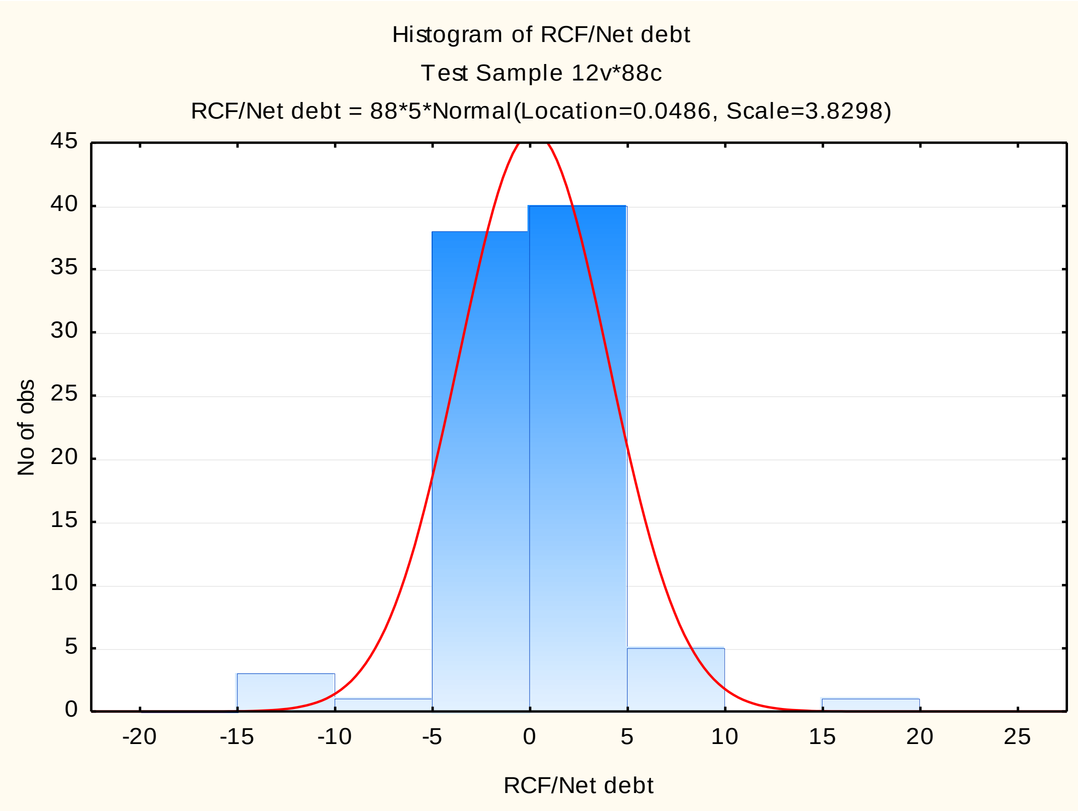
Histogram of FCF/Debt
Test Sample 12v*88c
FCF/Debt = 88*5*Normal(Location=0.256, Scale=3.7742)
No of obs
50
45
40
35
30
25
20
15
10
5
0
-20
-15
-10
-5
0
5
10
15
20
25
30
35
FCF/Debt



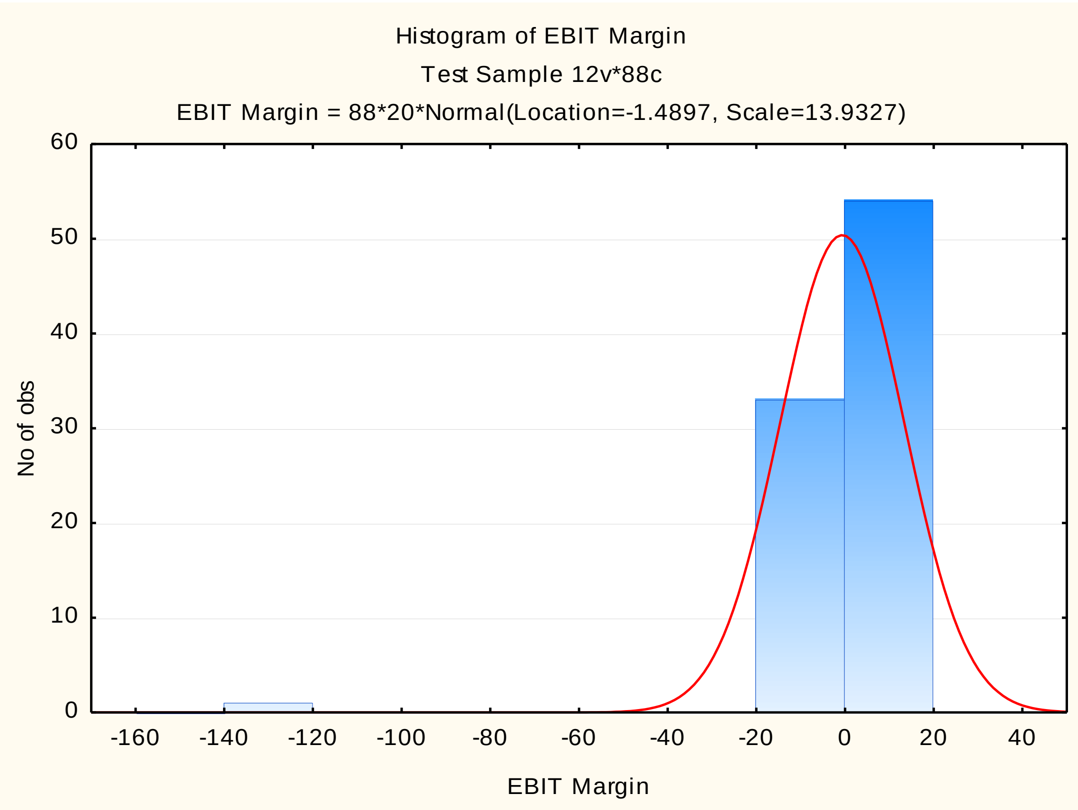
Histogram of RCF/Debt
Test Sample 12v*88c
RCF/Debt = 88*5*Normal(Location=1.0516, Scale=4.6502)
No of obs
50
40
30
20
10
0
-10
-5
0
5
10
15
20
25
30
35
40
RCF/Debt


Histogram of FFO/Debt
Test Sample 12v*88c
FFO/Debt = 88*5*Normal(Location=1.2657, Scale=4.7488)
No of obs
0
10
20
30
40
50
60
-10
-5
0
5
10
15
20
25
30
35
40
FFO/Debt

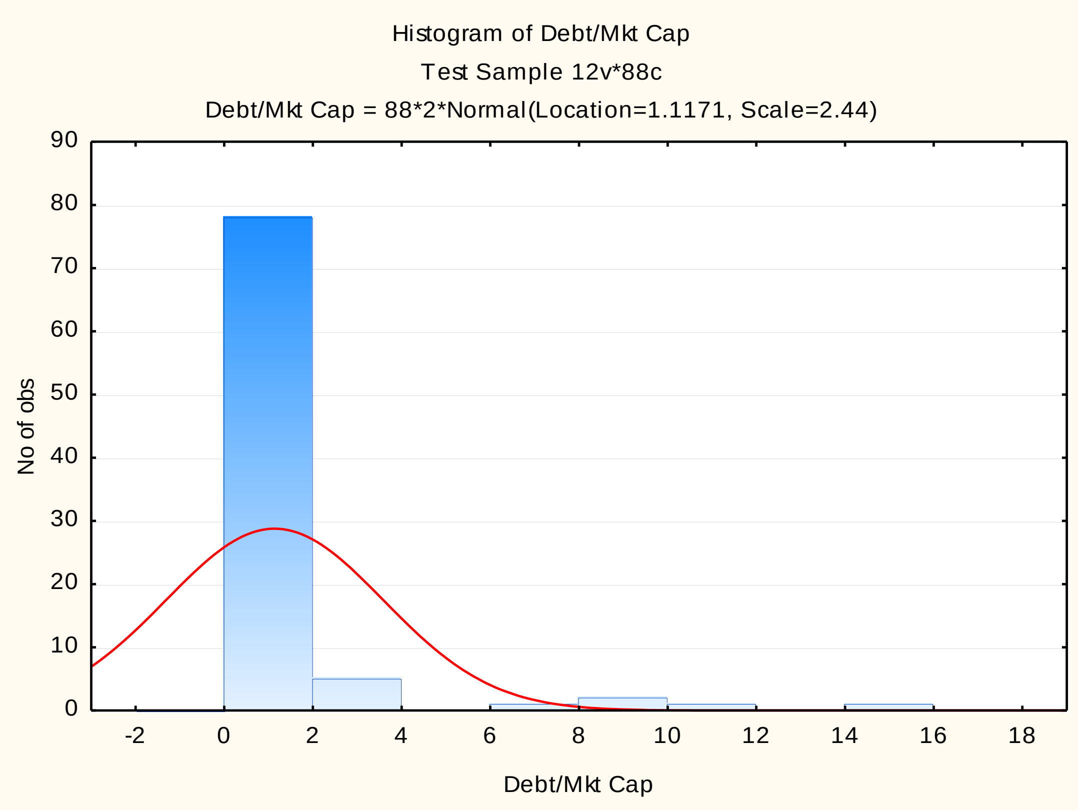

Histogram of Debt/BV
Test Sample 12v*88c
Debt/BV = 88*100*Normal(Location=8.4735, Scale=66.9865)
No of obs
0
10
20
30
40
50
60
70
80
90
-200
-100
0
100
200
300
400
500
600
700
Debt/BV



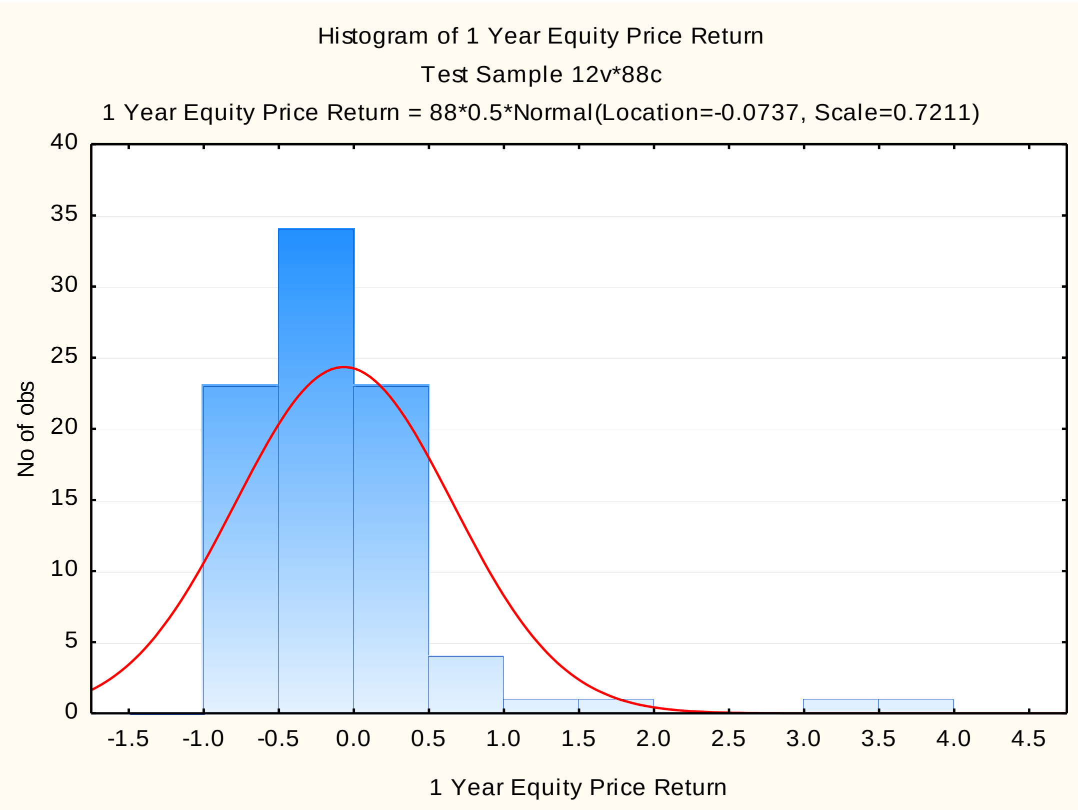
Histogram of RCF/Net debt
Test Sample 12v*88c
RCF/Net debt = 88*5*Normal(Location=0.0486, Scale=3.8298)
No of obs
0
5
10
15
20
25
30
35
40
45
-20
-15
-10
-5
0
5
10
15
20
25
RCF/Net debt



Histogram of EBIT Margin
Test Sample 12v*88c
EBIT Margin = 88*20*Normal(Location=-1.4897, Scale=13.9327)
No of obs
0
10
20
30
40
50
60
-160
-140
-120
-100
-80
-60
-40
-20
0
20
40
EBIT Margin

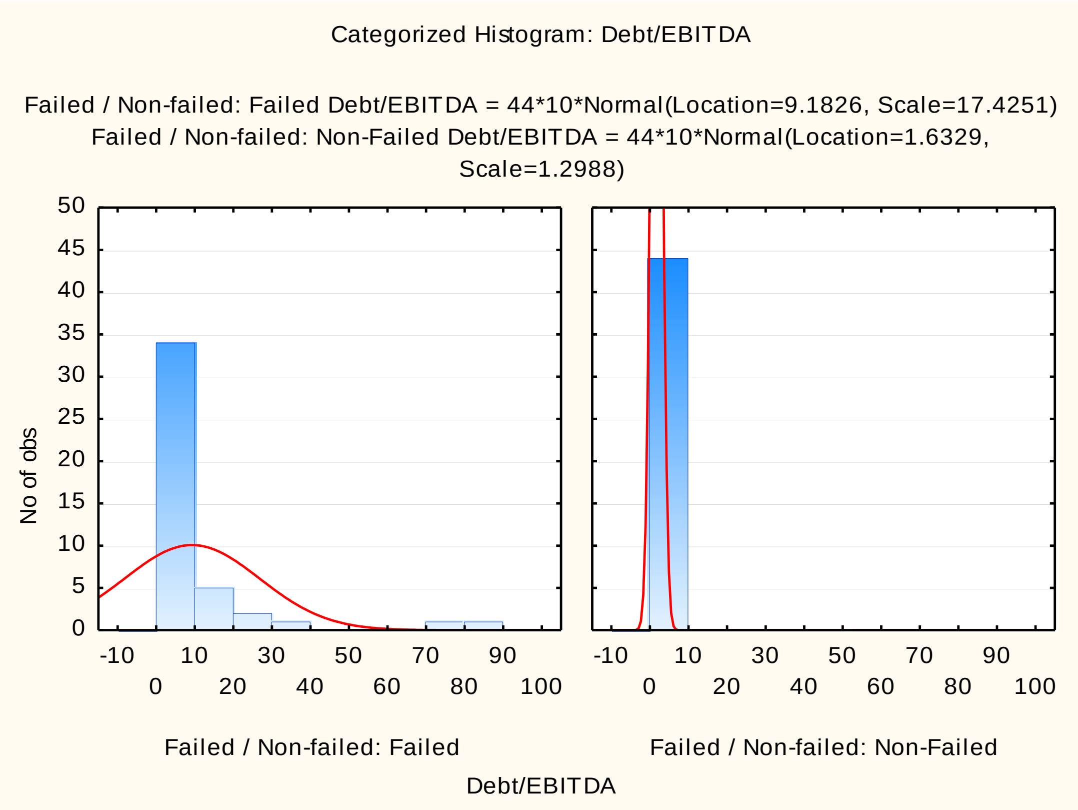


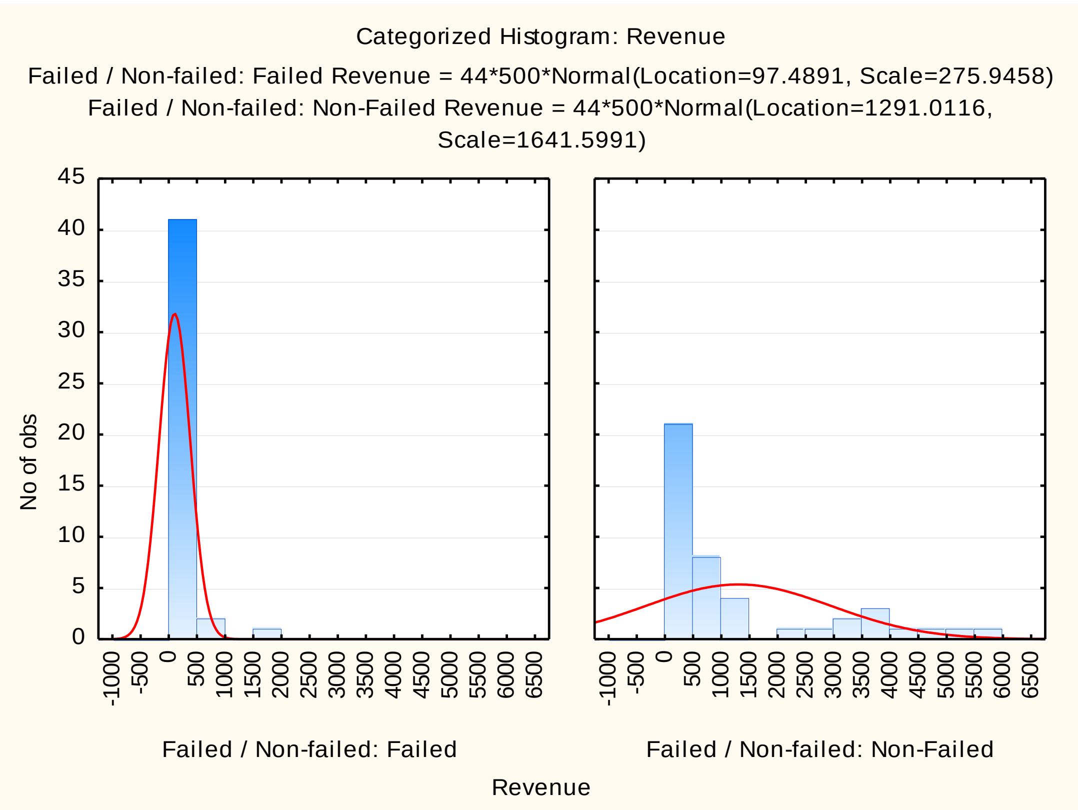
Histogram of Debt/Mkt Cap
Test Sample 12v*88c
Debt/Mkt Cap = 88*2*Normal(Location=1.1171, Scale=2.44)
No of obs
Debt/Mkt Cap

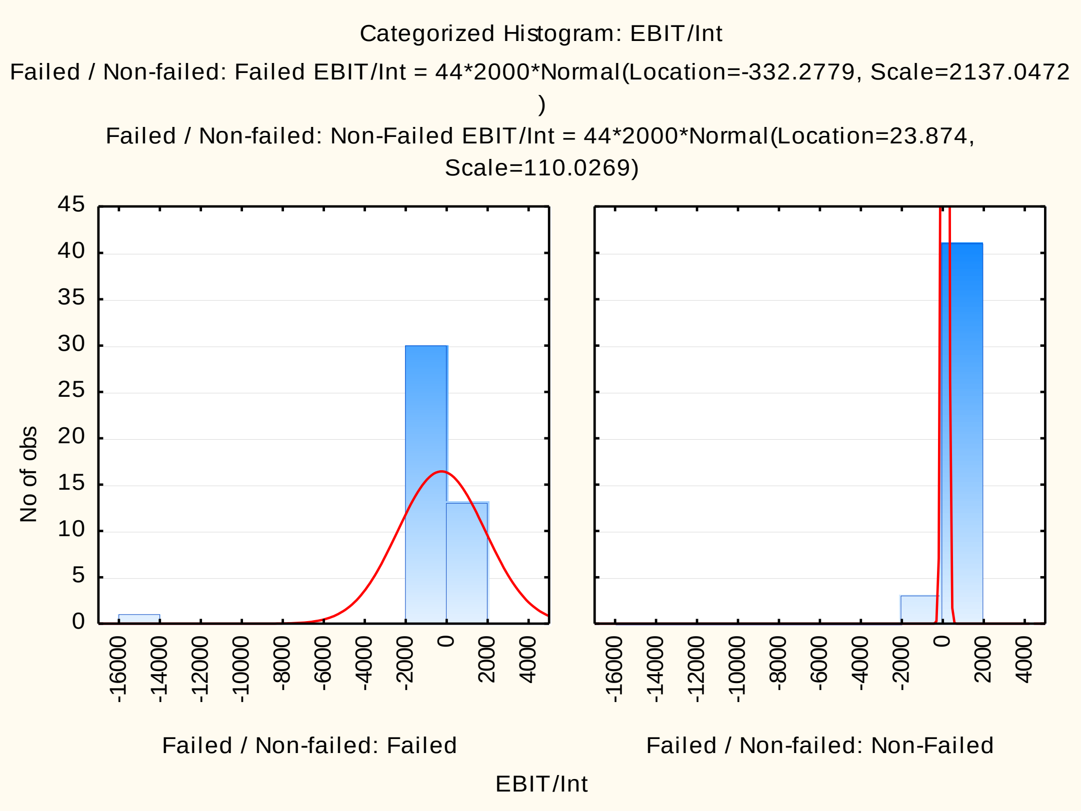


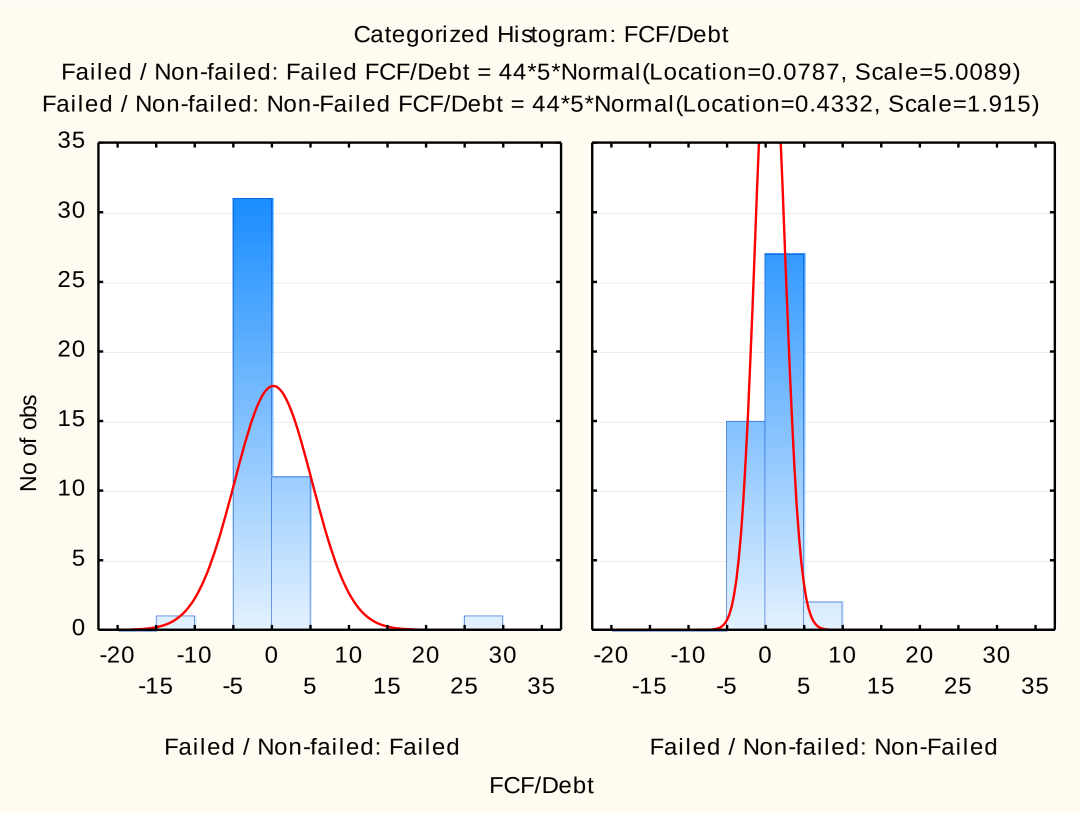
Histogram of 1 Year Equity Price Return
Test Sample 12v*88c
1 Year Equity Price Return = 88*0.5*Normal(Location=-0.0737, Scale=0.7211)
No of obs
1 Year Equity Price Return

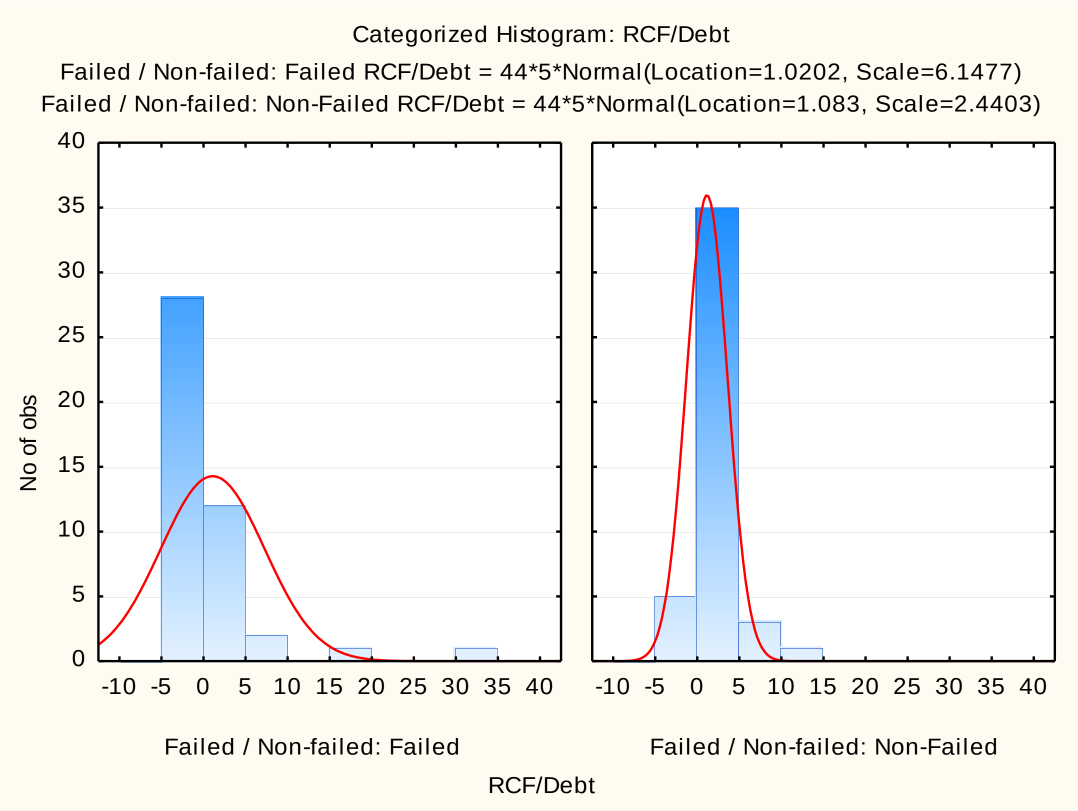
2. By failed or non-failed South African non-financial corporate groupings

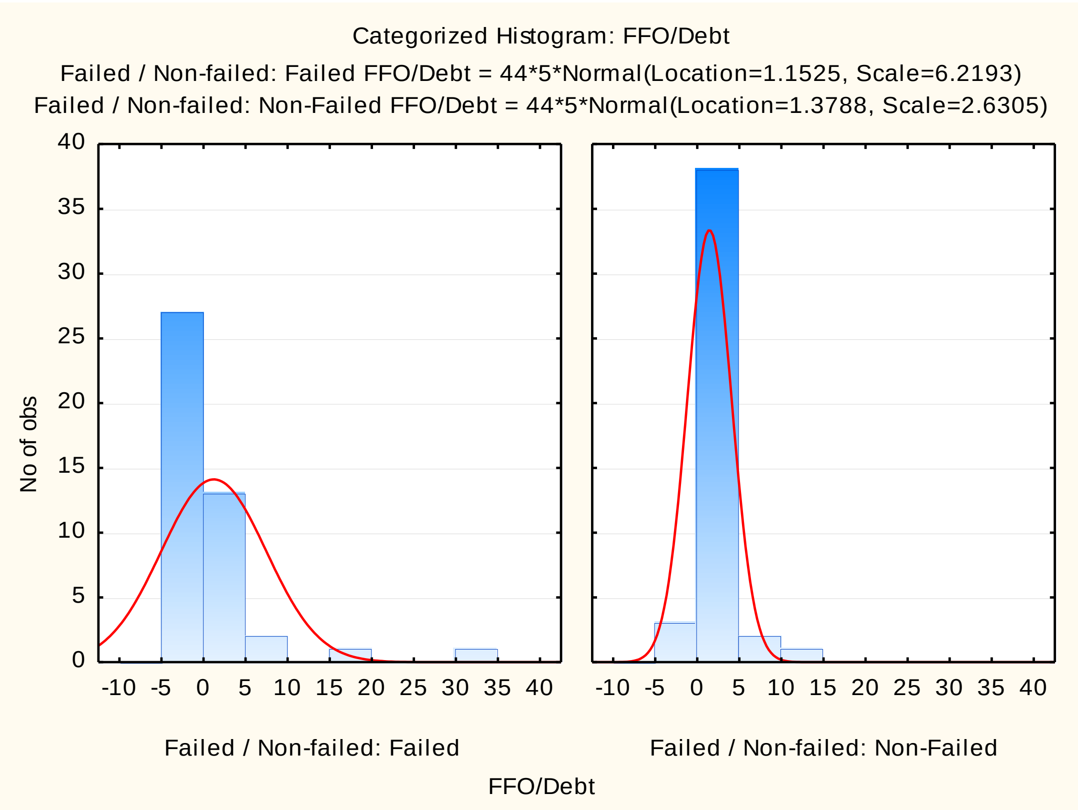


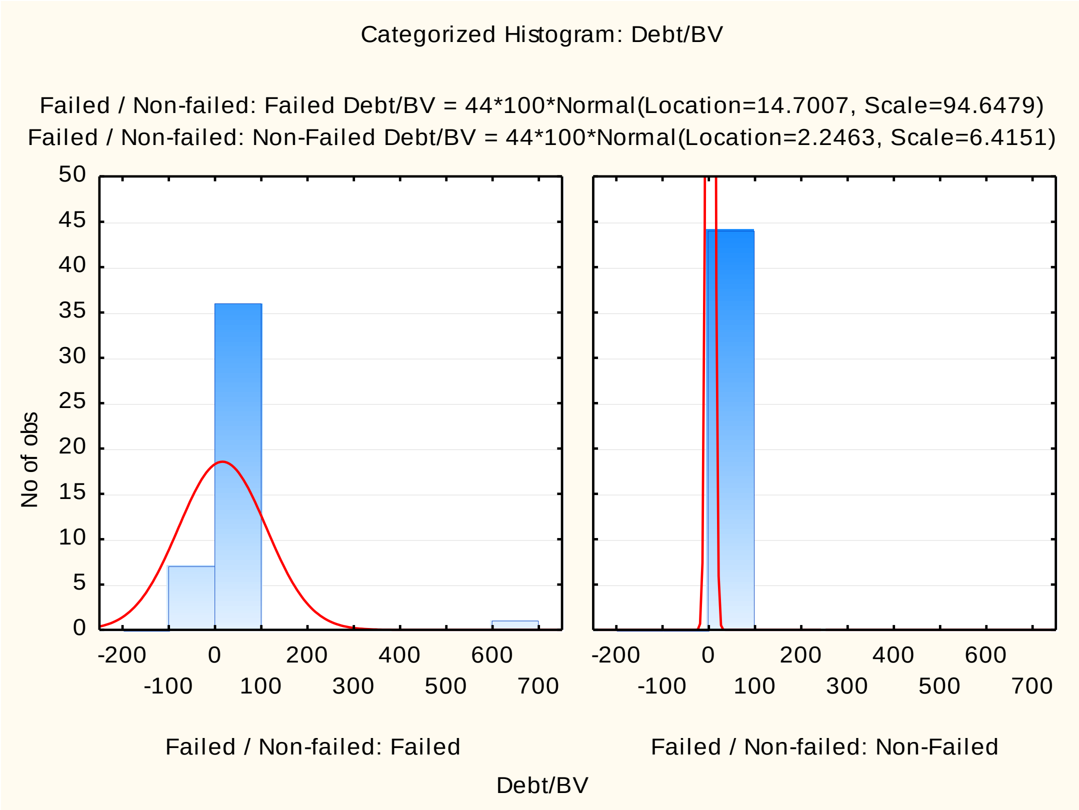



Categorized Histogram: EBIT/Int
Failed / Non-failed: Failed EBIT/Int = 44*2000*Normal(Location=-332.2779, Scale=2137.0472)
Failed / Non-failed: Non-Failed EBIT/Int = 44*2000*Normal(Location=23.874, Scale=110.0269)
No of obs
Failed / Non-failed: Failed
Failed / Non-failed: Non-Failed
EBIT/Int

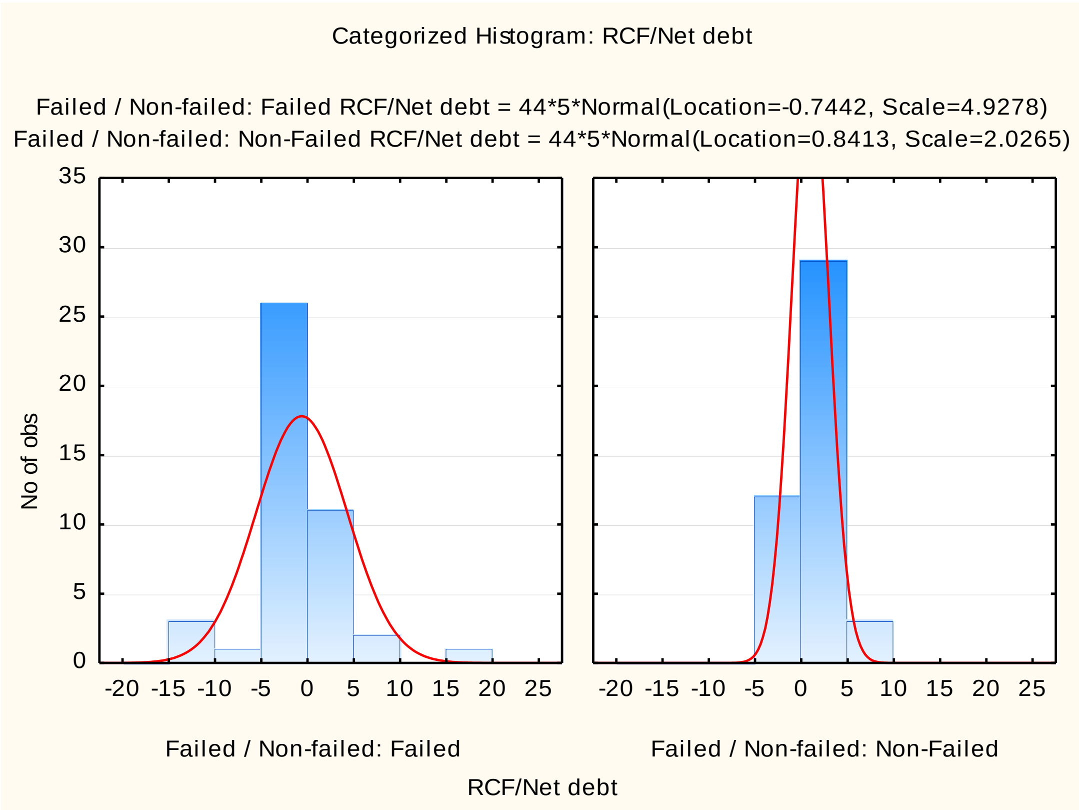

Categorized Histogram: FCF/Debt
Failed / Non-failed: Failed FCF/Debt = 44*5*Normal(Location=0.0787, Scale=5.0089)
Failed / Non-failed: Non-Failed FCF/Debt = 44*5*Normal(Location=0.4332, Scale=1.915)
No of obs
Failed / Non-failed: Failed
Failed / Non-failed: Non-Failed
FCF/Debt


Categorized Histogram: RCF/Debt
Failed / Non-failed: Failed RCF/Debt = 44*5*Normal(Location=1.0202, Scale=6.1477)
Failed / Non-failed: Non-Failed RCF/Debt = 44*5*Normal(Location=1.083, Scale=2.4403)
No of obs
Failed / Non-failed: Failed
Failed / Non-failed: Non-Failed
RCF/Debt

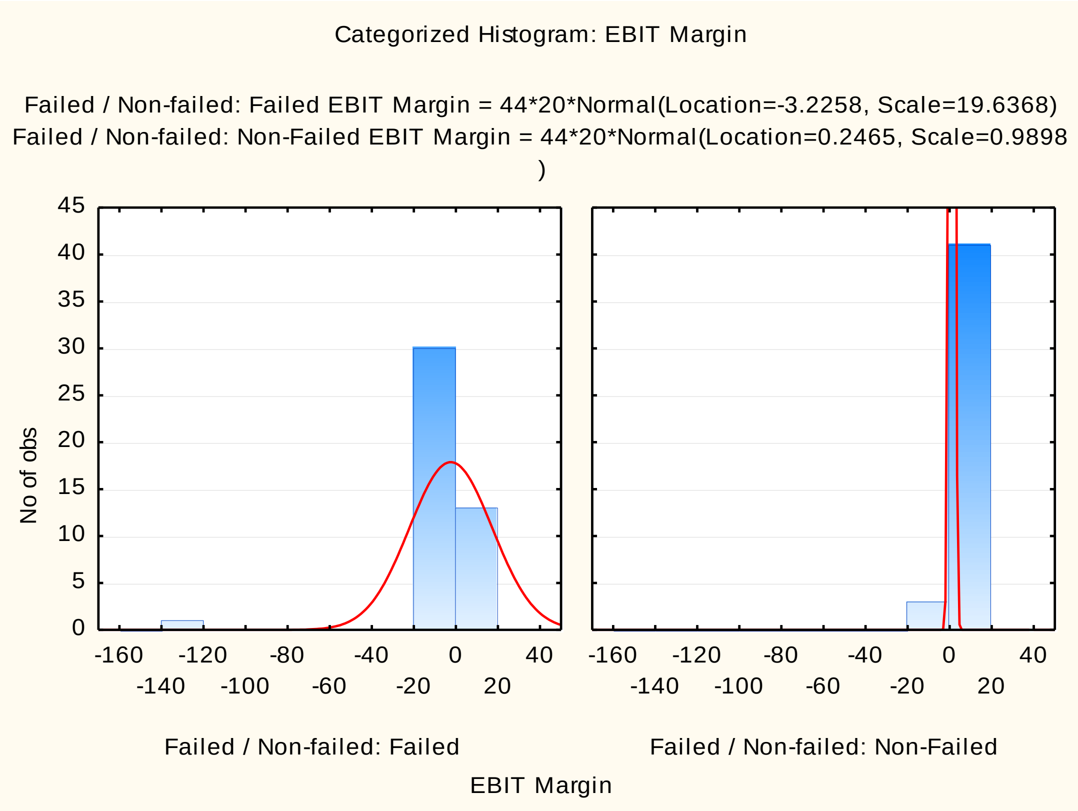

Categorized Histogram: FFO/Debt
Failed / Non-failed: Failed FFO/Debt = 44*5*Normal(Location=1.1525, Scale=6.2193)
Failed / Non-failed: Non-Failed FFO/Debt = 44*5*Normal(Location=1.3788, Scale=2.6305)
No of obs
Failed / Non-failed: Failed
Failed / Non-failed: Non-Failed
FFO/Debt

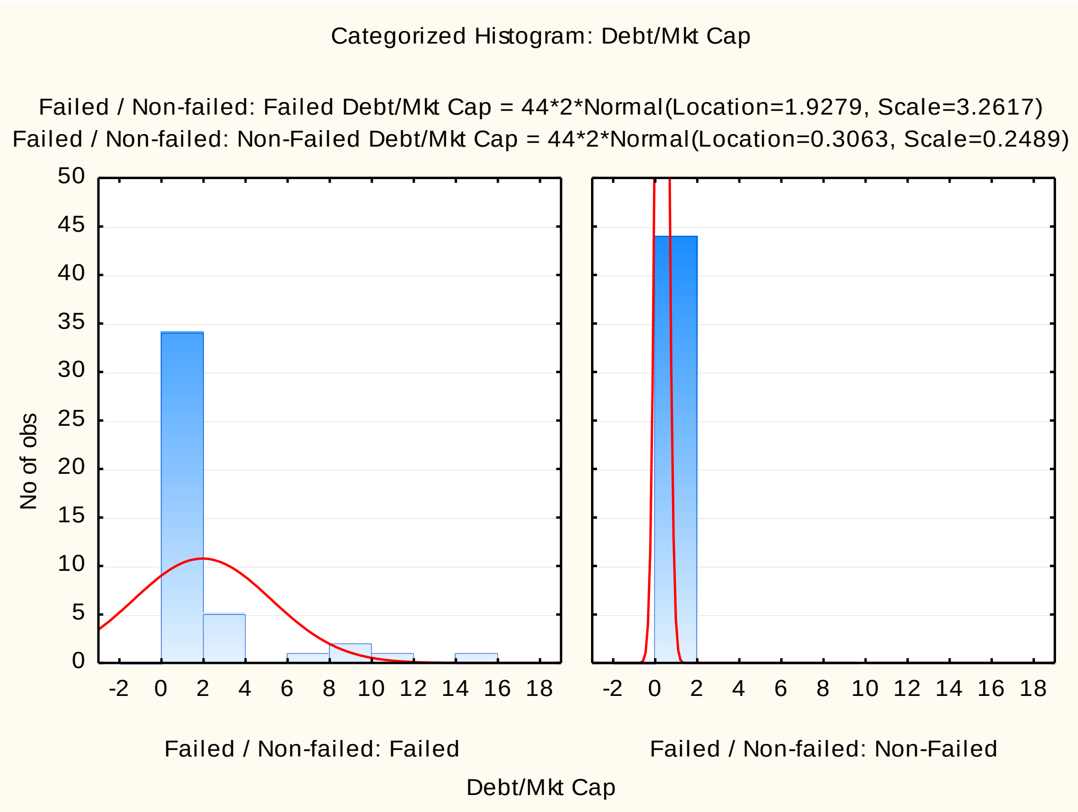


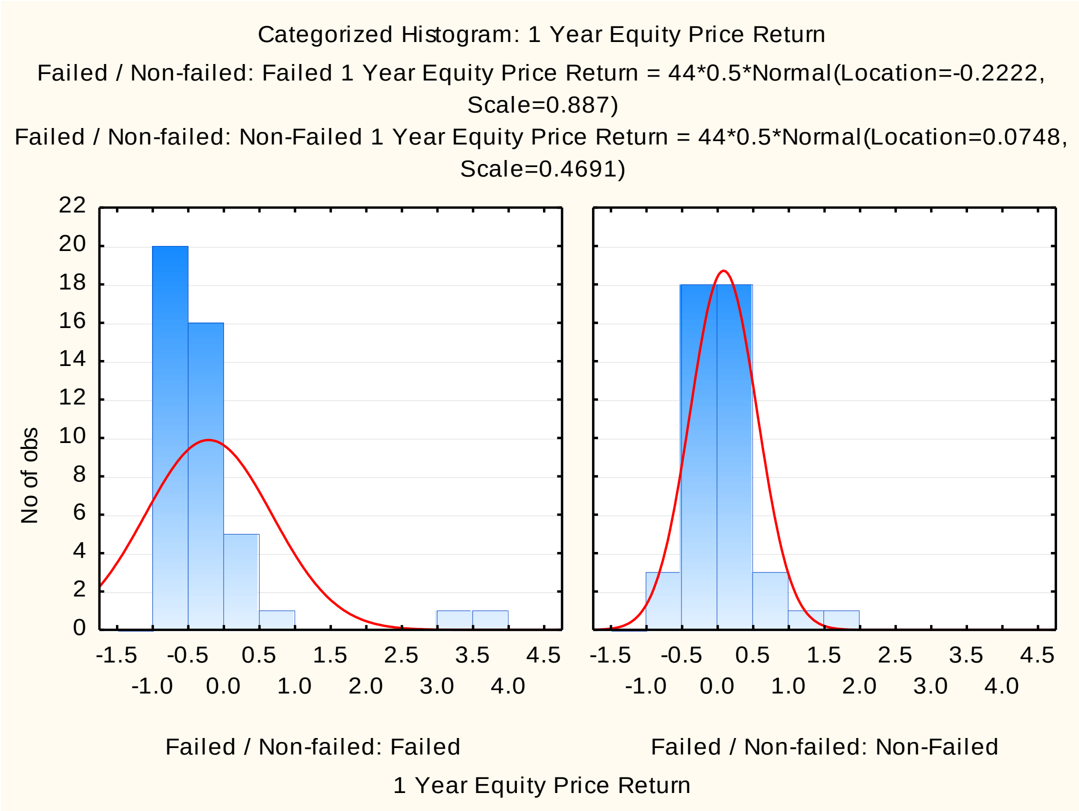
Categorized Histogram: Debt/BV
Failed / Non-failed: Failed Debt/BV = 44*100*Normal(Location=14.7007, Scale=94.6479)
Failed / Non-failed: Non-Failed Debt/BV = 44*100*Normal(Location=2.2463, Scale=6.4151)
No of obs
Failed / Non-failed: Failed
Failed / Non-failed: Non-Failed
Debt/BV



Categorized Histogram: RCF/Net debt
Failed / Non-failed: Failed RCF/Net debt = 44*5*Normal(Location=-0.7442, Scale=4.9278)
Failed / Non-failed: Non-Failed RCF/Net debt = 44*5*Normal(Location=0.8413, Scale=2.0265)
No of obs
Failed / Non-failed: Failed
Failed / Non-failed: Non-Failed
RCF/Net debt


Categorized Histogram: EBIT Margin
Failed / Non-failed: Failed EBIT Margin = 44*20*Normal(Location=-3.2258, Scale=19.6368)
Failed / Non-failed: Non-Failed EBIT Margin = 44*20*Normal(Location=0.2465, Scale=0.9898)
No of obs
0
5
10
15
20
25
30
35
40
45
-160 -140 -120 -100 -80 -60 -40 -20 0 20 40
Failed / Non-failed: Failed
Failed / Non-failed: Non-Failed
EBIT Margin


Categorized Histogram: Debt/Mkt Cap
Failed / Non-failed: Failed Debt/Mkt Cap = 44*2*Normal(Location=1.9279, Scale=3.2617)
Failed / Non-failed: Non-Failed Debt/Mkt Cap = 44*2*Normal(Location=0.3063, Scale=0.2489)
No of obs
0
5
10
15
20
25
30
35
40
45
50
-2 0 2 4 6 8 10 12 14 16 18
Failed / Non-failed: Failed
Failed / Non-failed: Non-Failed
Debt/Mkt Cap

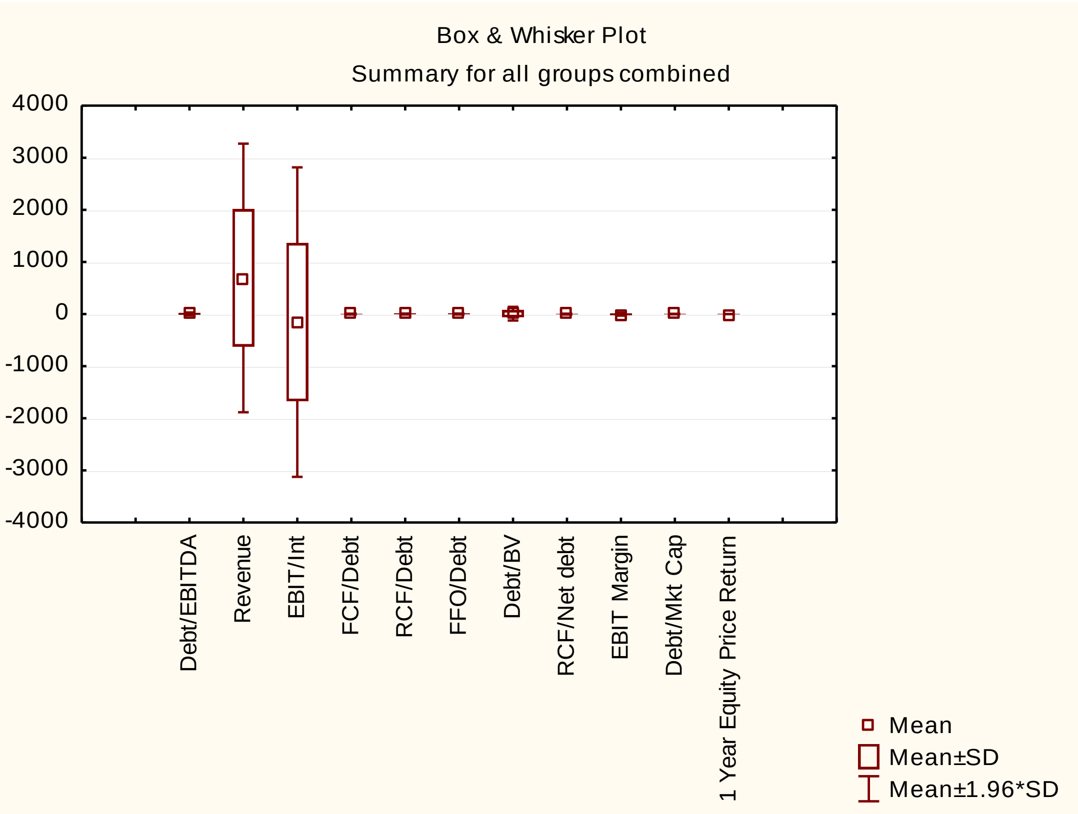


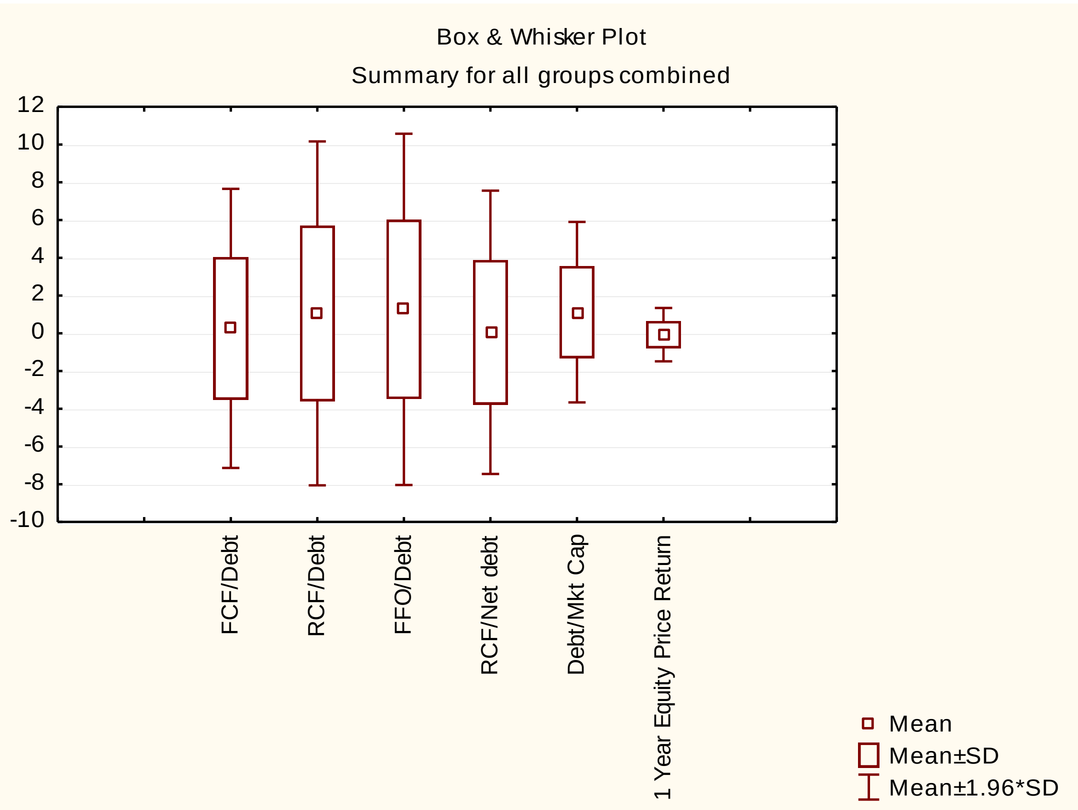
Categorized Histogram: 1 Year Equity Price Return
Failed / Non-failed: Failed 1 Year Equity Price Return = 44*0.5*Normal(Location=-0.2222, Scale=0.887)
Failed / Non-failed: Non-Failed 1 Year Equity Price Return = 44*0.5*Normal(Location=0.0748, Scale=0.4691)
No of obs
22
20
18
16
14
12
10
8
6
4
2
0
-1.5 -0.5 0.5 1.5 2.5 3.5 4.5
-1.0 0.0 1.0 2.0 3.0 4.0
Failed / Non-failed: Failed
Failed / Non-failed: Non-Failed
1 Year Equity Price Return

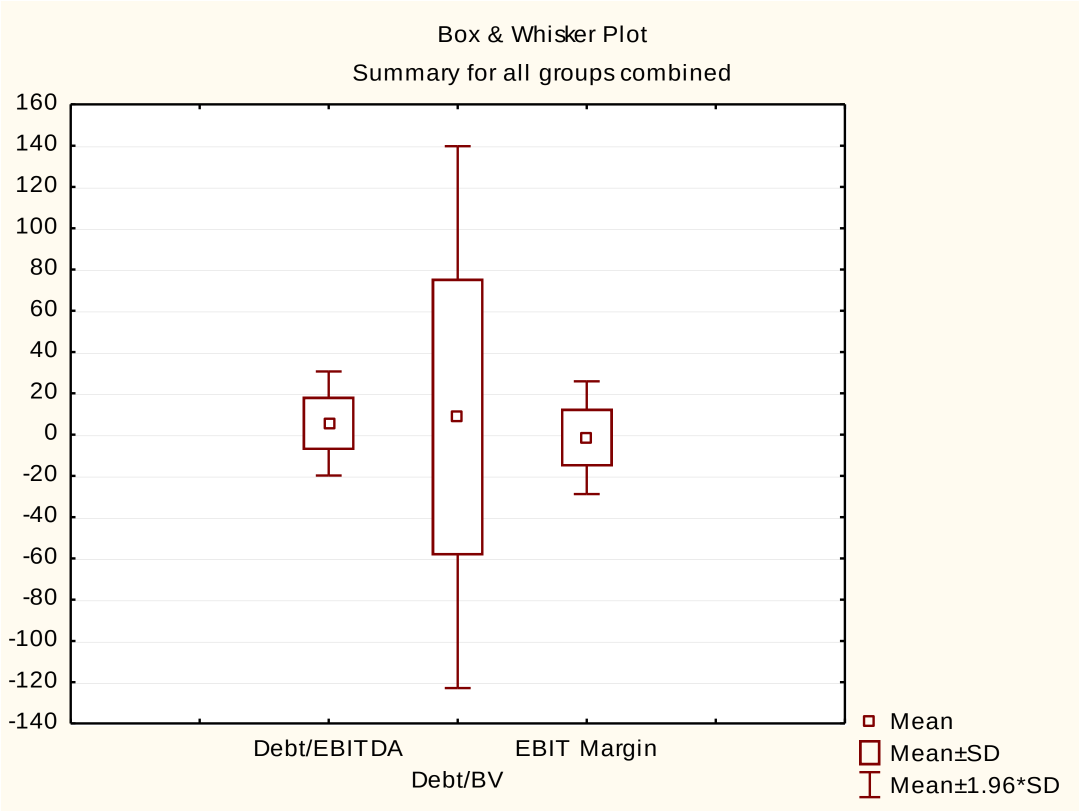
Appendix F

Box and whisker plot for South African non-financial corporates independent variables sample

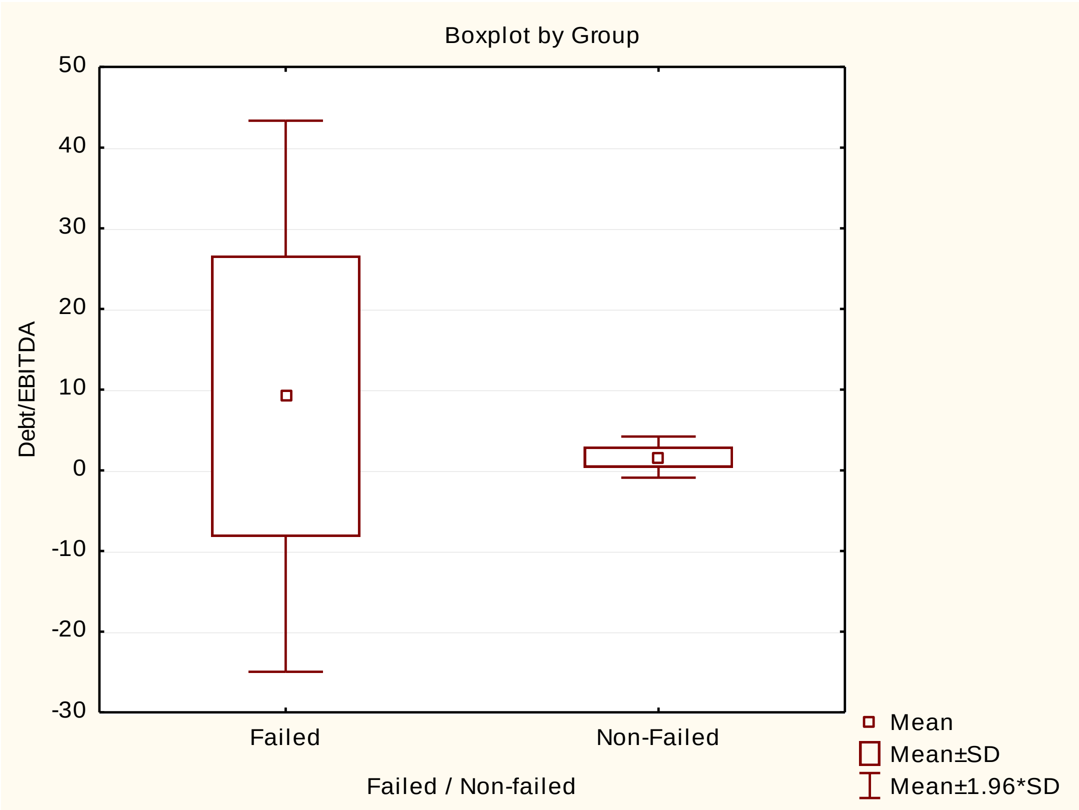
1. Combined for failed and non-failed South African non-financial corporates

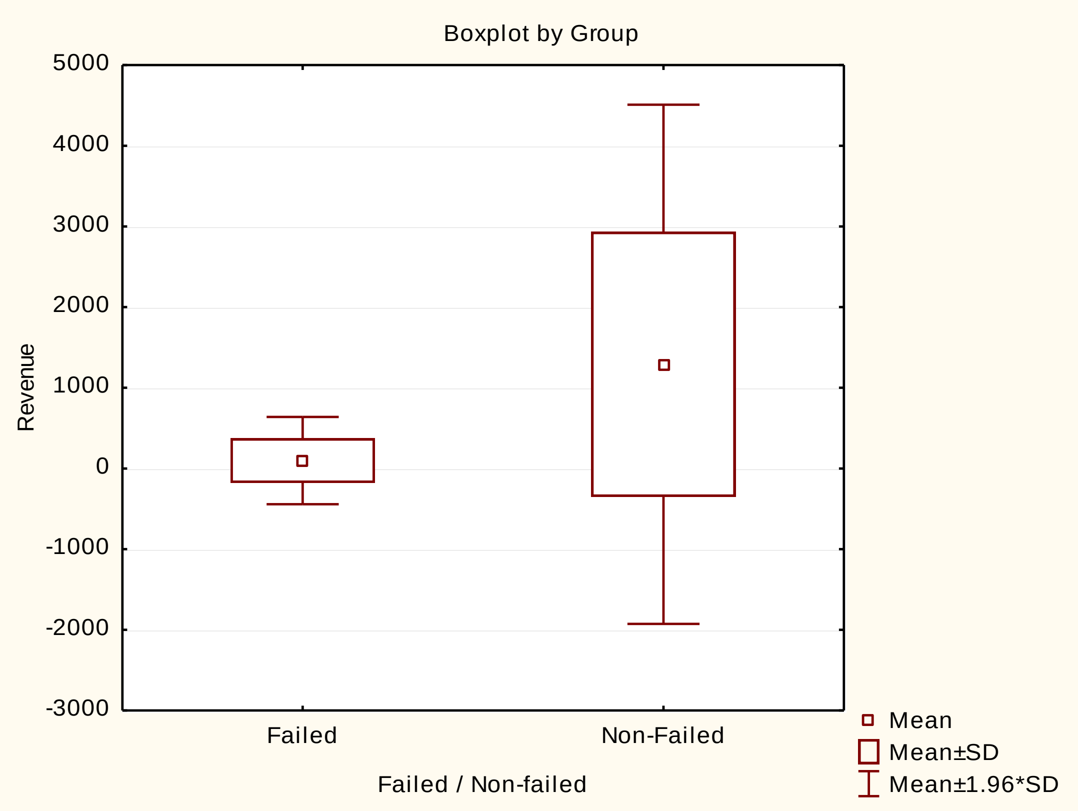




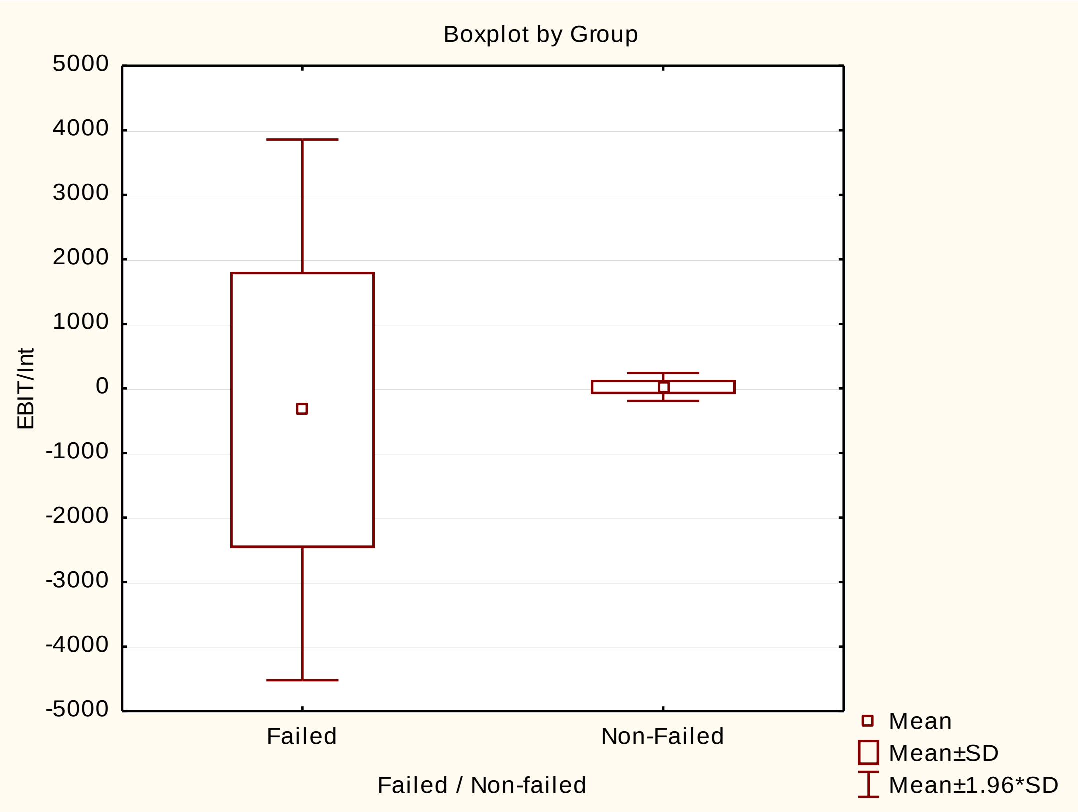


2. **By failed or non-failed South African non-financial corporate groupings**

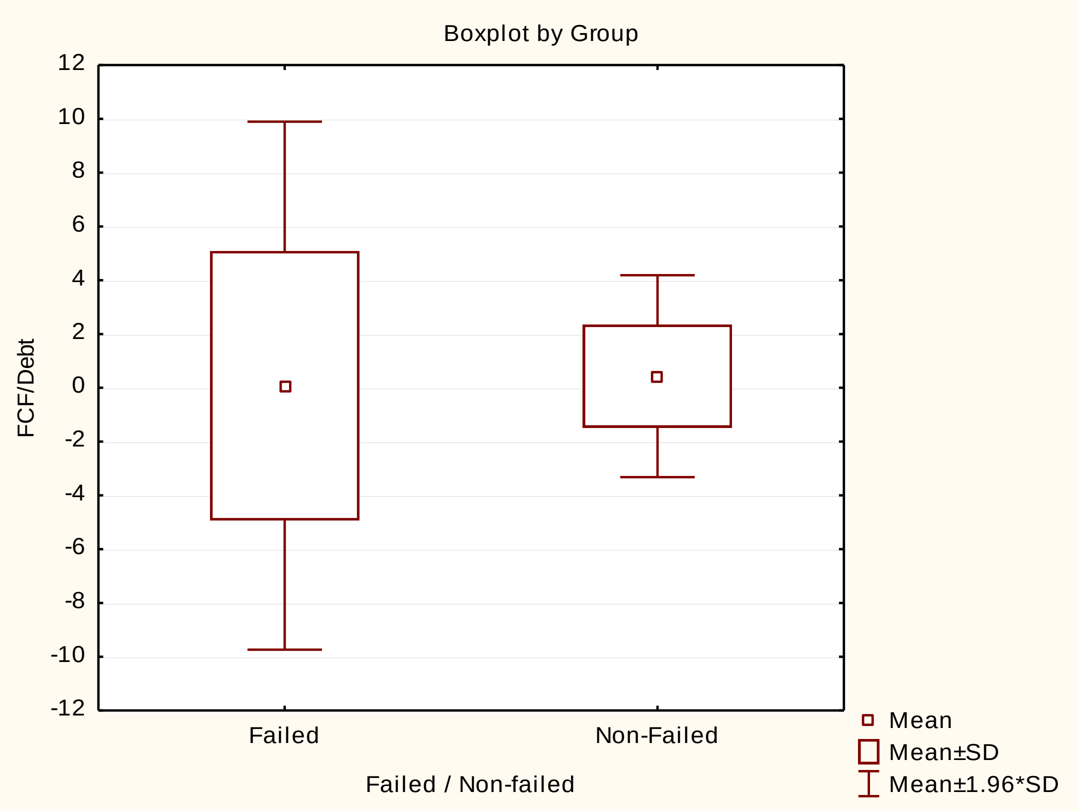


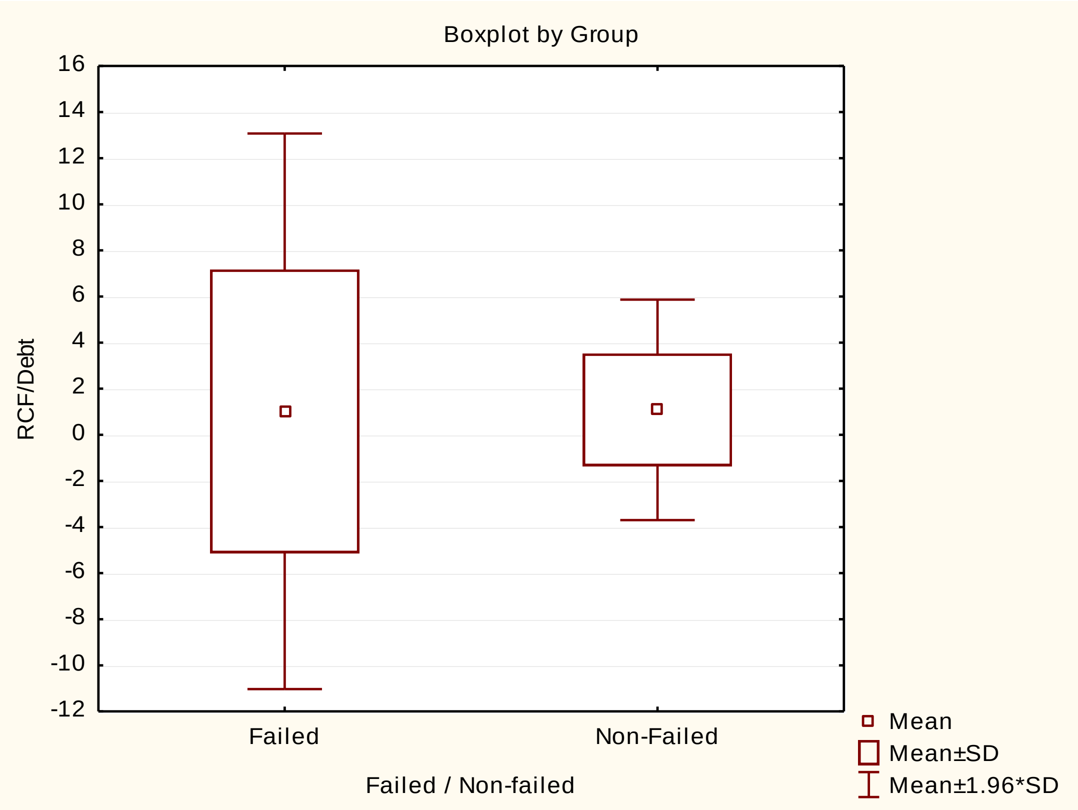


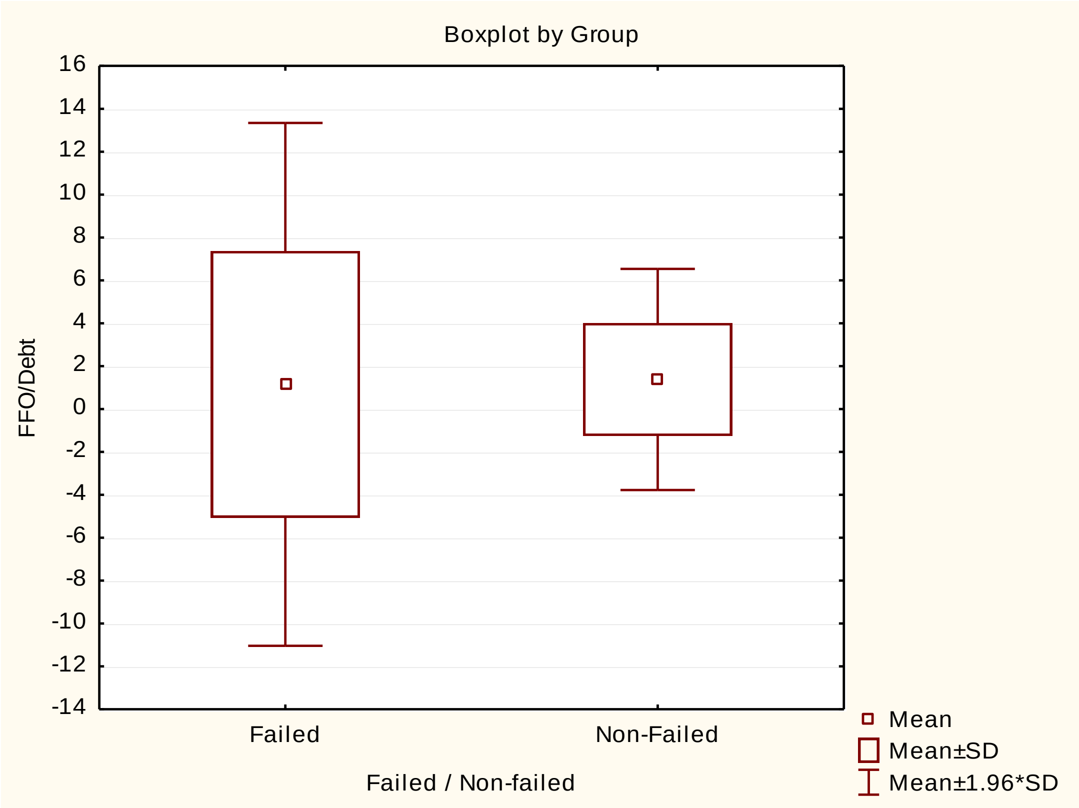
Boxplot by Group
Revenue
5000
4000
3000
2000
1000
0
-1000
-2000
-3000
Failed
Non-Failed
Failed / Non-failed
Mean
Mean±SD
Mean±1.96*SD



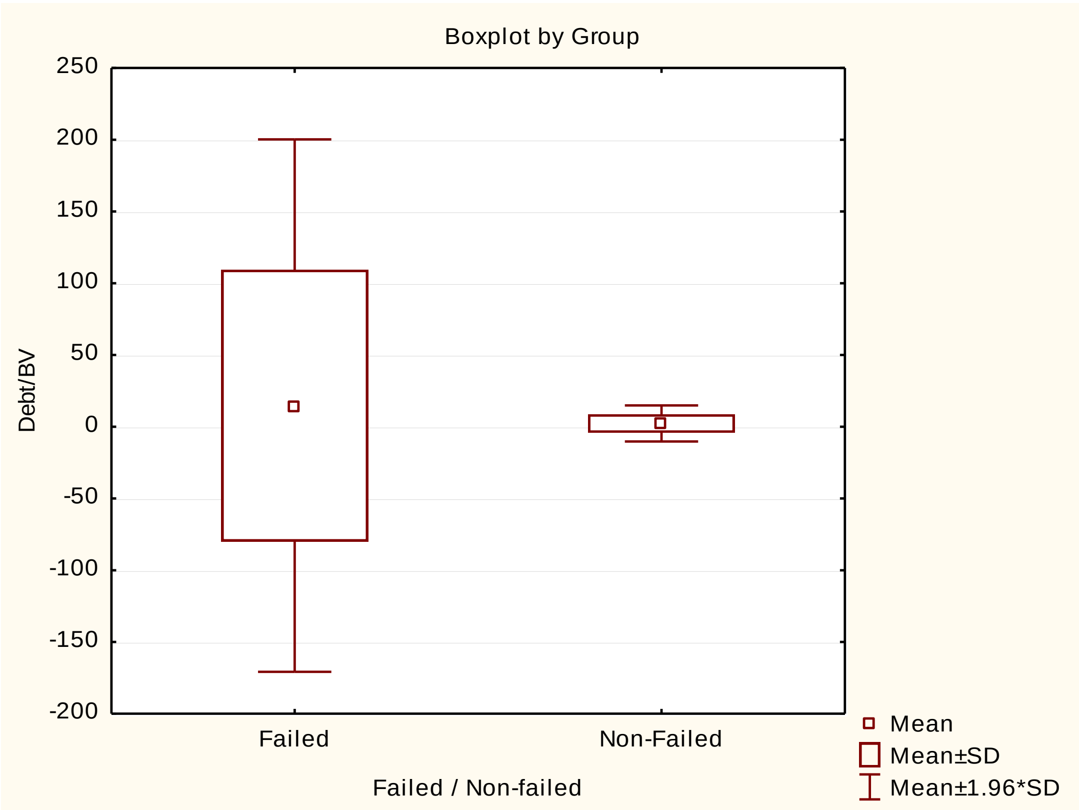
Boxplot by Group
EBIT/Int
5000
4000
3000
2000
1000
0
-1000
-2000
-3000
-4000
-5000
Failed
Non-Failed
Failed / Non-failed
Mean
Mean±SD
Mean±1.96*SD


Boxplot by Group
FCF/Debt
12
10
8
6
4
2
0
-2
-4
-6
-8
-10
-12
Failed
Non-Failed
Failed / Non-failed
Mean
Mean±SD
Mean±1.96*SD

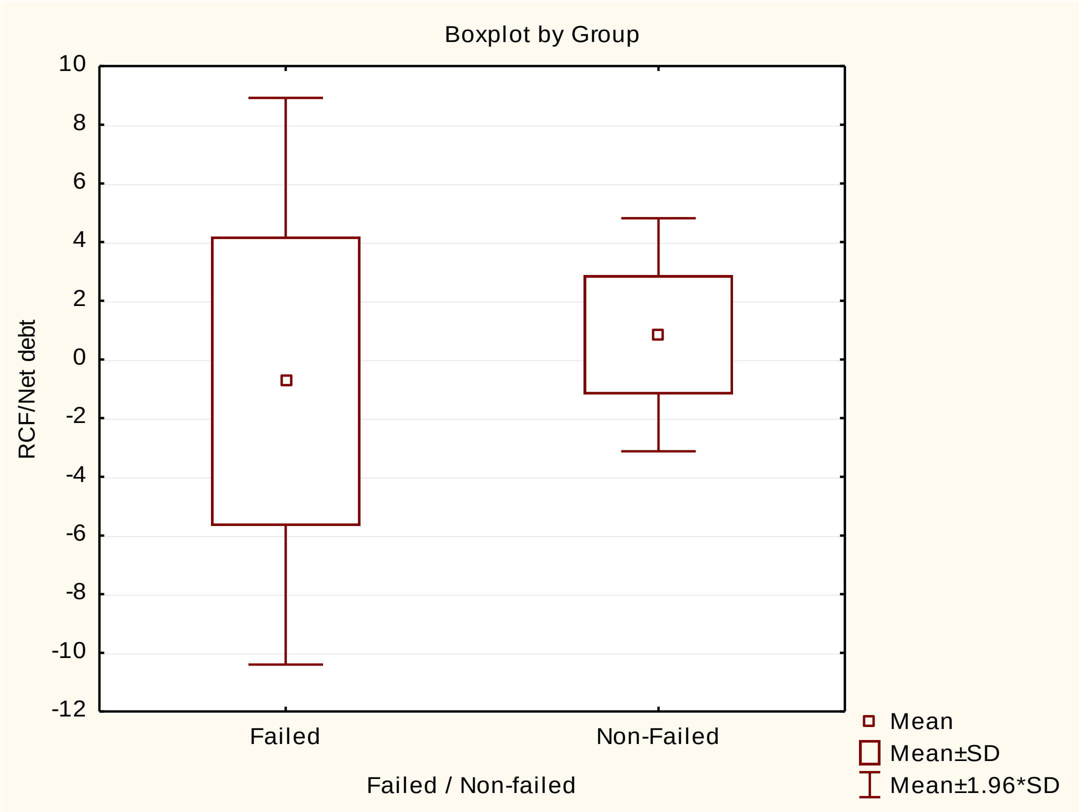

Boxplot by Group
RCF/Debt
16
14
12
10
8
6
4
2
0
-2
-4
-6
-8
-10
-12
Failed
Non-Failed
Failed / Non-failed
Mean
Mean±SD
Mean±1.96*SD



Boxplot by Group
16
14
12
10
8
6
4
2
0
-2
-4
-6
-8
-10
-12
-14
FFO/Debt
Failed
Non-Failed
Failed / Non-failed
Mean
Mean±SD
Mean±1.96*SD

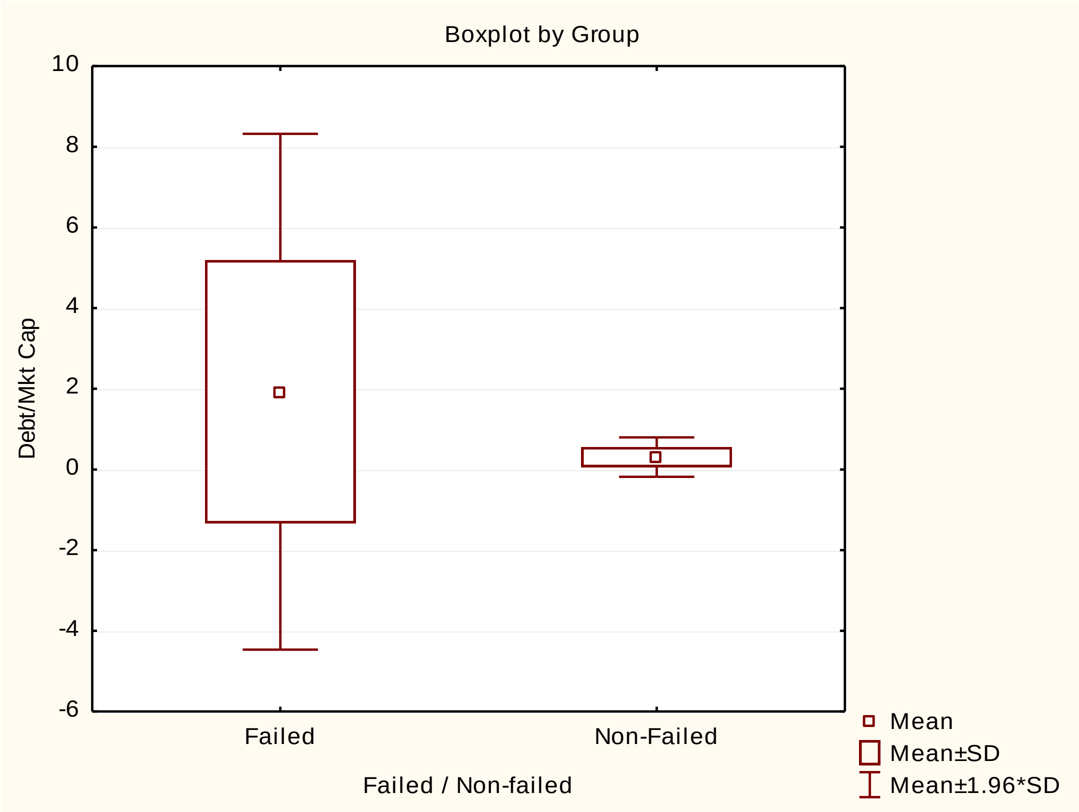


Boxplot by Group
250
200
150
100
50
0
-50
-100
-150
-200
Debt/BV
Failed
Non-Failed
Failed / Non-failed
Mean
Mean±SD
Mean±1.96*SD



Boxplot by Group
RCF/Net debt
10
8
6
4
2
0
-2
-4
-6
-8
-10
-12
Failed
Non-Failed
Failed / Non-failed
Mean
Mean±SD
Mean±1.96*SD

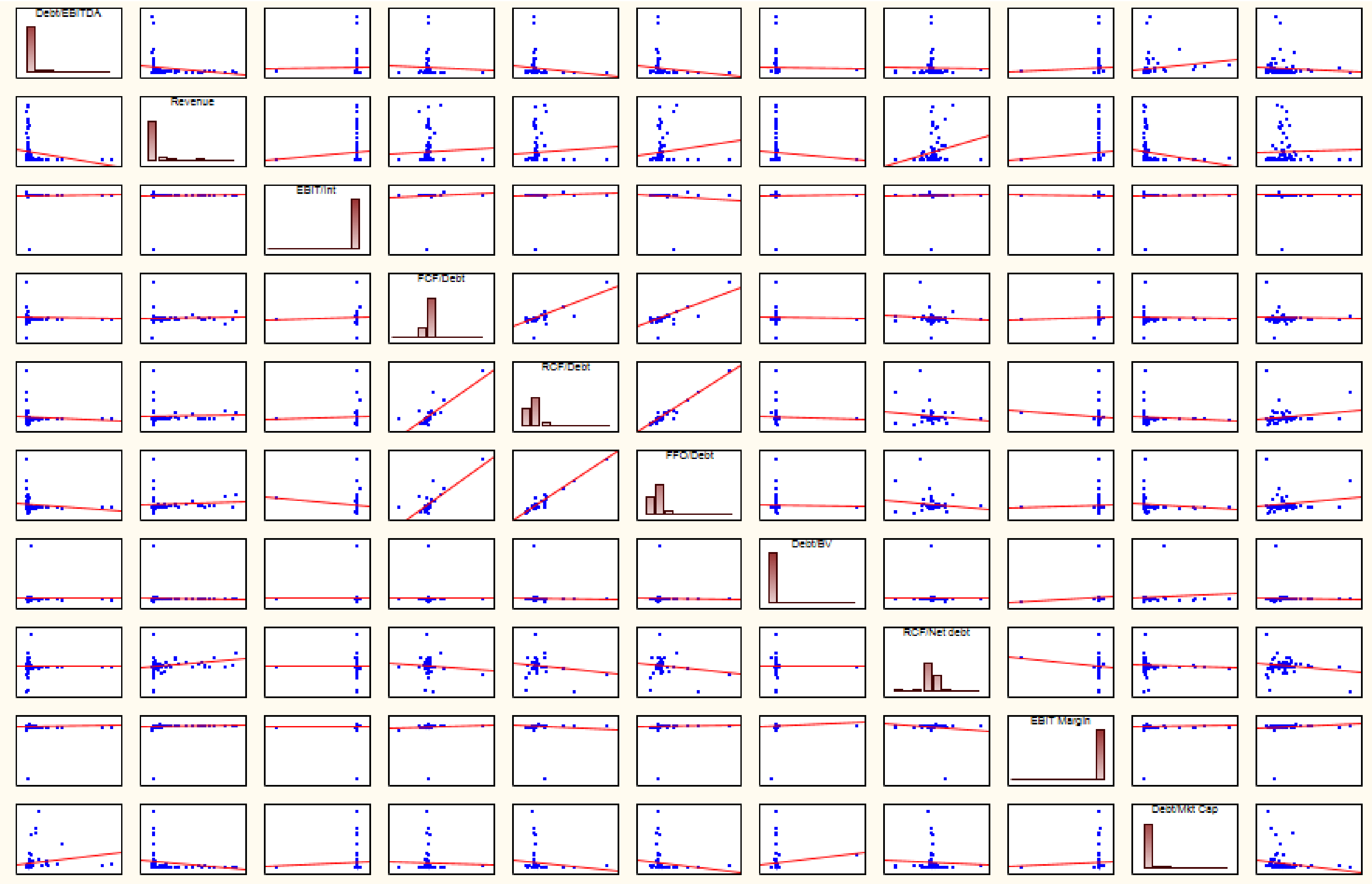
Boxplot by Group
EBIT Margin
40
30
20
10
0
-10
-20
-30
-40
-50
Failed
Non-Failed
Failed / Non-failed
Mean
Mean±SD
Mean±1.96*SD

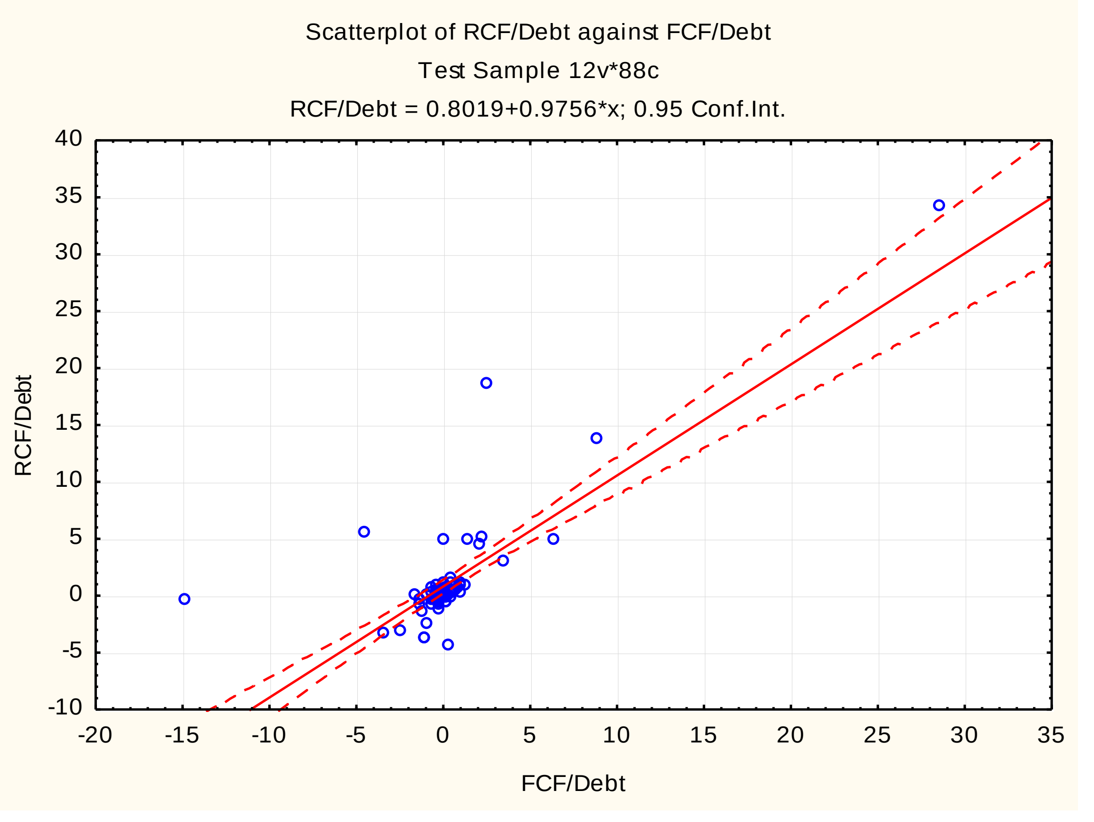


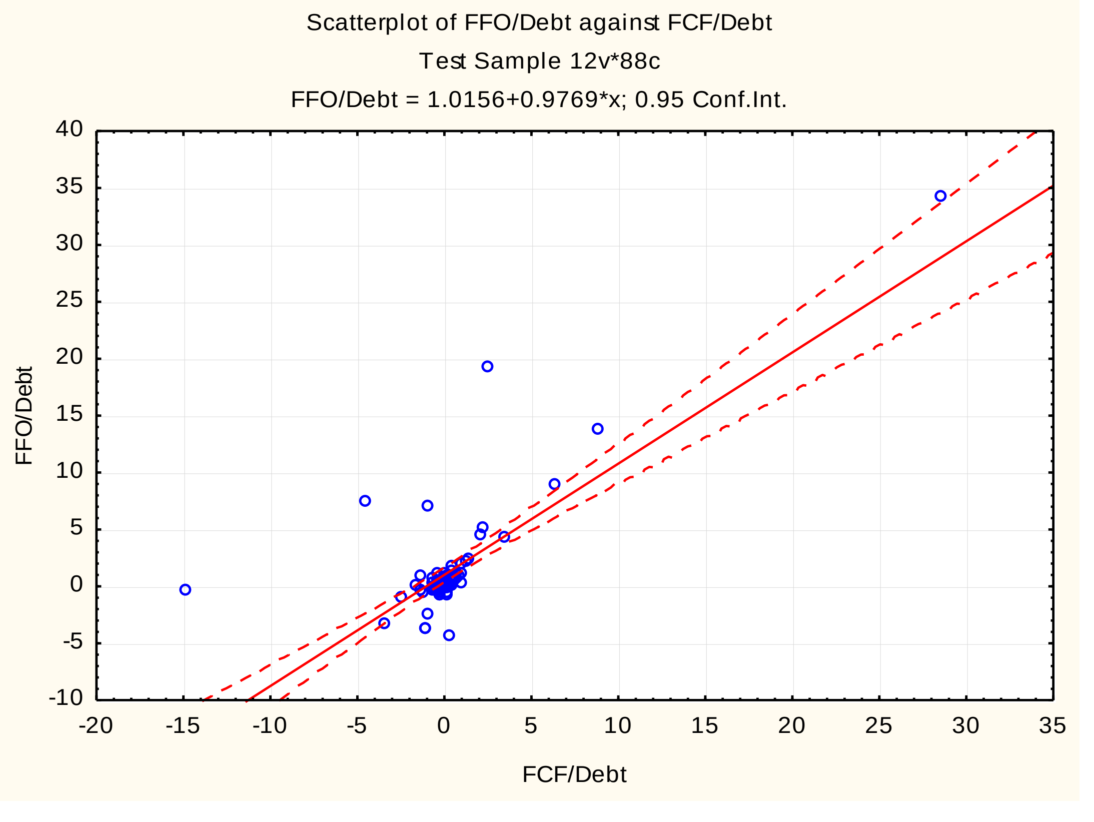
Boxplot by Group
Debt/Mkt Cap
10
8
6
4
2
0
-2
-4
-6
Failed
Non-Failed
Failed / Non-failed
Mean
Mean±SD
Mean±1.96*SD

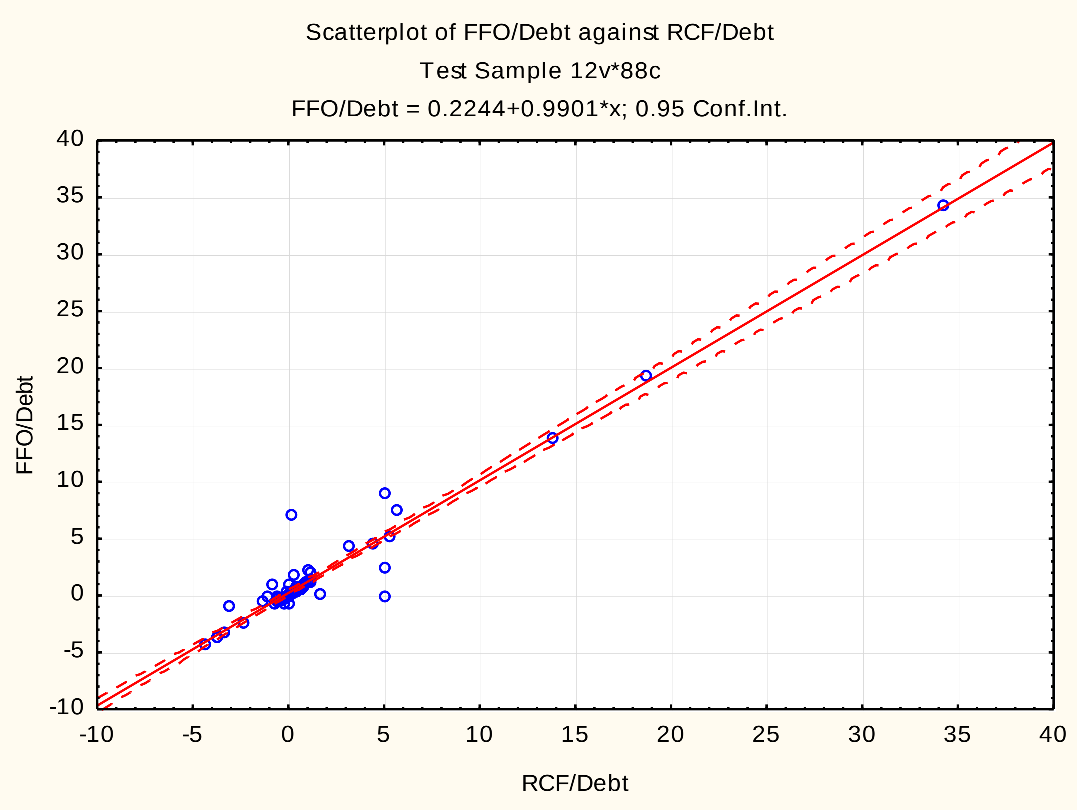
Appendix G

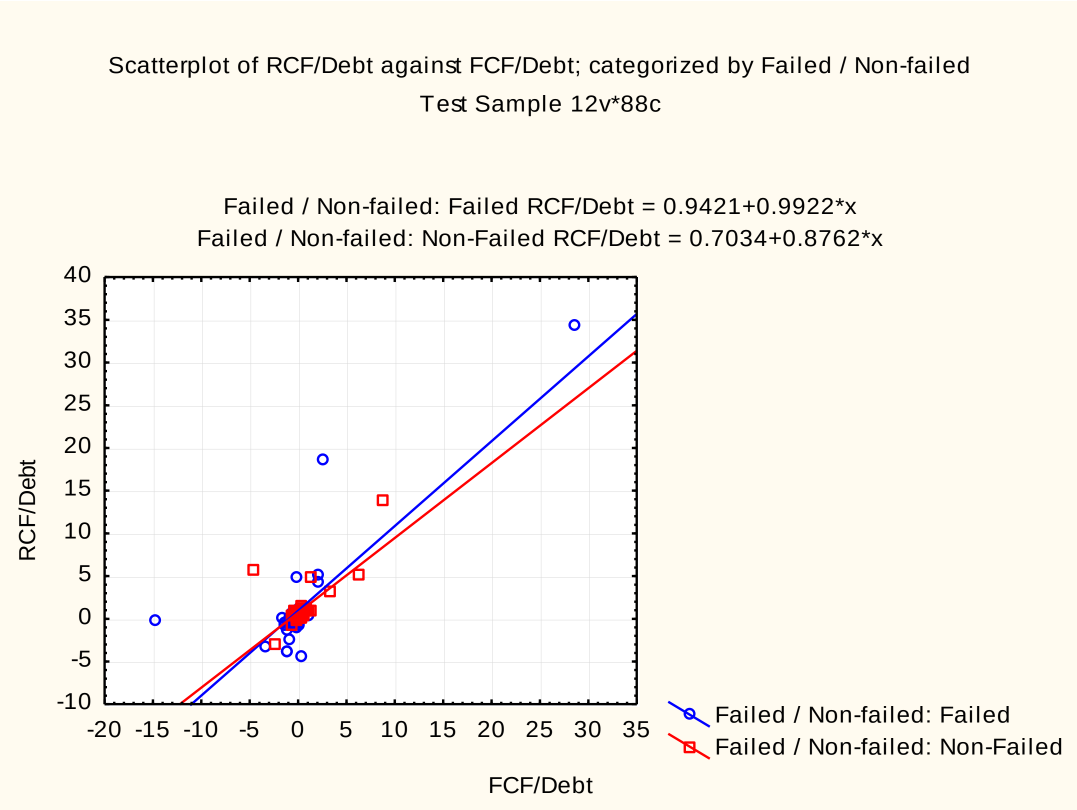
Scatter plot of correlations between sample of independent credit statistic variables

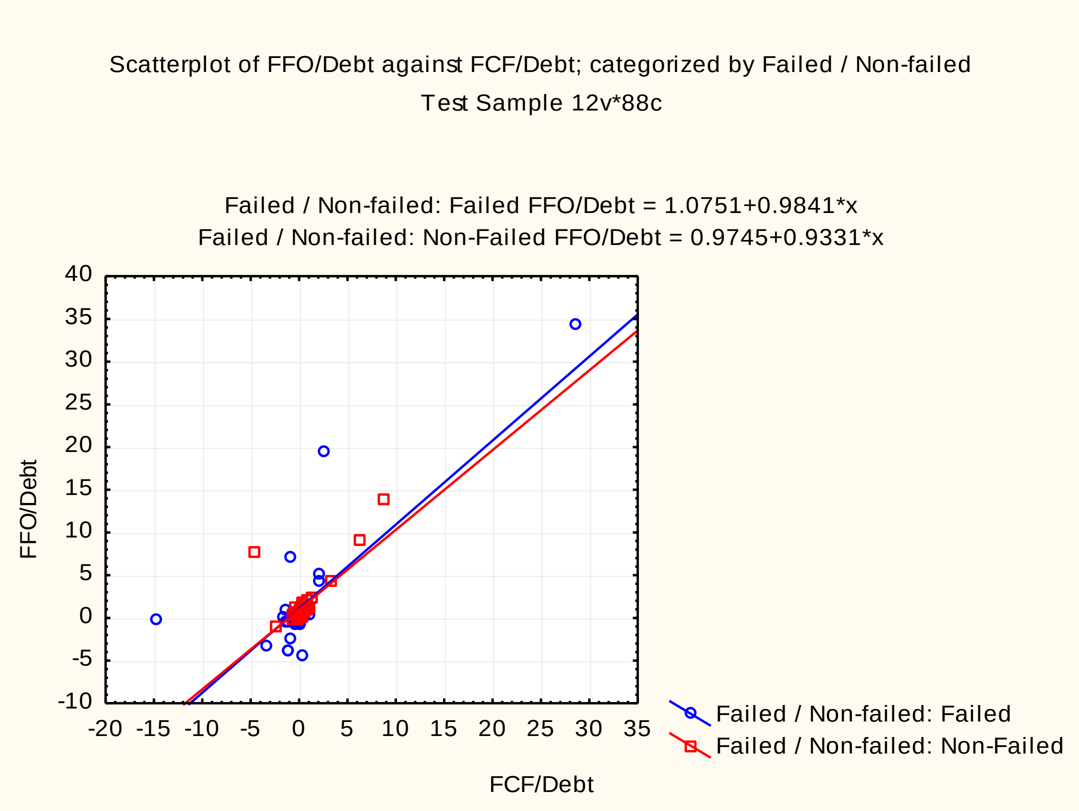


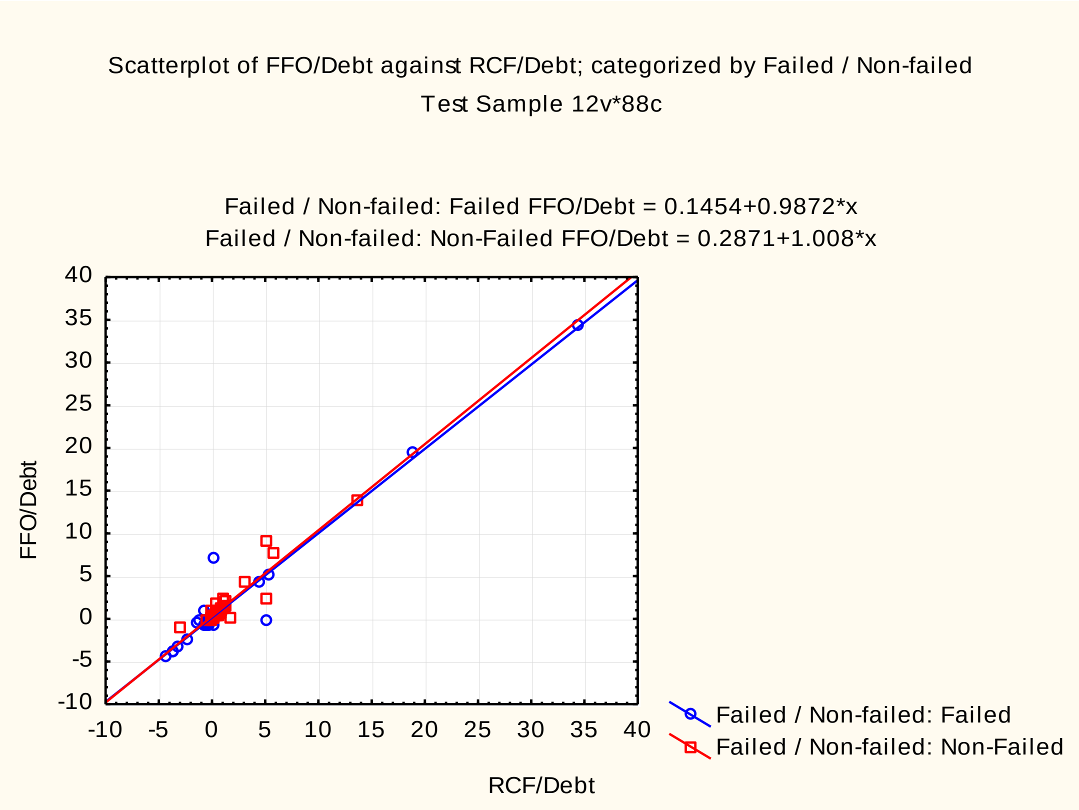

Scatterplot of RCF/Debt against FCF/Debt
Test Sample 12v*88c
RCF/Debt = 0.8019+0.9756*x; 0.95 Conf.Int.
RCF/Debt
FCF/Debt
40
35
30
25
20
15
10
5
0
-5
-10
-20
-15
-10
-5
0
5
10
15
20
25
30
35


Scatterplot of FFO/Debt against FCF/Debt
Test Sample 12v*88c
FFO/Debt = 1.0156+0.9769*x; 0.95 Conf.Int.
FFO/Debt
FCF/Debt
40
35
30
25
20
15
10
5
0
-5
-10
-20
-15
-10
-5
0
5
10
15
20
25
30
35


Scatterplot of FFO/Debt against RCF/Debt
Test Sample 12v*88c
FFO/Debt = 0.2244+0.9901*x; 0.95 Conf.Int.
FFO/Debt
RCF/Debt
40
35
30
25
20
15
10
5
0
-5
-10
-10
-5
0
5
10
15
20
25
30
35
40


Scatterplot of RCF/Debt against FCF/Debt; categorized by Failed / Non-failed
Test Sample 12v*88c
Failed / Non-failed: Failed RCF/Debt = 0.9421+0.9922*x
Failed / Non-failed: Non-Failed RCF/Debt = 0.7034+0.8762*x
RCF/Debt
FCF/Debt
40
35
30
25
20
15
10
5
0
-5
-10
-20
-15
-10
-5
0
5
10
15
20
25
30
35
Failed / Non-failed: Failed
Failed / Non-failed: Non-Failed


Scatterplot of FFO/Debt against FCF/Debt; categorized by Failed / Non-failed
Test Sample 12v*88c
Failed / Non-failed: Failed FFO/Debt = 1.0751+0.9841*x
Failed / Non-failed: Non-Failed FFO/Debt = 0.9745+0.9331*x
FFO/Debt
40 35 30 25 20 15 10 5 0 -5 -10
-20 -15 -10 -5 0 5 10 15 20 25 30 35
FCF/Debt
Failed / Non-failed: Failed
Failed / Non-failed: Non-Failed


Scatterplot of FFO/Debt against RCF/Debt; categorized by Failed / Non-failed
Test Sample 12v*88c
Failed / Non-failed: Failed FFO/Debt = 0.1454+0.9872*x
Failed / Non-failed: Non-Failed FFO/Debt = 0.2871+1.008*x
FFO/Debt
40 35 30 25 20 15 10 5 0 -5 -10
-10 -5 0 5 10 15 20 25 30 35 40
RCF/Debt
Failed / Non-failed: Failed
Failed / Non-failed: Non-Failed

Appendix H

Classification function table

Variable	Classification Functions; grouping: Failed / Non-failed (Test Sample)	
	Failed p=.50000	**Non-Failed p=.50000**
Revenue	0.00017	0.00095
Debt/Mkt Cap	0.36365	0.08043
Debt/EBITDA	0.06295	0.01387
1 Year Equity Price Return	-0.38248	0.30905
RCF/Net debt	-0.11446	0.02200
EBIT Margin	-0.03113	-0.00145
EBIT/Int	-0.00024	-0.00000
Constant	-1.51559	-1.34767

Appendix I

Classification of cases

Case	Classification of Cases (Test Sample) Incorrect classifications are marked with *		
	Observed Classif.	1 p=.50000	2 p=.50000
1	Failed	Failed	Non-Failed
2	Non-Failed	Non-Failed	Failed
3	Failed	Failed	Non-Failed
4	Non-Failed	Non-Failed	Failed
5	Failed	Failed	Non-Failed
6	Non-Failed	Non-Failed	Failed
7	Failed	Failed	Non-Failed
* 8	Non-Failed	Failed	Non-Failed
* 9	Failed	Non-Failed	Failed
10	Non-Failed	Non-Failed	Failed
11	Failed	Failed	Non-Failed
12	Non-Failed	Non-Failed	Failed
13	Failed	Failed	Non-Failed
* 14	Non-Failed	Failed	Non-Failed
15	Failed	Failed	Non-Failed
16	Non-Failed	Non-Failed	Failed
17	Failed	Failed	Non-Failed
18	Non-Failed	Non-Failed	Failed
19	Failed	Failed	Non-Failed
* 20	Non-Failed	Failed	Non-Failed
21	Failed	Failed	Non-Failed
22	Non-Failed	Non-Failed	Failed
23	Failed	Failed	Non-Failed
24	Non-Failed	Non-Failed	Failed
* 25	Failed	Non-Failed	Failed
26	Non-Failed	Non-Failed	Failed
27	Failed	Failed	Non-Failed
28	Non-Failed	Non-Failed	Failed
29	Failed	Failed	Non-Failed
30	Non-Failed	Non-Failed	Failed
31	Failed	Failed	Non-Failed
32	Non-Failed	Non-Failed	Failed
33	Failed	Failed	Non-Failed
34	Non-Failed	Non-Failed	Failed
35	Failed	Failed	Non-Failed
36	Non-Failed	Non-Failed	Failed
37	Failed	Failed	Non-Failed

Case	Classification of Cases (Test Sample) Incorrect classifications are marked with *		
	Observed Classif.	1 p=.50000	2 p=.50000
38	Non-Failed	Non-Failed	Failed
39	Failed	Failed	Non-Failed
40	Non-Failed	Non-Failed	Failed
41	Failed	Failed	Non-Failed
42	Non-Failed	Non-Failed	Failed
43	Failed	Failed	Non-Failed
44	Non-Failed	Non-Failed	Failed
45	Failed	Failed	Non-Failed
46	Non-Failed	Non-Failed	Failed
* 47	Failed	Non-Failed	Failed
48	Non-Failed	Non-Failed	Failed
* 49	Failed	Non-Failed	Failed
50	Non-Failed	Non-Failed	Failed
* 51	Failed	Non-Failed	Failed
52	Non-Failed	Non-Failed	Failed
53	Failed	Failed	Non-Failed
54	Non-Failed	Non-Failed	Failed
55	Failed	Failed	Non-Failed
56	Non-Failed	Non-Failed	Failed
57	Failed	Failed	Non-Failed
58	Non-Failed	Non-Failed	Failed
59	Failed	Failed	Non-Failed
60	Non-Failed	Non-Failed	Failed
* 61	Failed	Non-Failed	Failed
62	Non-Failed	Non-Failed	Failed
63	Failed	Failed	Non-Failed
64	Non-Failed	Non-Failed	Failed
65	Failed	Failed	Non-Failed
66	Non-Failed	Non-Failed	Failed
* 67	Failed	Non-Failed	Failed
68	Non-Failed	Non-Failed	Failed
69	Failed	Failed	Non-Failed
* 70	Non-Failed	Failed	Non-Failed
71	Failed	Failed	Non-Failed
* 72	Non-Failed	Failed	Non-Failed
73	Failed	Failed	Non-Failed
74	Non-Failed	Non-Failed	Failed
75	Failed	Failed	Non-Failed
76	Non-Failed	Non-Failed	Failed

Case	Classification of Cases (Test Sample) Incorrect classifications are marked with *		
	Observed Classif.	**1 p=.50000**	**2 p=.50000**
77	Failed	Failed	Non-Failed
*** 78**	Non-Failed	Failed	Non-Failed
79	Failed	Failed	Non-Failed
80	Non-Failed	Non-Failed	Failed
*** 81**	Failed	Non-Failed	Failed
82	Non-Failed	Non-Failed	Failed
83	Failed	Failed	Non-Failed
84	Non-Failed	Non-Failed	Failed
85	Failed	Failed	Non-Failed
86	Non-Failed	Non-Failed	Failed
*** 87**	Failed	Non-Failed	Failed
88	Non-Failed	Non-Failed	Failed

Appendix J

Mahalanobis distances and posterior probabilities

Case	Squared Mahalanobis Distances from Group Centroids (Test Sample) Incorrect classifications are marked with *		
	Observed Classif.	**Failed p=.50000**	**Non-Failed p=.50000**
1	Failed	0.73770	2.95651
2	Non-Failed	2.08718	0.56479
3	Failed	1.66366	2.69523
4	Non-Failed	1.45986	1.07822
5	Failed	15.02395	20.05675
6	Non-Failed	1.95475	1.84628
7	Failed	1.04711	1.47162
*** 8**	Non-Failed	1.65696	1.66706
*** 9**	Failed	23.50103	19.78477
10	Non-Failed	4.13410	1.66406
11	Failed	12.03440	17.11728
12	Non-Failed	2.54635	0.89561
13	Failed	1.98507	2.60353
*** 14**	Non-Failed	1.85006	2.49603
15	Failed	1.18206	2.49312
16	Non-Failed	5.60821	0.88078
17	Failed	28.94421	36.56746
18	Non-Failed	1.21347	1.13782
19	Failed	0.96103	3.68839
*** 20**	Non-Failed	0.86709	1.32029
21	Failed	37.65398	46.81110
22	Non-Failed	2.06980	2.04404
23	Failed	83.78095	90.56142
24	Non-Failed	15.26980	6.96405
*** 25**	Failed	4.18816	3.52307
26	Non-Failed	7.54019	2.56086
27	Failed	4.30316	6.74557
28	Non-Failed	21.91376	13.33150
29	Failed	1.13171	3.87984
30	Non-Failed	10.13336	4.17086
31	Failed	1.38325	1.95875
32	Non-Failed	2.86824	1.37190
33	Failed	1.13622	4.70005
34	Non-Failed	2.38606	0.15119
35	Failed	1.13546	2.29897

Case	Squared Mahalanobis Distances from Group Centroids (Test Sample) Incorrect classifications are marked with *		
	Observed Classif.	Failed p=.50000	Non-Failed p=.50000
36	Non-Failed	1.14975	0.28300
37	Failed	0.47033	1.96521
38	Non-Failed	1.27771	0.47988
39	Failed	2.29143	3.63170
40	Non-Failed	2.09873	0.63903
41	Failed	1.73247	4.32569
42	Non-Failed	1.89319	0.87238
43	Failed	9.59267	15.21566
44	Non-Failed	5.08790	3.15499
45	Failed	5.13876	8.10401
46	Non-Failed	9.01683	3.99036
* 47	Failed	0.93679	0.60693
48	Non-Failed	1.99483	0.90134
* 49	Failed	3.31857	1.77363
50	Non-Failed	7.42431	5.38842
* 51	Failed	29.52656	26.18622
52	Non-Failed	1.40191	1.06076
53	Failed	1.10610	3.12382
54	Non-Failed	1.51883	1.06395
55	Failed	0.93560	2.97826
56	Non-Failed	2.49869	0.39656
57	Failed	1.45088	2.57922
58	Non-Failed	11.13921	5.22209
59	Failed	33.47353	44.39691
60	Non-Failed	4.08301	1.37644
* 61	Failed	37.95055	36.19848
62	Non-Failed	6.07251	3.75916
63	Failed	0.77150	1.30156
64	Non-Failed	1.35148	0.28999
65	Failed	15.02395	20.05675
66	Non-Failed	18.15278	10.08812
* 67	Failed	1.39587	1.36463
68	Non-Failed	1.42718	1.26017
69	Failed	0.86421	3.01363
* 70	Non-Failed	0.90095	1.25431
71	Failed	7.59523	14.49842
* 72	Non-Failed	1.12243	1.85092
73	Failed	14.79354	22.36772
74	Non-Failed	1.02167	0.93711

Case	Squared Mahalanobis Distances from Group Centroids (Test Sample) Incorrect classifications are marked with *		
	Observed Classif.	Failed p=.50000	Non-Failed p=.50000
75	Failed	1.76698	2.52720
76	Non-Failed	6.09338	1.68798
77	Failed	0.62523	2.34011
* 78	Non-Failed	1.35704	2.84170
79	Failed	0.65157	3.86207
80	Non-Failed	26.36901	15.58249
* 81	Failed	1.79775	0.46595
82	Non-Failed	8.89232	3.20608
83	Failed	83.53243	90.46166
84	Non-Failed	6.09476	1.70742
85	Failed	3.73571	6.07410
86	Non-Failed	3.92560	1.92946
* 87	Failed	3.32649	0.22466
88	Non-Failed	1.43677	1.03277

Case	Posterior Probabilities (Test Sample) Incorrect classifications are marked with *		
	Observed Classif.	Failed p=.50000	Non-Failed p=.50000
1	Failed	0.752019	0.247981
2	Non-Failed	0.318387	0.681613
3	Failed	0.626161	0.373839
4	Non-Failed	0.452439	0.547561
5	Failed	0.925284	0.074716
6	Non-Failed	0.486445	0.513555
7	Failed	0.552865	0.447135
* 8	Non-Failed	0.501261	0.498739
* 9	Failed	0.134921	0.865079
10	Non-Failed	0.225305	0.774695
11	Failed	0.926996	0.073004
12	Non-Failed	0.304625	0.695375
13	Failed	0.576697	0.423303
* 14	Non-Failed	0.580051	0.419949
15	Failed	0.658256	0.341744
16	Non-Failed	0.085982	0.914018
17	Failed	0.978366	0.021634
18	Non-Failed	0.490545	0.509455
19	Failed	0.796357	0.203643
* 20	Non-Failed	0.556408	0.443592

Case	Posterior Probabilities (Test Sample) Incorrect classifications are marked with *		
	Observed Classif.	Failed p=.50000	Non-Failed p=.50000
21	Failed	0.989835	0.010165
22	Non-Failed	0.496780	0.503220
23	Failed	0.967398	0.032602
24	Non-Failed	0.015476	0.984524
* 25	Failed	0.417621	0.582379
26	Non-Failed	0.076586	0.923414
27	Failed	0.772275	0.227725
28	Non-Failed	0.013505	0.986495
29	Failed	0.798036	0.201964
30	Non-Failed	0.048280	0.951720
31	Failed	0.571445	0.428555
32	Non-Failed	0.321221	0.678779
33	Failed	0.855933	0.144067
34	Non-Failed	0.246488	0.753512
35	Failed	0.641471	0.358529
36	Non-Failed	0.393321	0.606679
37	Failed	0.678620	0.321380
38	Non-Failed	0.401574	0.598426
39	Failed	0.661533	0.338467
40	Non-Failed	0.325228	0.674772
41	Failed	0.785265	0.214735
42	Non-Failed	0.375098	0.624902
43	Failed	0.943294	0.056706
44	Non-Failed	0.275588	0.724412
45	Failed	0.814969	0.185031
46	Non-Failed	0.074935	0.925065
* 47	Failed	0.458861	0.541139
48	Non-Failed	0.366619	0.633381
* 49	Failed	0.315945	0.684055
50	Non-Failed	0.265427	0.734573
* 51	Failed	0.158402	0.841598
52	Non-Failed	0.457459	0.542541
53	Failed	0.732797	0.267203
54	Non-Failed	0.443384	0.556616
55	Failed	0.735231	0.264769
56	Non-Failed	0.259021	0.740979
57	Failed	0.637416	0.362584
58	Non-Failed	0.049333	0.950667
59	Failed	0.995772	0.004228

Case	Posterior Probabilities (Test Sample) Incorrect classifications are marked with *		
	Observed Classif.	Failed p=.50000	Non-Failed p=.50000
60	Non-Failed	0.205334	0.794666
* 61	Failed	0.294000	0.706000
62	Non-Failed	0.239272	0.760728
63	Failed	0.565872	0.434128
64	Non-Failed	0.370343	0.629657
65	Failed	0.925284	0.074716
66	Non-Failed	0.017424	0.982576
* 67	Failed	0.496094	0.503906
68	Non-Failed	0.479137	0.520863
69	Failed	0.745492	0.254508
* 70	Non-Failed	0.544055	0.455945
71	Failed	0.969279	0.030721
* 72	Non-Failed	0.590069	0.409931
73	Failed	0.977841	0.022159
74	Non-Failed	0.489432	0.510568
75	Failed	0.593900	0.406100
76	Non-Failed	0.099508	0.900492
77	Failed	0.702126	0.297874
* 78	Non-Failed	0.677505	0.322495
79	Failed	0.832751	0.167249
80	Non-Failed	0.004527	0.995473
* 81	Failed	0.339415	0.660585
82	Non-Failed	0.055038	0.944962
83	Failed	0.969664	0.030336
84	Non-Failed	0.100320	0.899680
85	Failed	0.762999	0.237001
86	Non-Failed	0.269321	0.730679
* 87	Failed	0.174954	0.825046
88	Non-Failed	0.449670	0.550330

Appendix K

Illustrative Example- Initial Model

$$Z = 0.000504(X_1) - 0.18426(X_2) - 0.03193(X_3) + 0.449887(X_4) + 0.088777(X_5) + 0.019311(X_6) + 0.000151(X_7) + 0.109247$$

		X1	X2	X3	X4	X5	X6	X7	C		Percentage Misclassified	0.170454545
		0.000504	-0.18426	-0.03193	0.449887	0.088777	0.019311	0.000151	0.109247		Classification Rate	0.829545455
Company	**Failed / Non-failed**	**Revenue**	**Debt/Mkt Cap**	**Debt/EBITDA**	**1 Year Equity Price Return**	**RCF/Net debt**	**EBIT Margin**	**EBIT/Int**	**Constant**	**Z Score**	**Classification**	**Correctly Classified**
1Time Holdings Ltd	Failed	177.0622526	1.792883	5.858986701	-0.714433983	-0.890629639	-0.08823074	-4.47235098		-0.722	Failed	Yes
Comair Ltd	Non-Failed	512.2378854	0.299977	1.504660862	0.286976028	1.133898367	0.032826108	3.340575805		0.495	Non-Failed	Yes
Afgem Ltd	Failed	0.136546166	0.015707	0.030797246	-0.572152696	-0.310426268	-7.84776463	-29.6357692		-0.336	Failed	Yes
Trans Hex Group Ltd	Non-Failed	146.9972194	0.077827	0.162054275	0.027442781	-0.615190356	0.067884971	8.081369957		0.1241	Non-Failed	Yes
Africa Cellular Towers Ltd	Failed	27.93338972	0.745188	1.205941234	-0.808828563	-13.61402245	-0.48458856	-18.3018887		-1.637	Failed	Yes
Raubex Group Ltd	Non-Failed	628.2372133	0.134296	0.684472084	-0.049184604	-3.685151109	0.144049438	14.92524217		0.035	Non-Failed	Yes
African Brick Centre Ltd	Failed	11.55278238	0.65489	0.171594324	-0.168564439	-0.531665184	-0.15485298	-6.52631176		-0.138	Failed	Yes
Mazor Group Ltd	Non-Failed	25.81085466	0.053108	0.046138024	-0.337272351	0.472952191	-0.04478774	-24.3342691		-0.003	Failed	No
AG Industries Ltd	Failed	85.9393507	0.651062	5.9727383	3.095531692	-0.246496836	-0.16999123	-3.59462613		1.2088	Non-Failed	No
KAP Industrial Holdings Ltd	Non-Failed	523.0132185	0.439692	2.535804549	0.708842969	1.6397	6.6	3.166666667		0.8033	Non-Failed	Yes
Aludie Ltd	Failed	1.729719429	9.212484	8.090299441	0.489379899	-0.243551049	-0.1124442	-26.8666667		-1.653	Failed	Yes
ADCORP Holdings	Non-Failed	341.7052946	0.055452	0.129886248	0.302887537	1.456943108	0.039258586	22.20005196		0.5368	Non-Failed	Yes
Beget Holdings Ltd	Failed	4.631155873	0.490087	0.685292907	-0.703170633	1.245453263	0.218896404	6.490458601		-0.201	Failed	Yes
Mix Telematics	Non-Failed	108.3040779	0.811065	1.212862587	-0.732479089	1.578928319	0.143221391	5.091118201		-0.21	Failed	No
Best Cut Ltd	Failed	8.124357506	0.613945	3.833227647	-0.642230316	-0.138197508	-0.14394673	-2.03982985		-0.426	Failed	Yes
Tiger Brands	Non-Failed	2262.870106	0.036089	0.625905673	0.196759039	2.491831492	0.152209453	7.127435251		1.5369	Non-Failed	Yes

$$Z = 0.000504(X_1) - 0.18426(X_2) - 0.03193(X_3) + 0.449887(X_4) + 0.088777(X_5) + 0.019311(X_6) + 0.000151(X_7) + 0.109247$$

		X1	**X2**	**X3**	**X4**	**X5**	**X6**	**X7**	**C**		**Percentage Misclassified**	0.170454545
		0.000504	**-0.18426**	**-0.03193**	**0.449887**	**0.088777**	**0.019311**	**0.000151**	**0.109247**		**Classification Rate**	0.829545455
Company	**Failed / Non-failed**	**Revenue**	**Debt/Mkt Cap**	**Debt/EBITDA**	**1 Year Equity Price Return**	**RCF/Net debt**	**EBIT Margin**	**EBIT/Int**	**Constant**	**Z Score**	**Classification**	**Correctly Classified**
Bioscience Brands Ltd	Failed	3.151446275	0.495725	74.49496658	-0.171119457	-0.408132863	-0.31339444	-7.85071386		-2.48	Failed	Yes
Ascendis Health	Non-Failed	43.46430319	0.2996	3.027	0.108	-0.040245232	0.013819987	0.112389846		0.0246	Non-Failed	Yes
Brikor Ltd	Failed	26.71257314	3.59759	3.923455873	-0.484635822	-0.076400358	0.149087171	1.422619301		-0.887	Failed	Yes
Insimbi Refractory and Alloy	Non-Failed	98.8868406	0.57421	3.89909349	-0.245838045	0.378382342	0.020259201	2.521562735		-0.147	Failed	No
CCI Holdings Ltd	Failed	0.963484579	1.005079	84.09756098	-0.453454886	-0.135998711	-0.08440403	-0.7		-2.979	Failed	Yes
Adaptit Holdings	Non-Failed	2.918972531	0.03216	0.085049828	-0.31378802	-0.760915938	0.231133509	731.5443529		0.0083	Non-Failed	Yes
Dialogue Group Holdings Ltd	Failed	40.8849755	0.138159	2.93963854	-0.091654163	-0.313319792	-0.19248927	-14182		-2.204	Failed	Yes
Datatect LTD	Non-Failed	4191.671042	0.16921	1.202043033	0.18	5.243748142	0.02112642	5.636296186		2.7001	Non-Failed	Yes
Dorbyl Ltd	Failed	19.26319005	0.170834	2.770042704	-0.517099602	5.297453424	-0.56439032	-62.4962963		0.2164	Non-Failed	No
Allied Electronics	Non-Failed	3137.027841	0.601335	0.48018648	-0.152275057	1.352117007	0.064445116	9.846666667		1.6184	Non-Failed	Yes
JCI Ltd	Failed	0.32400507	0.866531	29.79695844	0.55162591	-0.397166313	-0.181	-14.3135788		-0.794	Failed	Yes
Anglogold Ashanti	Non-Failed	5497.000132	0.142287	1.654582042	-0.109964694	0.390858232	0.160269238	3.069686411		2.7895	Non-Failed	Yes
Millionair Charter Ltd	Failed	9.411012246	3.862169	2.949317625	-0.384693909	-0.261162021	-0.27318788	-3.8045858		-0.894	Failed	Yes
Imperial Holdings	Non-Failed	3566.571479	0.560136	2.091811414	0.342080977	0.51605911	0.059051337	2.853293413		1.9381	Non-Failed	Yes
Pals Holdings Ltd	Failed	9.334294695	0.033545	0.91473969	-0.321683077	-1.340633765	-0.06748895	-4.8		-0.187	Failed	Yes
Avi LTD	Non-Failed	812.7145724	0.075443	0.311928105	0.56542987	-3.016679455	0.129069191	15.57319588		0.4864	Non-Failed	Yes
Pinnacle Point Group Ltd	Failed	19.65691686	1.698946	19.56440175	-0.625657194	-0.471186586	-0.87431014	-3.0279516		-1.159	Failed	Yes
Group Five LTD	Non-Failed	1252.522495	0.264191	1.329204507	0.248785723	-0.427209722	0.063249386	12.23559505		0.7265	Non-Failed	Yes

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		X1	**X2**	**X3**	**X4**	**X5**	**X6**	**X7**	**C**		**Percentage Misclassified**	0.170454545
		0.000504	**-0.18426**	**-0.03193**	**0.449887**	**0.088777**	**0.019311**	**0.000151**	**0.109247**		**Classification Rate**	0.829545455
Company	**Failed / Non-failed**	**Revenue**	**Debt/Mkt Cap**	**Debt/EBITDA**	**1 Year Equity Price Return**	**RCF/Net debt**	**EBIT Margin**	**EBIT/Int**	**Constant**	**Z Score**	**Classification**	**Correctly Classified**
Queensgate Hotel & Leisure Ltd	Failed	13.33569636	0.357454	5.939519425	-0.566914736	0.151911667	0.122530177	1.813625285		-0.378	Failed	Yes
Sun International	Non-Failed	891.3503528	0.945756	2.489288447	-0.099530172	0.184005343	0.243253327	3.896414343		0.2816	Non-Failed	Yes
Sea Kay Holdings Ltd	Failed	26.59679195	1.984886	2.307582292	-0.246122829	-0.60299588	-0.24043138	-3.99082242		-0.486	Failed	Yes
Distribution & W	Non-Failed	541.4889883	0.345772	1.527502297	-0.063416422	0.198706921	0.019388388	0.978352847		0.2593	Non-Failed	Yes
Shawcell Telecommunications Ltd	Failed	10.29587376	0.017164	0.292123063	-0.609321319	-3.095362124	0.473165006	12.3442285		-0.436	Failed	Yes
MTN Group Ltd	Non-Failed	1138.116496	0.144818	1.563312677	-0.452411507	0.756758627	0.185155866	5.834089191		0.4744	Non-Failed	Yes
Stocks Hotels & Resorts Ltd	Failed	17.16794071	0.427661	20.61437908	-0.511289201	0.073462917	-0.04255969	-0.42898292		-0.844	Failed	Yes
Tsogo Sun Holding	Non-Failed	225.66	0.11	0.8456	0.175	0.7643	0.4	12.8849		0.332	Non-Failed	Yes
Terexko Ltd	Failed	4.132878101	8.918416	3.856973294	-0.447308419	0.336193198	-0.09355115	-4.9772404		-1.829	Failed	Yes
Famous Brands LT	Non-Failed	29.19509042	0.387013	1.090992577	0.975274998	1.907063483	0.084209878	8.111477573		0.6287	Non-Failed	Yes
Terrafin Holdings Ltd	Failed	9.488016276	0.439713	0.213200935	-0.91240374	-6.509084389	-0.01432942	-14.1884058		-0.965	Failed	Yes
Barloworld LTD	Non-Failed	3509.536667	0.650678	2.134026574	-0.124668968	-0.02182342	0.049346931	4.491856678		1.6336	Non-Failed	Yes
Tiger Wheels Ltd	Failed	514.1347308	0.559793	3.416936825	-0.152197618	0.211333996	0.021581277	1.788346101		0.1071	Non-Failed	No
Hosken Cons	Non-Failed	329.8066936	0.212432	1.9878	0.450218994	-0.212859338	-0.04266419	-0.76225362		0.3556	Non-Failed	Yes
Viking Investments & Asset Management Ltd	Failed	50.6006522	0.091849	0.231600751	0.383033046	2.432191842	0.110542153	11.35291844		0.5025	Non-Failed	No
Brimstone Invest	Non-Failed	21.53518492	0.508751	2.238444238	1.533761247	0.171348034	0.090868491	2.449344458		0.6622	Non-Failed	Yes
Wesco Investments	Failed	2.124735297	0.372289	4.4403	-0.990829525	18.38162668	0.027	0.0292		1.0866	Non-Failed	No

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		X1	X2	X3	X4	X5	X6	X7	C		Percentage Misclassified	0.170454545
		0.000504	**-0.18426**	**-0.03193**	**0.449887**	**0.088777**	**0.019311**	**0.000151**	**0.109247**		**Classification Rate**	0.829545455
Company	**Failed / Non-failed**	**Revenue**	**Debt/Mkt Cap**	**Debt/EBITDA**	**1 Year Equity Price Return**	**RCF/Net debt**	**EBIT Margin**	**EBIT/Int**	**Constant**	**Z Score**	**Classification**	**Correctly Classified**
Ltd												
Metair Invts LTF	Non-Failed	397.2224468	0.126005	0.8571	0.059439887	-1.995278617	0.084	4.7751		0.1108	Non-Failed	Yes
William Tell Holdings Ltd	Failed	25.85179737	0.848385	18.98110706	0.001050015	-0.176643017	-0.04116133	-1.26172338		-0.656	Failed	Yes
York Timber Hold	Non-Failed	136.9406548	0.515087	3.246981519	0.326038022	0.204046343	0.162744241	1.979494268		0.1479	Non-Failed	Yes
Ububele Holdings Ltd	Failed	71.97394422	3.5136	4.588519932	-0.03903303	-0.001038126	0.066836391	1.95593524		-0.664	Failed	Yes
Clover Industrie	Non-Failed	885.701883	0.264	1.859971279	0.01301966	2.570423875	0.044110548	6.122660902		0.6834	Non-Failed	Yes
B&W Instrumentation & Electrical Ltd	Failed	43.715576	0.505747	1.441702927	-0.654864538	-0.682457929	-0.11963937	-10.5279489		-0.367	Failed	Yes
Murray & Roberts	Non-Failed	3868.174206	0.204549	0.8546	-0.172440712	0.076195774	0.004343873	0.648908297		1.9232	Non-Failed	Yes
First Uranium Corporation	Failed	92.46000438	15.21344	11.9264	-0.901395863	-1.231028056	-0.51407095	-2.11383692		-3.553	Failed	Yes
Harmony Gold MNG	Non-Failed	1486.382359	0.180894	0.4509	-0.611675653	3.863854914	0.009305211	7.525925926		0.8798	Non-Failed	Yes
Alliance Mining Corporation Ltd	Failed	44.11544031	0.021574	0.048780023	3.74366556	-14.10334975	0.34474796	33.89482266		0.5699	Non-Failed	No
Sentula Mining	Non-Failed	372.9232119	0.186499	4.432806956	1.329518436	0.355733888	0.037375204	4.131398476		0.7524	Non-Failed	Yes
Sanyati Holdings Ltd	Failed	211.8636399	1.182229	1.92894474	-0.310019288	0.330186651	0.031852593	2.939030996		-0.173	Failed	Yes
Basil Read HLDGS	Non-Failed	732.9539087	0.657109	2.531799281	-0.05282705	1.023564289	0.036841576	2.945236557		0.345	Non-Failed	Yes
African Cellular Towers	Failed	27.93338972	0.745188	1.205941234	-0.808828563	-13.61402245	-0.48458856	-18.3018887		-1.637	Failed	Yes
Aveng LTD	Non-Failed	4900.51667	0.021221	0.15553968	0.16607348	-0.315552658	0.040864012	23.97606838		2.6213	Non-Failed	Yes
Masonite Africa	Failed	55.76168311	0.043929	0.23653088	-0.143673114	0.026696197	-0.12268282	-310.497908		0.0102	Non-Failed	No

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		X1	X2	X3	X4	X5	X6	X7	C		Percentage Misclassified	0.170454545
		0.000504	**-0.18426**	**-0.03193**	**0.449887**	**0.088777**	**0.019311**	**0.000151**	**0.109247**		**Classification Rate**	0.829545455
Company	**Failed / Non-failed**	**Revenue**	**Debt/Mkt Cap**	**Debt/EBITDA**	**1 Year Equity Price Return**	**RCF/Net debt**	**EBIT Margin**	**EBIT/Int**	**Constant**	**Z Score**	**Classification**	**Correctly Classified**
Kaydav Group LTD	Non-Failed	70.22136939	0.2986	1.5276	-0.160495071	0.936478654	0.056816258	9.43257107		0.0543	Non-Failed	Yes
Chemical Specialities Ltd	Failed	57.29441794	0.669497	14.52213629	-0.495545671	-0.290867097	-0.06219946	-1.84031253		-0.699	Failed	Yes
Argent Indus	Non-Failed	185.9593873	0.658474	2.340690834	-0.292386192	0.093843701	0.043518237	3.003560156		-0.115	Failed	No
Total Client Services Limited	Failed	2.832289387	6.363705	34.62967691	-0.164689646	0.069625698	-0.48761178	-3.26378046		-2.245	Failed	Yes
African Equity E	Non-Failed	59.12003174	0.412985	3.791331653	-0.472667439	0.3589855	0.07853852	2.54315383		-0.237	Failed	No
Quantum Property Group	Failed	5.857997027	10.75643	8.0017	-0.758488871	-0.110441381	0.641968	0.969		-2.464	Failed	Yes
Hydrop Invest-UT	Non-Failed	199.8943416	0.427855	5.3499	0.120396647	0.002551325	0.65	1.0363		0.0274	Non-Failed	Yes
Erbacon Investment Holdings Limited	Failed	90.48358118	0.364148	0.744325769	0.12152598	-4.116214832	-0.02558033	-0.42620356		-0.247	Failed	Yes
Wilson Bayly Hom	Non-Failed	2688.17262	0.027364	0.034149694	-0.018382158	-0.286260581	0.038454655	45.75351584		1.4319	Non-Failed	Yes
Protech Khuthele Holdings Limited	Failed	97.553064	2.0327	2.397098516	-0.505001008	-0.386599086	-0.11683621	-9.41589481		-0.558	Failed	Yes
ESOR LTD	Non-Failed	159.451796	0.8556	3.071498788	-0.775108631	-0.732593761	-0.12541977	-4.70940594		-0.483	Failed	No
Alert Steel Holdings Limited	Failed	81.04953274	2.391795	12.4197045	-0.71213702	-0.397211367	-0.05600559	-2.89495084		-1.044	Failed	Yes
Kumba Iron Ore L	Non-Failed	5642.82237	0.020037	0.309016264	-0.369237982	8.018817021	0.523310259	71.96969697		3.5064	Non-Failed	Yes
Evraz Highveld Steel & Vanadium Ltd	Failed	537.7471603	0.186992	0.004347826	0.024030824	0.887897455	-0.07052023	-6.31034483		0.433	Non-Failed	No
Arcelormittal SO	Non-Failed	3359.210151	0.124626	0.626269036	-0.244569044	2.241447797	0.000308442	0.0330033		1.8483	Non-Failed	Yes
The Waterberg Coal Company Limited	Failed	1.512	0.083	0.7839	-0.56521439	5.0308	-130.283982	-0.48889105		-2.254	Failed	Yes
Exxaro Resources	Non-Failed	1489.2233	0.083	0.7839	0.35	5.0308	0.117834655	4.593		1.4265	Non-Failed	Yes

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		X1	**X2**	**X3**	**X4**	**X5**	**X6**	**X7**	**C**		**Percentage Misclassified**	0.170454545
		0.000504	**-0.18426**	**-0.03193**	**0.449887**	**0.088777**	**0.019311**	**0.000151**	**0.109247**		**Classification Rate**	0.829545455
Company	**Failed / Non-failed**	**Revenue**	**Debt/Mkt Cap**	**Debt/EBITDA**	**1 Year Equity Price Return**	**RCF/Net debt**	**EBIT Margin**	**EBIT/Int**	**Constant**	**Z Score**	**Classification**	**Correctly Classified**
Zarara Energy Limited	Failed	15.62676522	0.375444	0.052028705	-0.938449271	-4.459632624	0.111268248	59.74273859		-0.761	Failed	Yes
Aspen Pharmacare	Non-Failed	210.0367723	0.107771	1.175670473	0.440831263	3.281279233	0.080397516	2.290227344		0.6492	Non-Failed	Yes
Super Group Ltd	Failed	1731.199778	0.315199	1.510991407	-0.092411446	1.938166679	0.071570496	6.388370679		1.0083	Non-Failed	No
Onelogix Group	Non-Failed	120.9390519	0.373817	3.58912302	0.234119032	0.432575539	0.035931081	1.528484358		0.1314	Non-Failed	Yes

Appendix L

Company Name	JSE Code	Approximate date of failure	Industry/Sector
1Time Holdings Ltd	1TM	21 August 2012	Airlines
Afgem Ltd	AFG	31 August 2009	Other Mined Minerals
Africa Cellular Towers Ltd	ATR	01 June 2012	Infrastructure Construction
African Brick Centre Ltd	ABK	03 November 2011	Non Wood Building Materials
AG Industries Ltd	AGI	03 December 2010	Non Wood Building Materials
Aludie Ltd	ALD	23 May 2007	Security Services
Amlac Ltd	ALC	07 October 2003	Auto Parts
APS Technologies Ltd	APE	13 April 2006	Specialty Pharma
Beget Holdings Ltd	BEE	27 May 2011	Application Software
Best Cut Ltd	BCH	27 May 2011	Packaged Food
Bioscience Brands Ltd	BIO	08 November 2013	Specialty Pharma
Brikor Ltd	BIK	12 July 2013	Non Wood Building Materials
Bryant Technology Ltd	BRY	25 January 2001	Communications Equipment
CCI Holdings Ltd	CCG	16 April 2007	Application Software
Country Foods Ltd	CFO	01 April 2009	Packaged Food
Dialogue Group Holdings Ltd	DLG	13 February 2012	IT Services
Diamond Core Resources Ltd	DMR	11 February 2008	Other Mined Minerals
DNA Supply Chain Investments Ltd	DNA	14 November 2005	Logistics Services
Dorbyl Ltd	DLV	19 November 2012	Auto Parts
DTH Dynamic Technology Holdings Ltd	DTH	27 May 2010	Application Software
EC-Hold Ltd	ECH	30 November 2005	Infrastructure Software
Exxoteq Ltd	EXO	12 June 2007	Exploration & Production
Incentive Holdings Ltd	ICT	16 April 2007	Other Financial Services
JCI Ltd	JCD	16 April 2013	Precious Metal Mining
Kimberley Consolidated Mining Ltd	KCM	08 November 2010	Base Metals
Marshall Monteagle Holdings Societe Anonyme	MTE	25 February 2011	Other Financial Services
Millionair Charter Ltd	MLL	16 April 2007	Logistics Services
Pals Holdings Ltd	PAL	16 March 2009	Apparel, footwear, and Acc Design
Pinnacle Point Group Ltd	PNG	30 September 2014	Homebuilders
Queensgate Hotel & Leisure Ltd	QHL	18 February 2013	Lodging
Rentsure Holdings Ltd	RNT	06 June 2007	Life Insurance
Retail Apparel Group Ltd	RAG	16 April 2007	Specialty Apparel Stores
Samrand Development Holdings Ltd	SMR	05 December 2012	Real Estate Services
Sea Kay Holdings Ltd	SKY	05 October 2012	Homebuilders
Shawcell Telecommunications Ltd	SWL	16 April 2007	Telecom Carriers
Stocks Hotels & Resorts Ltd	SCH	16 April 2007	Lodging

Company Name	JSE Code	Approximate date of failure	Industry/Sector
Terexko Ltd	TRX	16 April 2007	Restaurants
Terrafin Holdings Ltd	TRF	16 April 2007	Logistics Services
Tiger Wheels Ltd	TIW	20 April 2009	Auto Parts
Tigon Ltd	TGN	16 April 2007	Other Financial Services
Top Info Technology Holdings Ltd	TOT	16 April 2007	IT Services
Viking Investments & Asset Management Ltd	VKG	16 April 2007	Investment Companies
Wesco Investments Ltd	WES	06 July 2009	Automobiles
William Tell Holdings Ltd	WTL	22 October 2012	Wood Building Materials
Zaptronix Ltd	ZPT	08 October 2013	Measurements Instruments
HALOGEN HLDGS SOC ANON	HAL	11 September 2009	Precious Metal Mining
Ububele Holdings Ltd	UBU	26 August 2014	Packaged Food
B&W Instrumentation & Electrical Ltd	BWI	01 August 2013	Infrastructure Construction
Witwatersrand Consolidated Gold Resources Ltd	WGR	07 May 2013	Precious Metal Mining
First Uranium Corporation	FUU	15 February 2012	Precious Metal Mining
Pamodzi Gold Ltd	PZG	17 September 2009	Precious Metal Mining
Alliance Mining Corporation Ltd	ALM	04 September 2010	Mining Services
Square One Solutions Group Ltd	SQE	19 May 2010	Infrastructure Software
Sanyati Holdings Ltd	SAN	04 June 2012	Engineering Services
African Cellular Towers	ATR	04 December 2015	Infrastructure Construction
Masonite Africa	MAS	23 September 2013	Wood Building Materials
Chemical Specialities Ltd	CSP	17 March 2015	Paints & Coatings
Total Client Services Limited	TCS	18 July 2014	IT Services
Quantum Property Group	QPG	27 August 2012	Multi Asset Class Own & Develolp
Great Basin Gold Ltd	GBG	20 November 2012	Precious Metal Mining
Erbacon Investment Holdings Limited	ERB	13 June 2013	Infrastructure Construction
Protech Khuthele Holdings Limited	PKH	28 July 2014	Transport Infra Construction
Alert Steel Holdings Limited	AET	15 May 2014	Iron & Steel
Evraz Highveld Steel & Vanadium Ltd	EHS	13 October 2013	Steel Producers
Firestone Energy Ltd	FSEO1	17 September 2015	Gold Mining
The Waterberg Coal Company Limited	WCC	17 September 2015	Coal Mining
Moulded Medical Supplies Limited	MUM	14 June 2004	Health Care Supplies
Zarara Energy Limited	ZRR	10 January 2013	Biotech & Pharma
Omega Alpha International Limited	OAI	22 February 2006	Application Software

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