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Default Prediction Models a Comparison between Market Based Models and Accounting Based: Case of the Zimbabwe Stock Exchange 2010-2013

Jacob Muvingi[1], Dingilizwe Nkomo[2], Peter Mazuruse[3] and Patricia Mapungwana

Abstract

Default prediction is relevant to equity investors in Zimbabwe. The study examined the performance of two bankruptcy prediction models, the accounting ratio-based (Z-Score) model and the market based (KMV distance to default) model. The Z-Score model developed has two variables, market value to long term debt and EBIT to current liabilities and uniquely describe Zimbabwe's corporate environment. The research concluded that accounting model (Z-Score) has superior bankruptcy prediction power. The model achieved 0.959 accuracy ratio against the market based model 0.509. Companies that went bankrupt during the period had shown signs of poor financial performance in prior years.

Keywords*:* Default, Prediction, accounting, market, Z-Score, Distance to Default, KMV
JEL classification numbers: D22; E47; G01; G33; K22

1 Introduction

Failure of listed companies gives rise to huge losses on stock market investors. Majority of stock market investors prefer investing in counters which are less likely to default or fail. The Z-Score, developed by Professor Edward Altman is perhaps the most widely recognized and applied model for predicting financial distress (Bemmann 2005). Professor Altman developed this intuitively appealing scoring method at a time when traditional ratio analysis was losing favour with academics (Altman 1968).literature has criticized the Z-Score as a poorly fit model. Specifically, although each individual ratio used as predictors in the Z-Score are believed to have some bankruptcy prediction ability,

[1]Harare Institute of Technology.
[2]Harare Institute of Technology.
[3]Harare Institute of Technology.

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the coefficients in the Z-Score calculation weaken its predictive ability to the point where it performs no better than its most predictive predictor variable (Bemmann 2005).
The development of the Z-Score model paved way for the development of other corporate bankruptcy prediction models. The option pricing model developed by Black and Scholes in 1973 and Merton in 1974 provided the foundation upon which structural credit models are built. KMV (now Moody's KMV), was the first to commercialize the structural bankruptcy prediction model in the late 1980s.
Since multi-currency regime adoption in Zimbabwe, the Zimbabwe Stock Exchange has suspended and delisted more than nine listed firms. The firms were suspended and delisted after either they were liquidated or placed under judicial management.
The research seeks to find the best predictor of default between market based models (KMV distance to default) and accounting based models (Z-Score) for the Zimbabwe Stock Exchange period 2010-2013

2 Literature Review

Accounting-based default prediction models take into consideration the firm's past performance as a base for predicting the firm's future likelihood of survival (Xu, Zhang, 2008). Several studies on accounting variables as predictors' corporate default are Beaver (1966), Altman (1968), Ohlson (1980), Dichev (1998), Shumway (2008), etc. The most fundamental and crucial works in default prediction field is Beaver's empirical study (1966). Altman (1968) study extended the work of Beaver by employing multivariate discriminant analysis on twenty two financial variables with a sample of 66 (33 bankrupt and 33 non-bankrupt) manufacturing companies. The Z-score and O-score developed by Altman (1968) and Ohlson (1980), respectively, prompted later researchers to find out the default prediction model with the best predictive ability Rashid et.al (2011).
Market-based bankruptcy prediction models use information derived from the market i.e., share prices. This approach follows the structural Black and Scholes (1973) and Merton (1974) option pricing theories that express probability of default occurring depends on the volatility between the market value of the assets and the strike price (value of debt obligations). The critical level where firm will default is that when the worth of firm's assets moves down below a certain level (i.e., debt obligations).
Many scholars and practitioners did a lot of work to examine the contribution and accuracy of the KMV Model distance to default by empirical analysis. McQuown (1993) pointed out that the approach can be accurate when the financial report and the market price are used at the same time.
The most noted drawback of accounting based models is their over-reliance on financial statements data that measures past performance of the firm and are sometimes difficult to apply on future perspectives because they are backward looking by Hillegeist (et al. 2004).
Market based bankruptcy prediction models overcome many of the fundamental shortcomings of accounting models. In efficient markets, prices reflect both historical financial information as well as the individual and market-wide outlook of a business. Share prices in contrast to balance sheet data are provided daily unlike balance sheet data which is available with lags and reported on a quarterly basis. Agarwal and Taffler (2008) pointed that market prices are less likely to be influenced by accounting policies and have impeccable theoretical grounding as they draw on the structural Black and Scholes (1973)

and Merton (1974) option pricing framework. In these models, equity is viewed as a call option on the firm's assets, and the probability of going bankrupt is simply the probability that the call option is worthless at maturity.

Aretz (2010) highlights that structural models is a one-size-fits-all approach and it does not contain any free (choice) parameters .The returns of a firm are modeled by a stochastic equation and bankruptcy filing occurs, if and only if the realization of the stochastic process is below the threshold at maturity.

Liu et.al (2010) did a comparison study of market based models versus accounting based models .The study points out that since the option based models are based on assumption that the market is efficient, the relative default prediction performance between the market-based model and accounting-based model should be related to the maturation of the securities market development. This suggests a paradox that performance of the market-based structural model can be outdone by the traditional accounting-based model in developing economies as theoretically expected.

Rashid et.al (2011) did a study to develop an accounting based model unique for the Pakistan (Karachi Stock Exchange) listed stocks corporate environment. Companies with complete five years of published data were only included in the sample .It was done for the period of 1996-2006. The total sample of both bankrupt and non-bankrupt companies used in this study was 52 consisting of 26 bankrupt and 26 non-bankrupt companies. All the twenty financial variables grouped under the leverage, liquidity, profitability and turnover ratios were examined separately for bankrupt and non-bankrupt companies by calculating their means and standard deviations for five years prior bankruptcy. In addition, T-tests and F- tests were employed to analyze the similarity and difference of financial variables each year prior to bankruptcy, from twenty four variables, only three variables , EBIT to current liabilities ratio, sales to total assets ratio and cash flow ratio were found to be highly significant.The model accuracy was 76.9% showing that the model has potential for practical application in predicting corporate failure in Pakistan. Mensah(1984) noted that ratios and coefficients change over time, hence need for regular re-estimation of the models. Zmijewski (1984) affirmed that using a already set model may produce a biased result as some of the models could be biased as they typically might have been constructed using an oversample of failed firms during model development.

Pongsatat et al. (2004) examined the predictive capability of Ohlson's and Altman's model for bankruptcy of small and large firms in Thailand. The study concluded that for bankrupt firms , Altman's model exhibits a higher predictive accuracy than Ohlson's model, for year one with an accuracy rate of 90.48% for year one and a 100% accuracy rate for both year two and year three. However, with regard to non-bankrupt firms, Altman's model exhibited less predictive accuracy.

Eljelly et.al (2001) replicated Altman Multiple Discriminant Analysis (MDA) to the sample but achieved low failure prediction rates relative to those obtained in the developed and developing economies. The study then re-estimates Altman original model parameters with a significant improvement in failure prediction rates. Using a stepwise MDA methodology, the study develops a three-variable model that improves upon Altman replicated and re-estimated models in classifying companies into failed and non-failed.

Ren et.al (2011) carried-out a study which applied KMV distance to default on Chinese stock exchange energy sector .The listed stock were dived into normal stocks and ST (special treatment) stocks which were not performing well .The results showed that the value of distance to default decreased during the two years before the companies become

to special treatment companies. A downward trend of DD, likewise, is seen as a means of warning the credit risk of companies. The lower the DD value is, the higher the credit risk is. The above studies indicated that the KMV model can be used to warn credit risk of the firms in energy sector of China. Moreover, the modified KMV model fitted the test requirements of Chinese market.
Ito et.al (2010 gave results on how three banks' distance to default moved in the last 12 months before the respective bank failure, from the study distance to default had been gradually falling and became very low before the news of the failure was announced. Looking at the distance to default for the period of 12 and 6 months prior to failure it concluded that the distance to default is a good measure for the cases of two banks.

3 Research Methodology

The research utilised a quantitative research design comprised of three stages. The first part involved developing an accounting based model that will be used to generate the z-scores (for 2010, 2011 and 2012). Multivariate discriminant analysis was used to formulate the accounting based model. Secondly the KMV distance to default (market based model) approach was be implemented on the listed firms. Finally the two models were compared to find the best model which predicted 2013 default firms early using 2011 outcome.

3.1 The Sample

The population for this study has all the companies on the Zimbabwe Stock Exchange (ZSE) currently and those that delisted .The companies are subdivided into two subsets "bankrupt" and "non-bankrupt" .Bankruptcy is as a result of liquidation/judicial management, i.e. violation of ZSE listing regulation section 1.81. Bankrupt firms will also include firms that were critically underperforming during the period.

Table 1: Sample

Sample One Code 1 Bankrupt/Trouble Company		**Sample Two Code 2 Non-Bankrupt Firms**
Cairns	Delisted	**Colcom**
Phoenix	Delisted	**Nts**
PG Industry	Delisted	**Radar**
Celsis	Delisted	**Hunyani**
Chemco	Delisted	**Medtec**
Interfresh	Delisted	**Hippo**
Star	"Troubled"	**Innscor**
Zeco	"Troubled"	**Masimba**
CFI	"Troubled"	**Seedco**
Ariston	"Troubled"	**Padenga**

3.2 Developing the Accounting Based Model

To develop the model two groups of firms “bankrupt (and troubled)” and “non bankrupt firms” were assumed. After the groups were established, data was collected for the companies in the groups. Multi-Discriminant Analysis would be used to generate an accounting-based z-score with the form below:

MDA take the form as follows.

$z = \beta_1 x_1 + \beta_2 x_2 + \beta_n x_n$

Z is the overall index β_1, β_2, β_n are discriminant coefficients, x_1, x_2, x_n are independent variables .The discriminant score (Z) is taken to estimate the bankruptcy character of the company .In this case financial variables which can be quantified for all companies in the analysis are used x_1, x_2, x_n . MDA determines a set of coefficients β_1, β_2, β_n When these coefficients are applied to the actual financial ratios , a basis for classification into one of the mutually exclusive grouping exist(bankrupt and non bankrupt.MDA is a technique determines a set of discriminant coefficient and transforms individual variable values to a single discriminant score or Z-value which is then used to classify the object. In this study the two groups of object are bankrupt and non-bankrupt companies. . Lower the value of Z, greater is the firm’s bankruptcy probability and vice versa.

3.3 Variable Selection

The study employed 22 financial ratios as independent variables, thus explorative discriminant analysis. These 22 financial ratios have been classified into four broad categories (see Appendix 3). Leverage ratios measure the capability of a firm in paying its debt obligations. We use 8 different ratios as a proxy for measuring leverage capability of a company (i.e., bankrupt and non bankrupt).Liquidity ratios measure the performance of a firm in availability of cash to pay its debt obligations. Beaver (1966) argues that the firms with lower liquid assets are more prone to bankruptcy and vice versa. This study uses four ratios as a proxy for measuring liquidity of a company. Profitability ratios measure the performance of firm in efficient and effective utilization of its assets and management of its expenditure to produce adequate earnings for its shareholders.

3.4 Procedure

Step 1: All the twenty two financial variables grouped under the leverage, liquidity, profitability and turnover ratios were examined separately for bankrupt and non-bankrupt companies by calculating their means and standard deviations for three(2010,2011,2012) years prior bankruptcy.

Step 2: T-tests were done .Here financial ratios were tested for significance in difference of the means of the two paired-samples (Bankrupt and Non Bankrupt).

The hypothesis was as follows

H_0 $\mu_1 = \mu_2$

H_1 $\mu_1 \neq \mu_2$

The T-test is applied in order to determine whether 22 financial ratios of two groups (bankrupt and non-bankrupt) are likely to have the same mean underlying three years. Significant ratios were noted down for the first year , second year and third and common ratios in the three years(2010,2011,2012) are pulled out. These are the ratios which show significant difference in the means.

Step 3: F-test was performed in order to determine whether 22 financial ratios of bankrupt and non-bankrupt group have different variances underlying four years. Financial ratios with a high significant variance (p-value) in all the three years were noted.

Step 4:(In SPSS) At this stage only significant variables from the stepwise discriminant analysis procedure proceeded, insignificant variables are removed by SPSS. The financial ratios which succeed to this point can be said that they have an ability to minimizes the overall Wilks' Lambda .At this step standardized canonical discriminant function coefficients are determined and ranked .The higher the coefficient of a financial ratio the higher the discriminant power.

Step 5: (In SPSS) Group centroids functions are then determined .These are the optimum Z value based on which a firm is classified as bankrupt and non-bankrupt. If a firm is above it its “Non-bankrupt” and if below it is below its “Bankrupt”.

Step 6: The model developed through this study will then be tested on the sample (years2010, 2011 and 2012) to calculate z-score and further to understand the accuracy and significance of the discriminant model.

3.5 Market Based Model

The Distance to default was calculated by a structural model of credit risk assessment pioneered by the option pricing theory of Merton (1974) and Black and Scholes (1973). The model defines a corporate default when the market value of assets becomes below the book value of liabilities (the default point). The DD is defined by the number of the standard deviation of the market value of assets away from the default point. The larger the DD, the greater is the distance of a company from the default point, and the lower is the probability of default. The option pricing theory determines the asset value and its volatility of a company from the observed stock prices and their volatility. Specifically, the value and the volatility of assets was calculated with Black and Scholes (1973)’s model by using the value and volatility of stock prices. Once the firm value of assets and volatility are iterated it was possible to calculate the probability with which the asset value declines to the default point within a specified time. This probability is the probability of default and it corresponds one to one with the DD.

3.5.1 Variable selection

V_E -The current market value of firm assets (daily stock prices *number of issued shares)
V_A -Firm asset value (unobservable)
D - Face Value of Debt maturing at time T
D_{KMV} - (Short term debt + Half Long term debt)/Default Point
u_t - Mean growth return of market value of the firm assets
σ_A - Standard deviation of firm assets (unobservable)
σ_E -Standard deviation of market value of equity.

3.5.2 Distance to default using the KMV approach

Merton (1980) views corporate debt as a call option .The Strike price is Debt and the maturity is the debt maturity date. If the firm asset value is less than Debt, shareholders transfer the total assets to creditors and there is default. If the total firm asset value is greater than Debt the shareholders gain the remaining profits.

dV= μVdt+ σvVdW

$$Debt_{levelT} == \frac{W_{n,T} - W_{n,t}}{\sqrt{T} - t} \tag{1}$$

The market value of equity was expressed using a pricing formula for call options. Adopting the formula by Black and Scholes analyzing a listed company, E_0 is known and is equal to the company's market capitalization. V_0 is the initial firm asset value

$$E_0 = V_0 \cdot N(d1) - Debt^{\wedge \text{mean growth shareprice}*(1)} N(d2) \tag{2}$$

Procedure

Step1: Firm asset value V_0 that is consistent with this empirical value of E_0 was iterated using solver function in excel(see appendix4), and in this way we could determine V_0 (which is not directly observable on the market). However, V_0 is not the only unknown in equation (1). d1 and d2 (as well as V_0) depend on asset volatility σ_A:

$$d_1 = \frac{\log\left(\frac{V_A^t}{D}\right) + \left(u_t - \frac{1}{2\sigma_A^2}\right)(T-t)}{\sigma_A \sqrt{T-t}} \tag{3}$$

$$d_{2=}d_1 - \sigma_A \sqrt{T-t} \tag{4}$$

Asset volatility is an unknown variable (since it cannot be observed on the market). Therefore, infinite pairs of values for V_0 and σ_A that are consistent with the observed value of E_0 can be made, and one cannot tell which of these the right one is.

Step 2: In order to find a unique solution, we found a second equation that connectsV_0 and σ_A, to create a system of two equations with two unknowns. This second equation was obtained by applying a theorem of stochastic calculus known as Ito's lemma, which can be shown to be the following:

$$\delta_E = \frac{V_o}{E_o} N(d1)\delta_V \tag{5}$$

The left-hand side member is the volatility of the market value of equity (σ_E), which was the share price volatility of the publicly listed firm which can be estimated empirically (e.g. as the standard deviation of the stock's past returns) and can therefore be considered a known variable. The right-hand side again includes our two unknowns, V_0 and σ_A (both explicitly and “hidden” in the term d1). As such, we united (1) and (2) into the following system

$$E_0 = V_0 \cdot N(d1) - \text{Debt}^{\wedge\text{mean growth shareprice}*(1)}\, N(d2) \tag{6}$$

$$\delta_E = \frac{V_o}{E_o} N(d1)\delta_V \tag{7}$$

and solved it for values of V_0 and σ_A that are consistent with the observed values of $E_0$and σ_E. The solution cannot be derived directly, isolating the unknowns V_0 and σ_V, because these unknowns appear multiple times in both equations (given that d1 and d2 are nonlinear functions of both V_0 and σ_A). Therefore, the system was solved iteratively: we choose two initial estimates of the unknowns and iteratively change both V_0 and σ_A until (1)–(2) generate the values of E_0 and σ_E that have been observed empirically on the stock market.(See excel snippet Appendix4)

Step 3: The system of equations was solved using solver function in excel to find V_0 and σ_A

Step 4: In Merton’s model default occurs when the value of assets falls below the face value of debt: a limitation of this model is that it assumes that debt is comprised of single liability with a maturity of T years. The KMV model, on the other hand, acknowledges that real companies finance their activities with a combination of both short-term and long-term debt. As a result, rather than considering the critical default threshold to be the total value of debt, the KMV model uses a value, which it calls the default point (DP), equal to all short-term debt (STD) plus 50% of long-term debt (LTD). Hence

$$\text{Default Point} = \text{Short term debt} + (1/2)\text{Long Term Debt} \tag{8}$$

Step 5: Moving on to Distance to default from Default point, Distance to default according to KMV is equal to the difference between asset value and the default point, expressed as a multiple of the standard deviation of assets. That is:

$$DD = \frac{V_o - DP}{V_o.\delta_V} \tag{9}$$

Step 6: Changing the distance to default to a probability of default at time (t) :
Probability of default (t)=P [$V_A \leq D$] =……………..= φ(-DD) as DD corresponds one to one to probability of default. This was done by employing an excel =NORMSDIST(-DD) function.

Step 7: The last phase KMV’s PD calculation procedure is based on the empirical link between DD and actual past rates of default in Zimbabwe. DD on past data from a vast sample of companies some of which ended in default is calculated and for various DD ranges the percentage of companies that actually defaulted. The data may suggest a fairly precise empirical correlation between DD and past default frequencies. Once a company’s DD is known, this correlation can be used to calculate the associated PD (which the authors of the KMV model refer to as expected default frequency, or EDF). However for this study this part was omitted owing to that the default database of non-financial firms in Zimbabwe is very small and some of the firms in the database defaulted in the pre-dollarisation error .Had this database been used the model would have yielded biased results.

3.6 Comparison of Accounting Based Models and the Market Based Model

The research compared the two models to determine which one of the two the accounting based model and the market based model has greater prediction ability. This is done using a cumulative accuracy profile and measuring accuracy ratio. Two years prior bankruptcy model's results would be used to see which of the models had assigned high risk scores or probability to the firms that went bankrupt in 2013. An analysis of the relative magnitude of type I and type II error was done. **Type I error:** predicting non-failure (ex-ante) for a company that in reality defaults (ex-post). **Type II** error: predicting a default when in fact the company should have been ranked very unlikely to default.

3.7 Cumulative Accuracy Profile (CAP)

CAP is a commonly used technique to measure the discriminating power between default predicting models. It does so by giving a graphical illustration of the model's ability to distinguish between failing and non-failing firms.

3.8 Accuracy Ratio (AR)

Accuracy ratio was also used to measure the quality of the rating models by using the accuracy ratio. The accuracy ratio is closely related to CAP as it uses the rating model's CAP curve to derive its value.

4 Data Analysis and Interpretation

4.1 Developing the Accounting Based Model

All the twenty-two financial variables grouped under the leverage, liquidity, profitability and turnover ratios were examined separately for bankrupt and non-bankrupt companies by calculating their means and standard deviations for three years prior bankruptcy (2010, 2011,2012) .The Multiple discriminant model was estimated (through SPSS software version 19) by employing stepwise discriminant analysis to derive the discriminant variables with their coefficients.

4.1.1 Means and standard deviations of bankrupt companies

The means and standard deviations of the 22 financial ratios (see Table 2 below) for the bankrupt firms revealed that the bankrupt companies have higher in-debtness , lower liquidity, poor profitability and turnover ratios that are in support of our predictions. In addition, most of ratios grouped under liquidity, profitability and turn over ratios have shown negative signs and declining trend with the movement of the company towards bankruptcy.

Table 2: Means and Standard deviations of bankrupt companies

Means and standard deviations of bankrupt companies			
1. Leverage Ratios	**2010**	**2011**	**2012**
Net income to total debt	0.3581700	-0.7077000	-1.5329000
	1.0840000	0.8478010	3.5775900
Cash flow to total debt	0.3361711	-0.0512400	-0.6478035
	1.0917910	0.3312600	2.0407100
EBIT to fixed assets at cost	-0.2589000	-1.9962000	-0.2170890
	0.5641000	0.2000000	0.2639800
EBIT to total liabilities	-0.1672500	-0.2146852	-0.1960818
	0.2425000	0.2550600	0.2360344
Equity to long term debt	2.2561000	1.3266400	-0.3388270
	2.7300000	3.9617300	6.3660000
Market value of equity to book V D	2.9860000	0.8917600	1.1635500
	4.0922000	0.7647000	1.1927000
Net income to fixed assets at cost	-0.2609300	-0.2672210	-0.3173630
	0.5424600	0.2273230	0.3469400
Total debt to total asset	0.2186100	0.2198420	0.3251615
	0.1270000	0.1095000	0.1641790
Current Liabilities/Total Assets	0.5821077	0.6912500	0.9399000
	0.4337000	0.5376300	0.9632000
2. Liquidity ratios			
Current assets to current liabilities	2.1327000	1.1927800	0.8249000
	1.4594000	0.6245000	0.4918082
Working capital to total assets	0.0351100	0.0400650	-0.0496100
	0.1238160	0.1095200	0.1233000
3. Profitability ratios			
EBIT to current liabilities	-0.9105600	-0.7972160	-0.7471990
	1.6886200	0.7906537	1.0803132
EBIT to sales	-1.7681610	-0.2900230	-0.3784520
	0.3006464	0.3673000	0.6412335
EBIT to total assets	-0.1376000	-0.1254030	-0.1716994
	0.2802800	0.1315383	0.2081126
Net income to sales	-0.6797000	-0.3545500	-0.4140000
	0.2555000	0.3321410	0.5044000
Net income to total assets	-0.1376926	-0.1695600	-0.2138000
	0.2656100	0.1801300	0.3691000
4. Turn over ratios			
Expenses to sales	-0.9602400	-0.9712230	-0.9837097
	0.2059200	0.2273900	0.2554360
Sales to fixed assets	1.3420000	1.1549430	1.8850000
	0.7550000	0.6038000	0.5493000
Sales to total assets	0.7885100	0.7196442	0.7781400
	0.4106510	0.3701400	0.3764700
Working capital to sales	0.0075015	0.0480000	-0.0818400
	0.1935137	0.1325000	0.1845657

4.1.2 Means and standard deviations of non-bankrupt companies

The means and standard deviation of non-bankrupt companies with 22 financial variables three years prior bankruptcy were calculated separately in order to determine the financial variables behaviour of the non-bankrupt firms during the critical period in which they survived. It was expected that the companies might have been survived by their strong financial variables. Unexpectedly, it was observed that some of the profitability, liquidity and turn over ratios have declining trend owing .Values of liquidity, profitability, leverage and turn over ratios of non-bankrupt companies were stable as compared to bankrupt companies and in some cases they were improving with the approach of the critical time period (i.e., bankruptcy), see Table 3 below.

Table 3: Means and standard deviations of non-bankrupt companies

Means and standard deviations of Non-bankrupt companies			
1. Leverage Ratios	**2010**	**2011**	**2012**
Net income to total debt	0.2095000	0.7880000	0.8446000
	0.3582000	0.7734000	0.7886000
Cash flow to total debt	0.2169760	0.2310000	-0.2872400
	0.3558600	0.6793500	1.8700000
EBIT to fixed assets at cost	0.1748940	0.2465150	0.2770280
	0.2299310	0.2260000	0.2036600
EBIT to total liabilities	0.2212060	0.2924800	0.2760000
	0.2811000	0.2222200	0.2116407
Equity to long term debt	6.0223000	6.8505800	7.3462500
	3.0849000	3.4959000	3.6168000
Market value of equity to book V D	7.6237110	12.8258507	7.3125600
	5.6230000	10.6965600	7.2236000
Net income to fixed assets at cost	0.0964400	0.1807416	0.1934780
	0.2706859	0.1549000	0.1538400
Current Liabilities/Total Assets	0.2641400	0.2933960	0.2608400
	0.2472000	0.1845200	0.1151203
Total debt to total asset	0.3497700	0.4163934	0.4273181
	0.6690000	0.1345000	0.4061000
2. Liquidity ratios			
Current assets to current liabilities	1.3253904	1.9817700	1.9358800
	0.7047800	1.4619300	1.4366100
Working capital to total assets	0.1772540	0.1868100	0.1966000
	0.1980823	0.1684700	0.1680840
3. Profitability ratios			
EBIT to current liabilities	0.4128500	0.4908300	0.4166500
	0.4876000	0.3885400	0.3203400
EBIT to sales	1.0775100	0.1257600	0.1099160
	0.0950820	0.9977000	0.0758000
EBIT to total assets	0.0689450	0.1030910	0.1045326
	0.0859957	0.0715040	0.0683182
Net income to sales	0.0817750	0.0791000	0.0694140
	0.9693960	0.0743757	0.0631230
Net income to total assets	0.0619700	0.0811600	0.0784000
	0.0847900	0.0661000	0.6577000
4. Turn over ratios			
Expenses to sales	-0.8459000	-0.8153620	-0.8312810
	0.1508510	0.1467000	0.1321000
Sales to fixed assets	2.8320000	3.5348500	5.2654400
	2.7199000	3.4658000	7.5113000
Sales to total assets	0.9176890	1.0940600	1.1749200
	0.5210400	0.6105220	0.7062000
Working capital to sales	0.2304400	0.2263100	0.2254000
	0.3177910	0.3193700	0.4108623

4.2 Statistical Testing

4.2.1 T-test for equality of means

T-test was applied in order to determine whether 22 financial ratios of two groups (bankrupt and non-bankrupt) are likely to have the same mean underlying three years. The statistical results presented in Table 4 indicate that there is a statistically significant difference for 9 financial ratios out of the 22 financial ratios in the first year, 10 financial ratios for the second year and 8 financial ratios are significantly different in the third year prior to bankruptcy. Of these, 3 financial ratios were found significant in all three years prior bankruptcy. Thus it is concluded that there is a significant difference between the two populations' means with 3 financial variables namely EBIT to Current liabilities, the market value of equity to the book value of debt and EBIT to Sales. Further, the results presented in Table 4 reveal that the significance of most of the financial variables increases with the movement of the company towards bankruptcy.

Table 4: T test for equality of means of bankrupt vs non bankrupt companies

T-Tests testing equality of means of ratios for bankrupt versus non-bankrupt			
1. Leverage Ratios	**2010**	**2011**	**2012**
Net income to total debt	0.686	0.010	0.055
Cash flow to total debt	0.747	0.253	0.686
EBIT to fixed assets at cost	0.037	0.000	0.000
EBIT to total liabilities	0.004	0.000	0.000
Equity to long term debt	0.100	0.004	0.040
Market value of equity to book V D	**0.046**	**0.002**	**0.016**
Net income to fixed assets at cost	0.079	0.000	0.000
Current Liabilities/Total Assets	0.611	0.293	0.324
Total debt to total asset	0.111	0.134	0.113
2. Liquidity ratios			
Current assets to current liabilities	0.133	0.134	0.033
Working capital to total assets	0.070	0.033	0.002
3. Profitability ratios			
EBIT to current liabilities	**0.028**	**0.000**	**0.040**
EBIT to sales	**0.011**	**0.003**	**0.036**
EBIT to total assets	0.039	0.000	0.001
Net income to sales	0.010	0.010	0.008
Net income to total assets	0.036	0.001	0.090
4. Turn over ratios			
Expenses to sales	0.174	0.085	0.111
Sales to fixed assets	0.112	0.046	0.108
Sales to total assets	0.460	0.115	0.134
Working capital to sales	0.074	0.121	0.045

4.2.2 F-test for equality of variances

F-test was performed in order to determine whether 22 financial ratios of bankrupt and non-bankrupt group have different variances underlying three years. It is evident from the Table 5 that 4 financial variables show significant variance for three years between the two groups. Therefore, it is concluded that 18% of the financial variables have shown significant variance between the bankrupt and non-bankrupt groups with the approach of the critical time period (i.e., bankruptcy).

Table 5: F tests of variances for bankrupt compared to non bankrupt companies

Testing equality of variance of ratios for bankrupt versus non bankrupt			
1. Leverage Ratios	**2010**	**2011**	**2012**
Net income to total debt	1.626	0.013	2.364
Sig:	0.2180	0.9120	1.4200
Cash flow to total debt	1.694	2.760	0.104
Sig:	0.2100	0.1140	0.7510
EBIT to fixed assets at cost	0.984	0.051	0.271
Sig:	0.3340	0.8240	0.6040
EBIT to total liabilities	0.264	0.006	3.130
Sig:	0.6140	0.9400	0.5830
Equity to long term debt	0.417	0.126	2.122
Sig:	0.5260	0.7270	0.1620
Market value of equity to book V D	2.419	17.828	13.056
Sig:	**0.060**	**0.0010**	**0.0020**
Net income to fixed assets at cost	0.926	1.236	3.495
Sig:	0.3490	0.2810	0.0780
Total debt to total asset	3.163	2.462	5.499
Sig:	0.9200	0.1340	0.3100
Current Liabilities/Total Assets	0.485	1.818	3.343
Sig:	0.4950	0.1940	0.0840
2. Liquidity ratios			
Current assets to current liabilities	1.800	1.763	2.528
Sig:	0.1960	0.2010	0.1290
Working capital to total assets	2.032	1.374	0.679
Sig:	1.7100	0.2560	0.4210
3. Profitability ratios			
EBIT to current liabilities	3.401	6.618	4.529
Sig:	**0.0502**	**0.019**	**0.0470**
EBIT to sales	9.133	4.710	4.312
Sig:	**0.0501**	**0.0440**	**0.0520**
EBIT to total assets	2.992	6.908	4.953
Sig:	0.1010	0.0170	0.0390
Net income to sales	7.350	7.422	9.724
Sig:	0.0140	0.0140	0.0600
Net income to total assets	3.113	8.783	7.853
Sig:	**0.0450**	**0.0050**	**0.0120**
4. Turn over ratios			
Expenses to sales	0.632	2.119	8.760
Sig:	0.4370	0.1630	0.0080
Sales to fixed assets	7.530	5.775	4.295
Sig:	0.1300	0.0270	0.0530
Sales to total assets	0.821	3.277	4.613
Sig:	0.3700	0.0870	0.0460
Working capital to sales	0.529	1.764	0.829
Sig:	0.4760	0.2010	0.3750

4.2.3 Statistical results of multivariate discriminant analysis (MDA)

The total sample of 22 companies with three years data resulted in 66 firm year observations. However, the data has been analyzed with an average of three years which becomes 66 observations for both bankrupt and non-bankrupt companies. The three financial variables proceeded for stepwise discriminant analysis that is EBIT to Current Liabilities, Market Value to Long Term Liabilities and EBIT to Sales. At each point the variable which minimized the overall Wilks Lambda was entered and unfortunately EBIT to Sales was removed from further analysis. Wilks' Lambda test is to test which variable contribute significance in discriminant function. The closer Wilks' lambda is to 0, the more the variable contributes to the discriminant function. If the p-value if less than 0.05, we can conclude that the corresponding function explain the group membership well.

Table 6: Wilks lambda - Stepwise Discriminant Analysis
Variables Entered/Removed[a,b,c,d]

		Wilks' Lambda							
						Exact F			
Step	Entered	Statistic	df1	df2	df3	Statistic	df1	df2	Sig.
1	EBIT to current liabilities ratio for the counters	.457	1	1	18.000	21.377	1	18.000	.000
2	Market Value to LTD ratio for the counters	.348	2	1	18.000	15.906	2	17.000	.000

At each step, the variable that minimizes the overall Wilks' Lambda is entered.
a. Maximum number of steps is 8.
b. Minimum partial F to enter is 3.84.
c. Maximum partial F to remove is 2.71.
d. F level, tolerance, or VIN insufficient for further computation.

The discriminant analysis procedure concluded significant variables and excluded insignificant variables for further analysis as shown in Table 5. Consequently from twenty two variables, only two variables EBIT to current liabilities ratio and Market Value to Long Term Debt ratio found highly significant at 5% significance level.

4.2.4 Standardized canonical discriminant function coefficients

Standardized canonical discriminant function coefficients were determined and ranked accordingly is shown in Table 7. EBIT to current liabilities ratio discriminated the most with the highest discriminant magnitude 0.795 followed by sales to total asset ratio with 0.604.

Table 7: Standardised canonical coefficients
Standardized Canonical Discriminant Function Coefficients

	Function
	1
Market Value to LTD ratio for the counters	.604
EBIT to current liabilities ratio for the counters	.795

The standardized canonical discriminant coefficients can be used to rank the importance of each variables .From the above it shows that the EBIT to current liabilities financial ratio is relatively more important at distinguishing non-bankrupt and bankruptcy.

4.2.5 Group centroids function

Group centroids function determines the optimum Z value based on which a firm is classified as bankrupt and non-bankrupt. Table 8 reveals that if a firm having Z score equals to -1.298 is classified as "Bankrupt" whereas firm having Z score equal to 1.298 is classified as "Non-bankrupt". The midpoint or the cut off value of bankrupt and non-bankrupt group centroid is zero, which suggests that the movement of a firm with the Z-value above zero is approaching toward "non-bankruptcy" whereas the movement of firm with the Z-value below zero is approaching towards "bankruptcy" at each year prior the event. At last, the firm having a Z value = -1.298 classified as "bankrupt" and the firm having a Z value = 1.298 classified as "non-bankrupt". This means that the firms having Z-value below zero fall into the "bankrupt" whereas the firms with Z-value above zero fall into the "non-bankrupt" category.

Table 8: Functions Group Centroids
Functions at Group Centroids

Counters "Bankrupt" or "Non-Bankrupt"	Function
	1
"Bankrupt"	-1.298
Non-Bankrupt	1.298

Unstandardized canonical discriminant functions evaluated at group means

Functions at group centroids

Group Z-Score
Bankrupt -1.298
Non-Bankrupt 1.298

4.3 Z score/ MDA Model

The final Z score/ discriminant score derived from table 7 and 8 respectively, takes the form as follows:

$$Z = 0.795X1 + 0.604\ X2 \tag{10}$$

Where:
Z = discriminant score;
X1 = EBIT(3) to current liabilities ratio;
X2 = Market Value to Long Term Liability (1);

The classification reported in Table 9 compares the actual and predicted results. It is evident that the model high classification power of the significant two financial variables on the underlying sample. The outstanding model's accuracy rate achieved implies that it has the potential for practical application in predicting the corporate failure of Zimbabwe.

Table 9: Classification results[a]

		Counters "Bankrupt" or "Non-Bankrupt"	Predicted Group Membership		Total
			"Bankrupt"	Non-Bankrupt	
Original	Count	"Bankrupt"	10	0	10
		Non-Bankrupt	0	10	10
	%	"Bankrupt"	100.0	.0	100.0
		Non-Bankrupt	.0	100.0	100.0

a. 100.0% of original grouped cases correctly classified.

4.3.1 Wilks' lambda of the estimated MDA model

Wilks Lambda (reported in Table 10) evaluates the overall discriminant function fitness. We obtain (0.348) overall Wilks Lambda, significant at 99% level of confidence that provide the evidence that our model has the potential to be applied practically.

Table 10: Model's overall Wilk's lambda
Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.348	17.931	2	.000

4.3.1 Using the developed Z-Score

Table 11 below shows the movement in the z-scores using actual ratios in market value to total debt and EBIT to current liabilities. It can be seen that for most of the firms in bankruptcy their z-scores are below 0 approaching -1.298(bankrupt) and further below. The safe firms thus the non-bankrupt firms have z-scores well above 0 and above 1.298(non-bankrupt) for all the three years

Table 11: Implementing the model on 2010, 2011, 2012 financial ratios

	2010				2011				2012		
Company	**Market/LTD**	**EBIT /CL**	**Z-Score**	**Company**	**Market/LTD**	**EBIT /CL**	**Z-Score**	**Company**	**Market/LTD**	**EBIT /CL**	**Z-Score**
Cairns	1.32	-2.055	-0.836	Cairns	0.56	-1.752	-1.054	Cairns	1.32	-1.116	-0.09
Phoenix	1.32	0.101	0.878	Phoenix	1.384	0.15	0.955	Phoenix	2.085	-0.162	1.13
PGI	1.453	-1.04	0.051	PGI	1.453	-1.045	0.047	PGI	0.782	-0.314	0.222
Celys	5.182	-5.221	-1.021	Celys	2.437	-2.171	-0.254	Celys	2.192	-3.502	-1.46
Chemco	2.408	-0.637	0.948	Chemco	0.515	-1.25	-0.683	Chemco	0.515	-1.88	-1.183
Interfresh	0.391	0.329	0.498	Interfresh	0.132	0.036	0.108	Interfresh	0.132	0.036	0.108
Star	13.863	-0.253	8.173	Star	0.192	-0.316	-0.135	Star	0.246	-0.184	0.003
Zeco	0.004	-0.745	-0.59	Zeco	0.109	-1.068	-0.784	Zeco	0.013	-0.925	-0.728
CFI	1.79	0.002	1.083	CFI	0.666	-0.028	0.38	CFI	0.59	-0.035	0.329
Ariston	1.458	0.416	1.212	Ariston	1.47	-0.528	0.468	Ariston	3.761	-0.023	2.254
Colcom	9.555	1.031	6.591	Colcom	18.314	0.956	11.822	Colcom	11.41	0.951	7.647
NTS	2.646	0.193	1.752	NTS	15.38	0.701	9.847	NTS	7.023	0.698	4.797
Radar	0.317	0.318	0.444	Radar	0.302	0.276	0.402	Radar	0.16	0.223	0.274
Hunyani	2.831	0.084	1.777	Hunyani	5.415	0.2	3.43	Hunyani	2.466	0.145	1.605
Medtech	6.984	-0.02	4.202	Medtech	6.984	-0.023	4.2	Medtech	0.807	0.007	0.493
Hippo	3.434	0.176	2.214	Hippo	2.704	0.477	2.012	Hippo	2.901	0.304	1.993
Seedco	12.382	0.989	8.265	Seedco	19.662	0.637	12.382	Seedco	18.978	0.414	11.792
Innscor	15.405	0.332	9.569	Innscor	35.981	0.342	22.005	Innscor	19.737	0.516	12.331
Masimba	16.387	-0.191	9.746	Masimba	17.216	0.126	10.499	Masimba	2.219	0.113	1.43
Padenga	6.2	1.216	4.712	Padenga	6.3	1.217	4.773	Padenga	7.416	0.809	5.122

In Table 11 above it can be noted that the accounting model generally assigned high z-scores to the non-bankrupt firms and z-scores below zero to the firms that were moving towards bankruptcy .A decreasing trend in z-scores can be observed on the firms that went bankrupt from 2010 to 2012. Some of the non-bankrupt firm's z-score show signs of improvement over the years while some are relatively stable.

4.4 Market Based Model

Inferred Inputs (firm asset volatilities and firm asset values) were iterated in excel solver.

Table 12: Calculated Equity Volatilities

	2010	**2011**	**2012**
Cairns	0.476	0.332	0.15
Phoenix	0.573	0.303	0.051
PGI	2.52	0.5301	0.4771
Celys	0.0616	0.0308	0.0308
Interfresh	0.11	0.07	0.07
Star	1.39	1.3	0.6048
Zeco	0.434	0.028	0.101
CFI	4.62	1.58	0.4424
Ariston	0.35	0.345	0.24
Colcom	8.3	3.64	3.71
NTS	0.38	0.8	0.27
Radar	6.98	9.92	2.99
Hunyani	0.09	0.08	0
Medtec	0.034	0.026	0.034
Hippo	21.57	17.66	6.46
Seedco	10.73	10.76	12.02
Masimba	2.05	3	3.32
Innscor	6.35	4.38	7.33
Padenga	0.21	0.51	0.51

Table 12 shows that stocks on the Zimbabwe stock exchange are generally highly volatile basing on the sample. Notable ones are Seedco, Chemco , Hippo with equity volatilities reaching as far as 1400% a year.

4.4.1 Inferred firm asset values & asset volatilities

Table 13: Inferred Firm Asset Values

Inferred Firm Asset Values	2010	2011	2012
Cairns	19,035,062	17,511,940	0.00011973
Phoenix	6,032,974	6,943,872	6,021,121
PGI	24,223,468	34,989,299	36,105,192
Celsis	4,153,442	4,657,782	5,474,025
Chemco	9,813,106	4,410,251	4,000,000
Interfresh	12,663,167	13,632,199	13,000,000
Star	12,497,430	48,541,340	45,469,667
Zeco	12,497,430	14,472,202	12,951,709
CFI	18,074,724	37,200,560	47,566,521
Ariston	12,750,436	13,344,791	25,050,418
Colcom	38,170,442	68,370,782	41,060,257
NTS	2,015,775	15,858,938	8,399,289
Radar	11,673,676	10,292,268	33,491,571
Hunyani	33,000,234	33,654,000	35,000,683
Medtec	5,860,292	6,484,065	5,092,147
Hippo	144,765	221,974	193,310
Seedco	66,000,567	67,000,564	68,000,345
Masimba	40,698,085	37,950,989	10,967,432
Innscor	254,092,174	537,668,810	320,866,513
Padenga	34,767,953	34,797,821	37,925,551

Table 14: Inferred Asset Volatilities

Company	**2010**	**2011**	**2012**
Cairns	0.08280	0.02775	0.0389
Phoenix	0.20430	0.07840	0.07599
PGI	0.17990	0.11040	0.06440
Celsis	0.02150	0.00430	0.00360
Chemco	0.29890	0.14190	0.1519
Interfresh	0.01270	0.00500	0.0567
Star	0.34650	0.06699	0.07380
Zeco	0.00900	0.03749	0.00109
CFI	4.13075	0.45340	0.04840
Ariston	0.17100	0.16610	0.16680
Colcom	8.30000	3.58800	3.63790
NTS	0.05729	0.70300	0.19590
Radar	6.12200	9.84810	0.98000
Hunyani	0.30300	0.01866	0.02000
Medtec	0.00550	0.00619	0.00080
Hippo	21.57000	17.66000	6.45400
Seedco	0.09000	0.09080	0.08950
Masimba	1.87670	2.81000	2.30610

4.4.2 Analysis of the inferred (Firm Asset Value and asset value)

It can be shown by Table 15 of the inferred firm asset volatilities that the firm asset values of the bankrupt firms three years before they went bankrupt are generally less volatile. The asset values are mostly moving in a down ward trend supported by Table 13 firm asset value. This could be because shares approaching bankruptcy are usually less liquid and rarely trade as shown in the equity volatility Table 12. This however affects input equity volatility equation (2) (left hand side) resulting in the solutions of the simultaneous equations for firm asset value and asset volatility. This is unlike the non-bankrupt firms which are highly change in share prices and hence high varying equity volatilities which result in high volatile firm asset value and asset volatilities.
Using the KMV model the results below were obtained

Table 15: KMV Distance to default

Company	2010	2011	2012
Cairns	1.7830	2.2298	3.6457
Phoenix	2.0518	3.7195	2.4088
PGI	1.6894	1.5171	2.8567
Celsis	12.9259	10.8490	6.6701
Chemco	2.3466	1.9494	1.790
Interfresh	13.3917	49.1506	12.456
Star	1.5886	4.3034	3.2048
Zeco	41.5594	11.0267	287.2809
CFI	0.1807-	0.2787-	2.2067
Ariston	3.5166	3.4297	4.5469
Colcom	0.0972	0.2472	0.2212
NTS	6.0281	1.2712	3.8192
Radar	0.2385-	0.2296-	0.2157-
Hunyani	1.9275	1.4286	1.3401
Medtec	13.5572	17.9384	95.4979-
Hippo	0.0204	0.0307	0.0719
Seedco	9.5139	9.2821	8.2345
Masimba	0.4517	0.2365	0.2179-
Innscor	0.1098	0.3236-	0.0866
Padenga	4.9903	2.0570	2.0370

4.4.3 KMV default probability

Changing the distance to default to a probability of default at time (t) :Probability of default (t)=P $[V_A \leq D]$=……………..= $\phi(-DD)$ as DD corresponds one to one to probability of default.(Table16)

Table16: KMV default probability

Company	**2010**	**2011**	**2012**
Cairns	0.0372943	0.0128808	0.0001334
Phoenix	0.0200924	0.0000998	0.0080032
PGI	0.0455672	0.0646245	0.0021406
Celsis	0.0000000	0.0000000	0.0000000
Chemco	0.0094733	0.0256235	0.030
Interfresh	0.0000000	0.0000000	0.00000001
Star	0.0560720	0.0000084	0.0006758
Zeco	0.000	0.0000000	- 0.000000
CFI	0.5716809	0.6097730	0.0136674
Ariston	0.0002186	0.0003021	0.0000027
Colcom	0.4612886	0.4023672	0.4124665
NTS	0.0000000	0.1018336	0.0000669
Radar	0.5942524	0.5908035	0.5853811
Hunyani	0.0269611	0.0765661	0.0901076
Medtec	0.0000000	0.0000000	1.0000000
Hippo	0.4918602	0.4877461	0.4713486
Seedco	0.0000000	0.0000000	0.0000000
Masimba	0.3257408	0.4065362	0.5862659
Innscor	0.4562818	0.6268855	0.4654877
Padenga	0.0000003	0.0198454	0.0208258

Table 16 above shows that the bankrupt firms shows a downward trend of distance to default per each firm as they approached default .The bankrupt firms probability of default per each firm increases as the firm approaches bankruptcy. However it is disappointing that the magnitude of the distance to default in inter companies is very wide .For instance Zeco has an outlier distance to default in 2012 (280) incomparable to blue-chip firms like Innscor and Seedco (with 0 to 8 in 2012). Distances to default are generally less stable compared to the accounting z-score model.The distances to default of the non-bankrupt firms are generally stable with some on a down ward trend. The probability of default of the non bankrupt firms in Table 16 is closer to zero in relation to the bankrupt firms.

4.4.4 Comparing the models

Since the two analysed models produce different credit risk measures, evaluating and comparing the accuracy of the credit risk models directly can be difficult. As described above, the z-score generates a continuous number, where certain thresholds(1.286 and -1.286) determine the supposed future of the company whereas distance to default generates default probabilities(between 0 and 1).

4.5 Data Input to Cumulative Accuracy Profile

Data input(*see appendix 1*) was following the ranked order of(risky to safe) done on data on all the three models in 2011.All the 20 companies were divided into pairs of (2, 4, 6,…,20) thus (2/20 companies*100%) thus the axis moves in 10% intervals to make the x-axis as shown in Table 19.(assume the companies are ranked first in order of risk to safe per each model under analysis). The y-axis is the made by checking in each cumulative 10%(x or 2 companies ranked) how many as a cumulative fraction of the ten bankrupt firms that delisted in 2013 are captured. By the time the axis moves to 100% (20/20 companies * 100%) thus all 20 companies captured all the default would have been captured as per where they are positioned. The only difference is each model places the bankrupt firms differently depending on the outcome of ranking score or probability as shown in *(appendix 1)* attached.

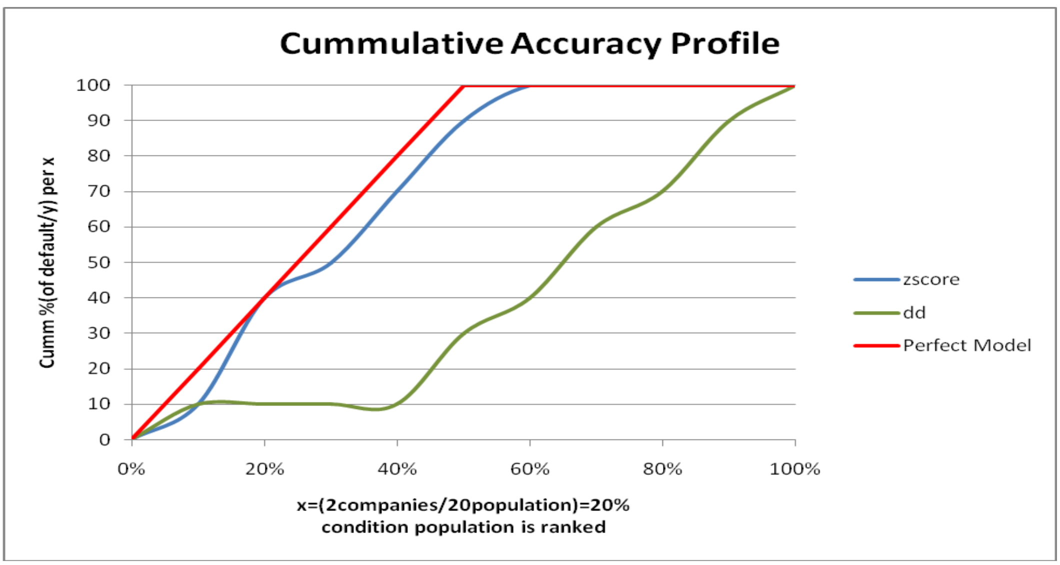

Figure 1: Cumulative accuracy profile

It can be seen on the Cumulative Accuracy curve Fig.1 above that the z-score(blue) is the most superior model as it is closer to the ideal model curve(red). This shows that the z-score model in 2011 was able to rank the scores and gave the high risky scores to the

firms that actually went bankrupt in 2013. It captured their default earlier in 2011 ahead of 2013 relative to distance to default, thus a better predictor of default.
This also shows that it has a very low Type 1 error and a very low Type II error. This model has less error in classifying potential bankrupt firms as non-bankrupt and non-potential bankrupt firms as bankrupt thus reputation risk .The distance to default curve is further away from the ideal curve showing that it was slow at capturing in 2011 the firms that went bankrupt in 2013.Thus it has a relative high Type I and Type II error.

4.6 Accuracy Ratio

Accuracy Ratio measures the quality of the rating model. It derives its value from CAP curve .It is the ratio of the area between rating model, and the area between the ideal model (perfect model).

Table 17: Accuracy Ratio Calculation using Trapezoidal rule

Accuracy Ratio								
Distance to Default data			Ideal Model data			z-score Area		
X%	Y%	Trapezoid	X%	Y%	Trapezoid	X%	Y%	Trapezoid
10	10	100	10	20	300	10	20	300
20	10	100	20	40	500	20	40	450
30	10	100	30	60	700	30	50	600
40	10	200	40	80	900	40	70	800
50	30	350	50	100	1000	50	90	950
60	40	500	60	100	1000	60	100	1000
70	60	650	70	100	1000	70	100	1000
80	70	800	80	100	1000	80	100	1000
90	90	950	90	100	1000	90	100	1000
100	100		100	100		100	100	
	area =	3750		area =	7400		area =	7100.00

Accuracy Ratio

Z-score/ideal model	0.959
Distance to default/ideal m.	0.507

In terms of quality of rating model for Zimbabwean corporate bankruptcy environment it can be shown from an accuracy ratio closer to 1 that accounting model Z-Score is a high quality model .It had an accuracy ratio of 0.959 in Table 17. Distance to default had a lower accuracy ratio of 0.507.Thus we can accept the null hypothesis that accounting based models are the best predictors of default. See appendix 2.

5 Conclusion

The study shows that the developed z-score accounting model can be used estimating bankruptcy prediction model for Zimbabwe .It had a superior accuracy ratio of 0.959 relative to market based model of 0.507. The study shows that most of the companies that went bankrupt during the period from 2010-2013 have shown signs of financial distress i.e., poor financial performance in prior years. It contributed in the existing literature by exploring two financial variables namely EBIT to current liabilities, Market Value of Equity to Long Term Debt that can be used to explore the bankruptcy risk in Zimbabwe. The study therefore accepts the null hypothesis and concludes that, the accounting model is the best predictor of default. The developed Z-Score model with the above established variables is supported by past researches, (Eljelly et al., 2001), Altman (1968) and Rashid (2010).

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Appendices

Appendix 1: Cumulative accuracy profile data input

VALIDATION OF MODELS	
Number of companies(population):	**20**
x axis (2/20)*100% of ranked companies:	**10%**
Number of defaulted companies by 2013:	**10**
Y axis y(x)-cummulative fraction of defaults over total defaults per unit of x	

CUMMULATIVE ACCURACY PROFILE DATA INPUT									
X AXIS			**Y- Z-SCORE**			**Y-D to D**			**Y.PerfectMode**
	z-score	**Actl defaults per x**	**Actl default Cumm % of y**	**dd(probablity**	**Actl defaults per x**	**Actl default Cumm % of y**	**Perfect Model**	**Actl defaults per x**	**Actl default Cumm % of y**
	0.1	2	20	0.626885498	1	10	1	2	20
10%	0.45			0.609773037			1		
	0.5554	2	40	0.590803511	0	10	1	2	40
10%	0.78			0.487746144			1		
	0.88	1	50	0.406536223	0	10	1	2	60
10%	0.9			0.402367232			1		
	1	2	70	0.101833626	0	10	1	2	80
10%	1.11			0.076566055			1		
	2	2	90	0.064624451	2	30	1	2	100
10%	2			0.025623452			1		
	2.2	1	100	0.019845354	1	40	<1	0	100
10%	2.22			0.012880778			<1		
	2.3	0	100	0.000302088	2	60	<1	0	100
10%	2.3			9.98248E-05			<1		
	3.1	0	100	8.41112E-06	1	70	<1	0	100
10%	4			8.30552E-21			<1		
	5	0	100	1.00787E-27	2	90	<1	0	100
10%	5			1.42104E-28			<1		
	6	0	100	2.95764E-72	1	100	<1	0	100
10%	8			0			<1		
TOTAL		10			10			10	

Appendix 2: Snippet for Trapezoidal Area Under Curve Calculation

	A	B	C
1	Area under curve		
2			
3	Trapezoid Rule, Method 1		
4	x	y	trapezoid
5	1	0	3
6	2	6	11
7	3	16	23
8	4	30	39
9	5	48	59
10	6	70	83
11	7	96	
12		area	218
13			

=(B6+B5)/2*(A6-A5)

=SUM(C5:C10)

Trapezoid Rule
Divide curve into series of trapezoids, each with area =(average height)(width)