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AN ASSESSMENT OF THE APPLICATION AND THE CORPORATE FAILURE PREDICTIVE VALUE OF ALTMAN'S Z-SCORE MODEL IN ZIMBABWE

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Abstract

This research focuses on testing corporate failure predictive value of Altman's Z-score model on Zimbabwe's financial institutions in order to establish whether the model can accurately predict risk of failure for these financial institutions and the extent to which the model is being employed by the institutions for failure prediction particularly after Zimbabwe faced unique economic conditions. A case study approach with ten selected financial institutions was used. The research found out that the Z-Score model can accurately predict risk of failure within two years with higher accuracy one year prior to failure and that financial institutions were not employing the model in failure prediction. The study concluded that the Z-score model is an effective tool for failure management and was therefore recommended.

Keywords-component; bankruptcy; corporate failure; financial institutions; Z-Score; Zimbabwe

I.INTRODUCTION AND BACKGROUND TO THE STUDY

Over the last 43 years, business failure prediction has become a major research domain within corporate finance. This was prompted in the post Enron-Andersen debacle era. There had been widespread debate among various stakeholders in the quest to identify firms likely to go bankrupt and or become financially distressed. Numerous corporate failure prediction models have been developed based on various modeling techniques. The most popular are the classic cross-sectional statistical methods which have resulted in various single-period or static models especially the multivariate discriminant models and logit models. Zimbabwe experience one of the toughest economic conditions, in late 2008, hyperinflation led to the abandonment of the Zimbabwe, the official recognition of the demise of the Zimbabwe dollar took place in February 2009, when authorities established a multicurrency system [1]. Faced with hyper inflation, liquidity crisis and high interest rates, Zimbabwe experienced high corporate failure especially in the financial sector. This study seeks to assess the application and corporate failure predictive value of Altman's Z- score model in Zimbabwe

According to [2], the univariate models, risk index models, multiple discriminant analysis models (MDA) and conditional probability models such as logit, probit and linear probability models are the classic cross sectional statistical methods that have widely been used in the development of corporate failure prediction models. MDA is by far the most dominant classic statistical method, followed by logit analysis [3].

Edward Altman's z-score model is one of the most popular multiple discriminant analysis model (MDA) first published in 1968. The z-score model is a simple, less complicated corporate failure prediction model which is based on an overall index known as the z-score. The z-score is calculated from specially selected ratios drawn from company financials. The z-score discriminates between firms that are likely to go bankrupt within two years from healthy firms by using a cut-off score for the overall index.

Despite, extensive researches on testing the predictive power of corporate failure prediction models, very little has been done regarding the application of these models in the context of less developed economies like Zimbabwe. Economies may differ economically, socially, politically and geographically. By so doing, the level of objectivity (truth and fairness) of the annual financial statements upon which the corporate failure predictive power or ability of the z-score model is tested would also differ depending upon the type of an economy. The level of objectivity of the financials of any given economy can be suppressed by the level of financial shenanigans and/or error regarding the preparation and presentation of the financials. This may result in the z-score model misclassifying firms. Healthy firms may end up being classified as risky whilst risky firms being classified as healthy. Accordingly, the researcher intends to investigate whether Altman's z-score model can still be valid in the Zimbabwean context considering the unique economic conditions experienced by the country.

Various renowned researchers ranging from academics to practitioners have debated on the issue of the ranking and selection of the failure prediction models on the basis of superiority. It seems no consensus has been reached yet in this regard.

Reference [4] contributed to this debate that despite the extensive literature, there seems to be no superior modeling method. Hand further argues that, it is impossible to ascertain a superior method from an examination of a large range of comparative studies that compare the ex-post classification results and/or the ex-ante prediction abilities of these different kinds of failure prediction models. He further puts forward that most studies reach heterogeneous conclusions and points in different directions.

Reference [3] argues that the MDA method (Altman's z-score is one of them) is by far the most dominant classic statistical method followed by the logit analysis. This study subscribes to this view hence test the model in the Zimbabwean set-up.

Financial institutions in Zimbabwe during the last quarter of 2003 and the first quarter of 2004, in particular, a number of

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banking institutions faced serious challenges that ranged from chronic liquidity problems, deep- rooted risk management deficiencies to poor corporate governance practices. The same has repeated in 2011-2012 after some banking institutions had been placed under curatorship after being proven insolvent by the Reserve Bank of Zimbabwe.

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By the end of 2004, ten banking institutions had been placed under curatorship whilst two went under liquidation. On the other hand, one discount house faced closure .This led the banking public into tremendous psychological, emotional, social and financial ruin. The public lost trust in the banking sector, [5]. The Reserve Bank of Zimbabwe Governor, in the same report published a rundown of the troubled banking institutions from 2003-2006, at least 15 financial institutions were catergorised as troubled.

The research problems is therefore that, major financial institutions are increasingly either being liquidated or placed under curatorship as evidence of failure yet prominent corporate failure prediction models had already been established for use in order to predict risk of failure way back before the failure materializes and avoid it.

The study therefore seeks to test the corporate failure predictive ability of Altman's z-score model within a two year time frame. The study intends to assess the effectiveness of the z-score model in predicting risk of corporate failure so that the model will be applied in future if found to be effective in failure prediction in order to minimize risk of failure of Zimbabwean companies.

Research objectives are summarized as follows:

- To establish the degree of corporate failure prediction accuracy of the z-score model one year prior to firm failure.
- To establish the degree of corporate failure prediction accuracy of the z-score model two years prior to firm failure.

Accordingly it is hypothesized that;

H1- Altman's z-score model can effectively predict risk of corporate failure of financial institutions in Zimbabwe within two years.

H2- Altman's z-score model cannot effectively predict risk of corporate failure of financial institutions in Zimbabwe within two years

Research gap

As already alluded to in the background to the study, many researches on assessing corporate failure predictive power of Altman's z-score model were focusing on developed economies at the expense of less developed economies like Zimbabwe. In addition Zimbabwe experienced unique economic crisis which require a review of applicability of failure prediction models during or after such crisis. Moreover, the researchers decided to concentrate on Altman's z-score model neglecting all other models in partial adoption of [4]'s argument that there is no superior model in assessing risk of corporate failure. He further argues that the choice of a model is the researcher's discretion. However, Hand goes further to say that there is ample evidence supporting the assertion that large gains in classification accuracy of whether a firm is facing risk of failure or not are yielded by the relatively simple models like Altman's z-score whereas the more sophisticated models yield rather small marginal improvements. He further argues that the simple MDA models (Altman's z-score one of them) can produce over 90% of the predictive power that can be achieved by the more complex models and they are less likely to over-fit. In partial support of [4] and [3] suggest that MDA are by far the most dominant models followed by logit analysis. Simplicity of Altman's Z-score model will jig saw fit with the financial literacy level of Zimbabwe and other developing nations. In view of the above, this study will test corporate failure predictive value of Altman's z- score model in a Zimbabwean.

Delimitations of the Study

The study was conducted in Zimbabwe. All financial institutions in Zimbabwe during the period 2001 and 2012 represented the targeted population of the study. Altman's z-score model was tested on the annual financial statements of the selected bankrupt and non-bankrupt institutions in order to assess its failure predictive value within two years. The research was mainly secondary data based with minor concentrations on qualitative aspects. The z-score model was tested on data from the five selected bankrupt and five non-bankrupt financial institutions. Thirty-five questionnaires were administered to the thirty-five selected risk managers of the conveniently selected financial institutions in order to gather the desired data concerning the extent to which the z-score model was being used by the institutions as a corporate failure prediction tool.

I. LITERATURE REVIEW

A. Theoretical Literature Review

It has been decades now of vibrant researches on business failure prediction models although no consensus has been reached on the best business failure prediction model. Researches on business failure prediction models are coming from different dimensions. Whilst some researchers have focused on testing the predictive value of these models, others have concentrated on other issues like proposing modifications to the models to enhance their failure predictive ability and making comparative evaluations of the models to gather their strengths and weaknesses just to mention a few. This section provides a synopsis of both theoretical and empirical review of literature related to business failure prediction models.

Preliminary review of literature indicates that corporate failure has been in the accounting and corporate finance literature for quite some time. Several models have been developed by various researchers to predict corporate failure. There has been extensive work for developing failure prediction models since the pioneering work by Beaver in 1966. According to [2], univariate models, risk index models, multiple discriminant analysis models (MDA) and conditional analysis models such as logit, probit and linear probability models are the classic cross sectional statistical methods that have been widely used in the development of corporate failure prediction models. Reference [6] outlined the aforementioned cross-sectional statistical modeling methods as follows:

Multiple Discriminant Analysis (MDA) Models, An MDA model consists of a linear combination of variables which provide the best distinction between failing and non-failing firms. There is a linear MDA and quadratic MDA. As the linear MDA is by far the most popular MDA method, there is no need to further elaborate on the quadratic MDA method. The discriminant function for a linear MDA model is as follows as a linear function:

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$$D_i = d_0 + d_1x_{i1} + d_2x_{i2} + \ldots + d_nx_{in} \quad (1)$$

where $\mathbf{D_i}$ = is the discriminant score for firm **i**; $\mathbf{x_i}$ is the value of attribute $\mathbf{x_j}$ (with **j**=1, . . . , n) for firm **i** ; d_0 is the intercept; and $\mathbf{d_j}$ is the linear discriminant coefficient for attribute **j**. Several firm characteristics or attributes are combined into one single multivariate discriminant score, $\mathbf{D_i}$. **Di** has a value between -∞ and +∞ and gives an indication of a firm's financial health. Altman's z-score model is an MDA model.

Risk Index Models, a risk index model is a simple and intuitive point system which includes various ratios. A firm is attributed a certain number of points between 0 and 100 according to the values of the ratios involved in the model, so that higher total points indicate a better financial situation. Points are allocated so that the most important ratios have higher weights (i.e a higher maximum of points). However, the allocation of points is subjective.

Conditional Probability Models, a conditional probability model allows the use of non-linear maximum likelihood method to estimate the probability of failure conditional on a range of firm characteristics. These models are based on certain assumptions concerning the probability distribution.

In a univariate failure prediction model, an optimal cut-off point is estimated for each measure or ratio in the model and a classification procedure is carried out separately for each measure, based on a firm's value for the measure and the corresponding optimal cut-off point. Univariate analysis is based on the stringent assumption of a linear relationship between all measures and the failure status.

In 1996, Beaver pioneered a corporate failure prediction model with financial ratios. He employed "univariate" in that each ratio was evaluated in terms of its ability to predict failure without consideration of the other ratios. In applying multivariate discriminant analysis (MDA), [7] tried to improve upon Beaver's pioneering work. Although this method proved to suffer certain limitations, researchers continued with Altman's approach with the hope that more appropriate and higher classification accuracy would be achieved. Examples of such study attempts are: (1) assignment of prior probability membership classes; (2) consideration of more appropriate "quadratic classifier" [8]; (3) use of cash flow based models; (4) use of quarterly financial statement and (5) investigation of the use of the current cost information [9]. However, none of these efforts yielded higher or numerically significant classification results than Altman's earlier work.

With the limitations of MDA due to its restrictive statistical requirement imposed, other models were introduced by subsequent researchers. Reference [10] employed logistic regression for the prediction of corporate failure, a model that avoids the cited limitations of MDA techniques. Logit analysis (logistic regression) together with probit (a variation of logit) did not improve the results of the various discriminant analysis, indicating the need for further improvement. Among the first application of logit analysis in the UK according to [11] was by Peel in 1986. The researchers added a number of non-conventional ratios and variables in an attempt to refine the classic financial ratio-based failure models.

Several MDA models were developed in the UK during the 1970s and 1980s. Despite the major improvement in statistics that occurred over the subsequent years, MDA continued to be the most popular most widely used failure prediction technique in the UK [11] used multiple regression analysis to develop a failure prediction model for the Bank of England.

Various classification techniques continued to be employed by various researchers with the hope of discovering the "perfect" model. The list of these models ranges from recursive partitioning, neural networks, the human information processing approach and survival analysis to multi-dimensional scaling approach. Other scholars concluded that there is no superior method has been found although the accuracy of the various failure prediction methods varies. Also, earlier researchers did not examine the usefulness of operating cash flow information in explaining financial collapse [11], hence the collapse of super-profit giants like Enron and WorldCom.

Notwithstanding the numerous researches on corporate failure prediction models, none of these can predict with exact accuracy a firm's financial health.

Definition of Corporate Failure

An attempt to find the definition for the term "corporate failure" proved futile as the thorough search of the literature indicated there is no such definition. There is the notion that an attempt to uniquely define corporate failure is likely to prove problematic due to the fact that corporate failure is a process rather than a point in time event. The term is used in reference to firms that are financially distressed, ranging from bankruptcy at one end of the spectrum to failings in business at the other end.

Reference [12] noted that large firms defined failure as either creditor's compulsory or voluntary liquidation. In contrast, some scholars described corporate failure as inability of companies to meet set mission. Apparently, this line of definition is narrow in scope, because there are endless list of companies that are yet to accomplish their mission but are of sound financial footing. Consequently, prior studies in corporate failure defined failure within the premise of companies that had ceased trading.

Corporate failure as noted by [13] faintly encompasses "bankruptcy", and for a company, that effectively means a creditor's liquidation or the appointment of a receiver. He further contributed that the net could be widened to include instances of evidence of "financial distress". Morris then gave an outline of indicators of company distress as follows:

- Creditors' or voluntary liquidation and appointment of a receiver;
- Suspension of stock exchange listings;
- Going concern qualification by auditors;
- Composition with the creditors;
- Protection sought from creditors;
- Breach of debt covenants, fall in bond ratings and new charges taken over the assets of the company or its directors;
- Company reconstructions;
- Resignation of directors and appointment of a company director;
- Company take-over (although not all take-overs are witness to financial distress, of course);
- Closure or sale of part of the business;
- A cut in dividends or the reporting of losses; or
- The reporting of profits below a forecast or acceptable level, and/or the fall in relative share price of the company.

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The Use of Annual Account Information

The majority of the classic cross-sectional models use only annual account information in the form of financial ratios in order to predict failure [14]. Financial ratios are used because they are hard, objective measures and because they are based on publicly available information [15]. On the other hand, financial ratios have been subject to many criticisms. However, despite the criticisms, the role of financial ratios in failure prediction is very important.

An initial problem related to the use of annual account information (financial ratios) is that the obligation to prepare and/or publish annual accounts is restricted and mostly depends on the criteria concerning firm type and/or firm size. In many countries including the USA, UK and Germany, only those firms which meet certain criteria concerning asset size, sales level and/or number of employees are obliged to publish their annual accounts [16]. In Zimbabwe, all companies listed on the Zimbabwe Stock Exchange are obliged to publish their annual financials whereas the preparation and publishing of the annual financials, is discretionary, for the unlisted companies.

When predicting corporate failure on the basis of financial ratios, researchers implicitly assume that the annual accounts give a true and fair view of the financial situation. However, it seems reasonable to assume the opposite. First, there is much anecdotal and academic evidence that firms in general, and unhealthy or failing firms in particular, have incentives to manipulate or manage their annual account figures [17]. By means of creative accounting practices, failings firms adjust their earnings upwards and give a more positive presentation of their financial situation, especially when the moment of failure is very near. Second, annual financials may be unreliable, especially in smaller firms, usually because of the lack of an effective internal control system or because of annual account adjustments made by the auditor in the light of a bankruptcy filing referred to as accommodated annual accounts .

Reference [18] pointed out that results based on erroneous annual account information may become worthless and added that the problem of annual account errors is often under estimated. For example, several studies on the quality of Belgian annual accounts have shown that the quality of many annual accounts is poor, especially in small firms [15]. A large number of annual accounts have missing values. In many studies, annual accounts with missing values are simply deleted from the analysis. Possible solutions to these annual account problems are to trim the ratios with extreme values at certain percentiles and to replace the missing values by mean or random values [19]
.

Finally, although many studies have compared the predictive abilities of accrual-based financial ratios and cash flow-based ratios, there seems to be no consensus as to which types of financial ratios are the best failure indicators. Some studies have suggested using cash flow-based funds flow components instead of accrual-based financial ratios in failure prediction modeling or, at least, improving model accuracy by adding cash flow ratios to models based on accrual-based financial ratios [20].

Number of Factors (Variables) in a Model

According to [21], one area that appears to have little influence on the predictive abilities of models is the number of factors considered in the model. For the sixteen models that provided 100% classification accuracy, the number of factors ranged from 2 to 21. Models that considered as few as two factors had predictive accuracies ranging from 86% to 100%. Models which considered an extremely higher number of factors had comparable accuracies. Therefore, a higher number of factors does not guarantee a higher predictive ability of a model.

Prediction Timeframe

It is important to consider how far ahead the model is able to accurately predict bankruptcy. Most of the accuracies discussed above are the accuracy rates obtained one year prior to failure. However, some models are able to predict bankruptcy much sooner than the others. For instance, a model could predict bankruptcy with 96% accuracy two years prior to the failure. Similarly, other models predicted bankruptcy with 97% accuracy three years prior to failure. Clearly, a model that is able to accurately predict bankruptcy earlier becomes more valuable [22].

Model Accuracy

The bankruptcy prediction literature continually refers to Type I and Type II errors. Type I errors are the misclassification of bankrupt firms as non-bankrupt. Type II errors are the reverse, non-bankrupt firms misclassified as bankrupt firms. It is generally agreed upon that type I errors are costly than Type II errors for several reasons including loss of business (audit clients), damage to a firm's reputation and potential lawsuits/court costs. Therefore, the predictive accuracies discussed here refer to the accuracies obtained for bankrupt firms unless the results were not separately presented for bankrupt and non-bankrupt firms. If results were not separately presented, the overall predictive accuracies are discussed [23]. The predictive values of models vary across time and method. The following table shows predictive abilities by method and model.

Table 1: Predictive Ability by Method and Model

Method	Lowest Accuracy	Highest Accuracy	Studies Which Obtained Highest Accuracy
MDA	32%	100%	Edmister (1972) Santomero and Vinso (1977) Marais (1980) Betts and Belhoul (1982) EI Hennawy and Morris (1983) Izan (1984) Takashashi et al (1984) Frydman et al (1985) Patterson (2001)
Logit Analysis	20%	98%	Dambolena and Shulman (1988)
Probit Analysis	20%	84%	Skogsvik (1990)
Neural Networks	71%	100%	Messier and Hansen (1988) Guan (1993) Tsukuda and Baba (1994) EI-Temtamy (1995)

Source: [24]

To promote an enlightened understanding of the predictive values of different corporate failure modeling methods, [24] further presented an analysis of the predictive values of the modeling methods by decade as follows:

Table 2: Predictive Ability by Decade and Method

Period	Lowest Accuracy	Highest Accuracy	Method(s) Used to Obtain Highest Accuracy
1960s	79%	92%	**Univariate DA** [Beaver (1966)]

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1970s	56%	100%	**Linear Probability** [Meyer and Pifer (1970)] **MDA** [Edmister (1972); Santomero and Vinso (1977)]
1980s	20%	100%	**MDA** [Marais (1980); Betts and Behoul (1982); E. I Hennawy and Morris (1983); Izan (1984) Takahashi et al (1984); Frydman et al (1985) **Recursive Partitioning Algorithm** [Frydman et al (1985)] **Neural Networks** [Messier and Hansen (1988)]
1990s	27%	100%	**Neural Networks** [Guan (1993); Tsukuda and Baba (1994); EI Temtamy (1995); **Judgemental** [Koundinya and Puri (1992)] **Cumulative Sums** [Theodossiou (1993)]
2000s	27%	100%	**MDA,**[Patterson (2001)]

Source: [24]

It appears that as model development evolved, models were able to predict at the maximum accuracy of 100%, however, the low end of the range dropped severely from 79% in the 1960s to as low as 20% in the 1980s. These results do not suggests that newer models are more promising than older models [24]

In numerous studies, MDA and neural network models have provided the highest success rates. Logit analysis also performed quite well in Dambolena and Shulman's (1988) study. However, the method which has had the best accuracy range (71% to 100%) is neural networks. These results imply that MDA and neural networks are the most promising methods for bankruptcy prediction models [24 and 22]

Altman's Z-Score Model

Edward. I. Altman first published the model in 1968. The z-score model was developed to predict firm bankruptcy and provide a basis for safer investment decisions and better assessment of supplier and customer creditworthiness. The z-score model claimed to predict bankruptcy correctly in approximately 95% of the cases one year prior to failure and, in 83% of the cases two years in advance. The model was created with an initial dataset of 66 US manufacturing firms (33 bankrupt and 33 non-bankrupt firms) using multiple discriminant analysis (MDA). This statistical method distinguishes two or more classes of objects (in this case bankrupt and non-bankrupt firms) by making a linear combination of attributes of each class. The input for the model requires only publicly available data from annual reports. The main equation to predict bankruptcy is as follows:

$$Z=1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5 \quad (2)$$

The variables are calculated as factors as follows:

X_1 = Working Capital/ Total Assets

= (Current Assets – Current Liabilities)/ Total Assets.

This factor (X_1) measures firm liquidity. Low liquidity (low X_1) is a predicting factor for bankruptcy since it measures a company's ability to pay its bills. Other liquidity ratios such as current ratio (Current Assets/ Current Liabilities) and quick ratio [(Current Assets – Inventory)/Current Liabilities] have shown smaller significance in predicting bankruptcy.

X_2 = Retained Earnings/Total Assets.

This factor measures age and leverage. Retained earnings are part of the Balance Sheet (Statement of Financial Position) as an element of equity. Retained earnings represent the equity that the company has earned and not paid out to shareholders over its lifetime. Younger companies that have had less time to retain earnings (lower X_2) have a higher risk of bankruptcy when their profitability drops.

X_3 = Earnings before Interest and Taxes/Total Assets.

This factor measures productivity (the earning power of the firm's assets). The earning power is the basis of each firm's existence. A firm can only survive if it can make money. More earning power signifies low risk of bankruptcy.

X_4 = Market Value of Equity/Book Value of Total Liabilities.

This factor measures solvency. An insolvent company is not able to meet its obligations and may go bankrupt when its creditors move in to reclaim their dues. The market value of equity is used because it more accurately predicts bankruptcy than book value.

X_5 = Sales/Total Assets.

This factor measures the firm's sales generating ability and somewhat similar to earning power (X_3). However, when used in combination with earnings before interest and taxes (EBIT) in the z-score model, this factor contributes a high discriminating power because of its statistical relation with the other factors.

Z = Overall Index.

The overall z-score discriminates between firms that are likely to go bankrupt within two years from healthy firms by using a cut-off score for the overall index. The z- score conditions are as follows:

When**:**

- **Z < 1.81,** it implies high degree of bankruptcy for the firm
- **1.81 < Z < 2.99,** it implies an uncertain situation in which anything will be possible (Gray Area)
- **Z > 2.99,** it implies low probability of bankruptcy for the firm.

In a stricter version of the model, 2.69 rather than 2.99 is used as a cut-off score. However, this increases the chance of falsely assigning a lower bankruptcy probability to a particular firm. Technically, this is a choice between having relatively more false negatives (Type II errors) and relatively more false positives (Type I errors)

2.1.7 Accuracy and Effectiveness of Altman's Z-Score Model

Altman's z-score model had high predictive ability for the initial sample one year before failure of 95%. However, the model's predictive ability dropped off considerably from 95% with only 72% accuracy two years before failure, down to 48%, 29% and 36% accuracy three, four and five years before failure respectively[4].

In a series of subsequent tests of the model (up until 1999), the model was found to be approximately 80% - 90% accurate in predicting bankruptcy one year before the event, with a Type II error (classifying the firm as bankrupt when it does not go bankrupt) of approximately 15% - 20% [25], Altman's z-score model gained wide acceptance by auditors, management accountants, courts and database systems used for loan evaluation. The authors further write that the formula's approach has been used in a variety of contexts and countries, although it was designed originally for publicly held manufacturing companies with assets of more than US$1 million.

B. Empirical Literature Review

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Reference [26] tested the applicability of Altman's z-score model on Kenya's Commercial Banks. The results showed that Altman's model has prediction accuracy of 68.8% and 56.3% one year and two years prior to failure respectively. The researcher concluded that the model could be applied in Kenya. However, Altman's model was not being applied in Kenya as most banks used the Central Bank standard ratios. The study highly recommended Altman's z- score model for use by Kenyan banks for failure prediction. This research is very similar to the current research as it also assesses Altman's z-score model's predictive value on Zimbabwean banks. In [26] research, financial statements of 10 banks between 1994 and 2003 were collected. Their z- scores were calculated, compared with z-score cut-off limit, and then grouped as either bankrupt or non-bankrupt. The grouping was then compared with the prevailing bank situations.

In another research, [27] studied the financial distress on Oslo Stock Exchange as an application of Altman's z-score model to the financial crisis. The researcher wanted to determine the predictive value of Altman's z-score model during the crisis. In the study, Altman's z-score model proved to be accurate in correctly classifying the financial distress of firms. The model proved to be relevant even during a crisis. However, the Type II error of classifying firms as bankrupt when they do not go bankrupt increased substantially during the crisis, with as much as 40% - 50% of the enterprises incorrectly classified as bankrupt. This indicates that the z-score's ability to predict bankruptcies significantly worsened in the financial crisis although its ability to identify financial distress in general, still, might be intact. All enterprises on the Oslo Stock Exchange (OSE) listing during 2004 to 2009 constituted the population of the study. For the purposes of the study, the researcher considered a sample of 180 enterprises on the OSE. The input data for Altman's z-score model was obtained from the annual financials retrieved the ORBIS database which contains company information across the world.

In the same context, [28] conducted a research to assess the corporate financial distress in automobile industry of India applying Altman's z-score model. The major objective of the research was to test whether Altman's z-score model could foresee correctly the corporate financial distress of the automobile industry in the Indian context for the study period, 2003 – 2004 to 2009 – 2010. The study revealed that the automobile industry was just on the range of the intermediate zone. The z values for all the seven years were more than 1.81 but less than 3 (Z-score = In between 1.81 and 3.0 = Indeterminate). The research was secondary data based. Data from published sources was the basis for the analysis. The required accounting information for z-score analysis was obtained from CMIE Prowess database. The annual financial data used was for 62 publicly traded companies listed on the Bombay Stock Exchange.

Reference [29] in their study to assess business failure predictive value of Altman's z-score model on HAFED during 2004 – 2005 to 2008 – 2009 found out that HAFED stood in the healthy zone in terms of its financial viability throughout the study period as revealed by the z-score model.

Reference [30] took a different dimension in their study in which they studied the efficacy of Altman's z-score model in predicting bankruptcy of specialty retail firms doing business in contemporary times. In this study, all but two of the bankruptcies (94%) would have been accurately predicted. Despite some criticism of the model's efficacy, two firms were misclassified yet latter potential financial distress was revealed. More specifically, the researchers made eight comparisons, four each in 2007 and 2008, of bankrupt and non-bankrupt firms in retail specialties. The z-score model accurately predicted bankruptcy filing 94% of the time and accurately predicted financial distress over 90% of the time. A sample of 17 retail firms whose annual financials were used to provide input data for Altman's z-score model was considered for the study. The comparable firms were identified from the key competitor information listed on Yahoo! Finance and/or directly from company documents.

In their study to determine corporate failure predictive value of Altman's z-score model in Greece, [31] discovered that the model could predict the majority of companies that could go bankrupt , even when the z-scores of those companies were computed up to six years earlier. The study also revealed that the success rate for failed companies varied from 66% (year one) and gradually diminished to 52%, 39% and 20% for year two, three and four respectively. Therefore, the z-score gave a good indication of problems at least one year before the firm would exhibit problems. However, the model performed poorly when prediction time horizon increased. The study revealed Type II error of 66% (year one), 52% (year two), 39% (year three) and 20% (year four).
On the other hand, the model had been successful in classifying the majority of non-bankrupt firms in all the examined periods (-1, -2, -3 and -4 years). In particular, 78% of the firms were correctly classified for the long time spans, that is, four years. The percentage diminished to 54% for a year time span. Overally, the model succeeded to identify bankrupt and non-bankrupt firms. The research was secondary data-based and covered the period 1999 to 2006. The researchers considered a sample of 373 companies listed on the Athens Stock Exchange. Forty-five of the companies bankrupted or had their shares suspended permanently and three hundred and twenty-eight companies did not go bankrupt or had their shares permanently suspended.

Altman's z-score model was also used to rank a basket of European companies and discovered that companies with statements of financial positions underperformed the market more than two thirds of the time. They also found that a company with an Altman z-score of less than one tended to underperform the wider market by more than 4%.

Reference [32] studied the robustness Altman's z-score model under the assumption that it was no longer significant due to market factors. Reference [32] concluded that Altman's z-score model could be used as an indicator of financial distress in firms one year prior to bankruptcy. However, [32] warned that the calculations needed to be cautiously used because of the questioned significance of some of the variables in the model. He further cautioned that Altman's z-score predictions for periods longer than one year had a tendency of losing some of their significance.

In another study by [33], Altman's z-scores were calculated from IDBI financials following recommendations by other researchers to use Altman's model as an indicator of financial distress in firms. The study attempted to assess the vulnerability of the organization to financial distress in future. The study concluded that IDBI was likely to become insolvent in the following years.

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III. RESEARCH METHODOLOGY

A case study approach was adopted for the study. The study was meant to establish the corporate failure predictive value of Altman's z-score model on Zimbabwean firms. However, only banks in Zimbabwe represented the case under study. The research findings were then generalized to the remaining organizations in Zimbabwe.

Considering the number of organizations in Zimbabwe, a sweeping statistical survey was not feasible. It was impracticable to test the z-score model on the financials of every organization but rather narrowing down the scale was reasonable. Restricting the study only to selected banks in Zimbabwe would allow greater attention to specific trends observed with few data. Also, when informing others of the research results, case studies make more interesting topics than purely statistical surveys. The simple reason is that, the general public has little interest in pages of statistical calculations but some well-placed case studies can have a strong impact and catch the public's attention. Moreover, case studies are known to be highly flexible, for instance, whilst a pure scientist is trying to prove or disapprove a hypothesis, a case study might introduce new and unexpected results during its course and results in the research taking new direction.

All financial institutions in Zimbabwe resembled the targeted population. However, convenience sampling restricted the study only to selected banks in Zimbabwe. The sample consisted of 5 banks declared bankrupt by the Reserve Bank of Zimbabwe and 5 non-bankrupt banks in Zimbabwe on which the z-score model was tested. Thirty-five institutions were selected for the purposes of gathering qualitative data regarding the z-score model utilization.

For financial institutions not declared bankrupt financials for 2009 and 2010 were used, these were named NBI 1 to NBI 5

Table 3: Financials for the banking institutions "once declared bankrupt during 2001 and 2012"

Institution	Financials
BI 1	▪ Statements of Financial Position as at end of years 2002 and 2003 ▪ Statements of Comprehensive Income for the years 2002 to 2003
BI 2	▪ Statements of Financial Position as at end of years 2010 and 2011 ▪ Statements of Comprehensive Income for the years 2010 to 2011
BI 3	▪ Statements of Financial Position as at end of years 2002 and 2003 ▪ Statements of Comprehensive Income for the years 2002 and 2003
BI 4	▪ Statements of Financial Position as at end of years 2009 and 2010 ▪ Statements of Comprehensive Income for the years 2009 and 2010
BI 5	▪ Statements of Financial Position as at end of years 2002 and 2003 ▪ Statements of Comprehensive Income for the years 2000 and 2003

Major research instruments used were the annual bank financials prepared and/or published during the research period. In addition, questionnaires were administered to the risk managers of the selected banking institutions in order to gather data regarding the level of awareness for the corporate failure prediction models and the extent to which the models were being applied in corporate failure prediction. The use of secondary data in this research was inevitable despite the major criticism that the reliability of results from a secondary data source depends upon the reliability of the source.

Unstructured questionnaires were used. These were made up of open-ended or free response questions. Such questions gave the respondents freewill to express themselves. The questions were unaided and called for responses in the respondents' own words as no set of alternative responses were supplied.

In order to abide by the ethical principles, anonymity of the respondents was ensured by not disclosing their names on the questionnaires and names of financial institutions will not be used, rather they will be allocated a study name e.g NBI 1

Regarding, the financials of the banks currently in operation, the financial statements were retrieved from the banks' annual reports retrieved from their web sites. The financials of the bankrupt firms were obtained from the Zimbabwe Stock Exchange. For every bank, financials dating back to two years were obtained. Relevant data for the z-score model was extracted from the financials and z-score computations were done for each of the two years. The questionnaires were hand-delivered to the risk managers of the thirty five selected financial institutions and the filled-in questionnaires were personally collected from the respondents.

IV. RESULTS AND DISCUSSIONS

This section presents data gathered from secondary sources and by questionnaires. Data presentation was a process which started by scanning and sifting data to ensure completeness, accuracy, consistency and relevance of the data. Data scanning and sifting enabled the researchers to watch for trends which might have emerged in the scanned data. The data was then organized into manageable and meaningful chunks in a bid to make sense of it. The data presentation process ended with data summarising in which the researcher resorted to the use of tables and statistical summaries as different ways of summarizing large amounts of data. The study made use of the thematic approach in which the research themes were derived from the research questions. The data was then analysed and interpreted. The research findings were then compared with other research findings.

Z-score Computations

The z-score computations for years one and two for the selected bankrupt and non-bankrupt institutions are outlined in the following sections. The computations are followed by explanations.

$$\textbf{Z-score} = \sum X_i . F_i = 1.2x_1 + 1.4x_2 + 3.3x_3 + 0.6x_4 + 1.0x_5 \quad (3)$$

X_i=variables x_1 to x_5, F_i= factors for x_1 to x_5
X_1=working capital/total assets
X_2=retained assets/total assets
X_3=earnings before interest and tax/total assets
X_4=market value of equity/book value of debt
X_5=sales/total assets

Notes:

- All the forthcoming amounts have been divided by 1000 and then rounded off to the nearest dollar for the purposes of simplicity
- **EBIT** refers to Earnings Before Interest and Taxation
- All the amounts corresponding to the bankrupt institutions are in Zim$ save for those of BI 4 and BI 2 which are in US$

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- For the non-bankrupt institutions, all the amounts are in US$
- The sales amount has been replaced by the net operating income amount

Relevant Data for Z-score Computations Table 4: Non - bankrupt Institutions (NBI): Data Two Years in Advance

	Working capital	Total assets	Retained earnings	EBIT	Sales (Income)	Market value of equity	**Book value of debt**
NBI 2	84 973	90 481	13 998	2 194	12 130	231 131	79 349
NBI 4	23 264	105 691	-1 110	-1 264	14 549	34 383	71 308
NBI 3	87 361	39 708	2 003	1 665	8 419	51 568	31 140
NBI 1	-1 426	452 492	9 278	8 687	14 388	63 247	389 245
NBI 5	32 248	21 494	828	7 731	9 804	8 988	12 506

The table above discloses relevant input data for the z-score computations. The data had been retrieved from the financial statements of the above outlined institutions for the financial year 2009. All the above institutions were known to have not been declared bankrupt during 2009 and 2011. This data was two years in advance from the base year 2011. The data was deliberately used to calculate the respective z-scores in order to establish the extent to which the z-score model could accurately predict the **"non-bankruptcy"** regarding the institutions two years in advance. This was in compliance with one of the research objectives.

Table 5: Bankrupt Institutions(BI): Data Two Years Prior to Failure

Financial Institution	**Working capital**	**Total assets**	**Retained earnings**	**EBIT**	**Sales (Income)**	**Market value of equity**	**Book value of debt**
BI 3	973	70 471	12 698	1 134	11 243	31 131	79 349
BI 5	13 265	102 641	-1 230	-1 144	13 559	32 283	61 238
BI 4	-7 361	39 708	1 213	1 541	8 351	11 261	31 140
BI 1	-1 322	422 472	6 674	7 388	13 275	61 139	259 245
BI 2	42 278	23 254	769	3 212	864	33 255	13 412

The data above was retrieved from the financial statements of the above outlined institutions which were known to have been declared bankrupt. Such data was deliberately used to calculate the respective z-scores of the above institutions in order to establish the extent to which the z-score model could accurately predict the **"bankruptcy"** of the above institutions two years prior to the bankruptcy. This was in line with one of the research objectives.

The data below was retrieved from the financial statements of the previously explained bankrupt institutions. The data was from the financial statements prepared one year prior to bankruptcy. The data was deliberately used to calculate the z-scores of the respective institutions in order to determine the extent to which the z-score model could accurately predict the **"bankruptcy"** of the respective bankrupt institutions one year prior to bankruptcy. This was in line with one of the research objectives

Table 6: Bankrupt Institutions: Data One Year Prior to Failure

	Working capital	**Total assets**	**Retained earnings**	**EBIT**	**Sales(Income)**	**Market value of equity**	**Book value of debt**
BI 3	-55 490	73 702	39 597	36 673	18 535	12 723	62 980
BI 5	14 154	100 542	-1 123	-1 033	12 550	30 279	59 765
BI 4	-6 962	38 876	1 312	1 439	7 896	10 992	30 245
BI 1	-4 417	516 321	101 430	33 514	96 460	44 321	70 000
BI 2	-1 324	231 264	769	2 114	772	33 255	126 457

Table 7: Non-bankrupt Institutions: Data One Year in advance

Banking Institutions	Working capital	Total assets	Retained earnings	EBIT	Sales(Income)	Market value of equity	Book value of debt
NBI 5	42 158	23 500	1 470	8 741	9 804	3 749	19 751
NBI 2	75 987	159 916	1 321	9 934	14 395	16 275	143 641
NBI 4	423 244	169 833	3 236	15 803	3 454	719 388	150 446
NBI 3	282 341	102 840	2 088	7 814	17 280	98 833	84 007
NBI 1	1054 547	686 787	28 100	69 709	81 568	876 832	599 954

The above data relating to the known non-bankrupt institutions was retrieved from the financial statements of those non-bankrupt institutions prepared one year in advance of the cut-off year 2011. The data was deliberately used in order to establish the extent to which the z-score model could accurately predict the **"non-bankruptcy"** of the institutions one year earlier. This was in line with one of the research objectives.

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Table 8: Z-score Failure Prediction: Two Years in Advance

Non-bankrupt Institutions	X_1	$Factor_1$	X_2	$Factor_2$	X_3	$Factor_3$	X_4	$Factor_4$	X_5	$Factor_5$	$\sum X_i.F_i$
NBI 2	0.939	1.2	0.155	1.4	0.024	3.3	2.913	0.6	0.134	1.0	3.305
NBI 4	0.220	1.2	(0.011)	1.4	(0.012)	3.3	0.482	0.6	0.138	1.0	0.636
NBI 3	2.200	1.2	0.050	1.4	0.042	3.3	1.656	0.6	0.212	1.0	4.054
NBI 1	(0.003)	1.2	0.021	1.4	0.019	3.3	0.162	0.6	0.032	1.0	0.218
NBI 5	1.500	1.2	0.039	1.4	0.360	3.3	0.719	0.6	0.456	1.0	3.930
Bankrupt Institutions											
BI 5	0.129	1.2	(0.012)	1.4	(0.011)	3.3	0.257	0.6	0.132	1.0	0.388
BI 4	(0.185)	1.2	0.031	1.4	0.039	3.3	0.362	0.6	0.210	1.0	0.377
BI 1	(0.003)	1.2	0.016	1.4	0.017	3.3	0.236	0.6	0.031	1.0	0.248
BI 2	1.818	1.2	0.033	1.4	0.138	3.3	2.480	0.6	0.037	1.0	4.208
BI 3	0.014	1.2	0.180	1.4	0.016	3.3	0.392	0.6	0.160	1.0	0.717

The table above illustrates the computations of the z-scores two years in advance for the bankrupt and non-bankrupt institutions. The z-score corresponding to each institution is represented by the function $\sum \mathbf{X_i.F_i}$

Findings

Non-bankruptcy Cases

- The z-scores computed two years in advance of the cut-off year managed to accurately predict 3 of the 5 non-bankruptcy situations as indicated on the table above.
- The non-bankruptcy situation is meant if the **∑Xi.Fi ≥ 2.99**.
- Hence, there was a 60% failure prediction accuracy rate.
- However, there was a type II error of 40% (misclassifying non-bankrupt firms as bankrupt). (2 out of 5 non-bankrupt institutions were misclassified as bankrupt).

Bankruptcy Cases

- The z-scores computed two years prior to bankruptcy managed to accurately predict 4 of the 5 bankruptcy cases as shown on the table.
- The bankruptcy situation is meant if the **∑Xi.Fi≤ 1.81.**
- The 4 out of 5 cases resembled an 80% failure prediction accuracy rate. There was a type I error of 20% (misclassifying bankrupt firms as non-bankrupt). (1 of the 5 bankrupt institutions was misclassified as non-bankrupt)

Table 9: Z-score Failure prediction: One Year in Advance

Bankrupt Institutions	X1	Factor1	X2	Factor2	X3	Factor3	X4	Factor4	X5	Factor5	∑Xi.Fi
BI 3	(0.753)	1.2	0.537	1.4	0.498	3.3	0.020	0.6	0.251	1.0	1.755
BI 5	0.141	1.2	(0.011)	1.4	(0.010)	3.3	0.507	0.6	0.125	1.0	0.550
BI 4	(0.179)	1.2	0.034	1.4	0.037	3.3	0.363	0.6	0.203	1.0	0.376
BI 1	(0.009)	1.2	0.196	1.4	0.065	3.3	0.633	0.6	0.187	1.0	1.045
BI 2	(0.006)	1.2	0.003	1.4	0.009	3.3	0.263	0.6	0.003	1.0	0.188
Non-bankrupt Institutions											
NBI 2	0.475	1.2	0.008	1.4	0.062	3.3	0.113	0.6	0.090	1.0	0.944
NBI 4	2.492	1.2	0.019	1.4	0.093	3.3	4.782	0.6	0.020	1.0	6.213
NBI 3	2.745	1.2	0.020	1.4	0.076	3.3	1.176	0.6	0.168	1.0	4.446
NBI 1	1.535	1.2	0.041	1.4	0.102	3.3	1.461	0.6	0.119	1.0	3.232
NBI 5	1.794	1.2	0.063	1.4	0.372	3.3	0.190	0.6	0.417	1.0	3.999

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The table above illustrates the computations of the z-scores one year in advance for the bankrupt and non-bankrupt institutions. The z-score corresponding to each institution is represented by the function **∑Xi.Fi**

Findings

Non-bankruptcy Cases

- The z-scores computed one year in advance of the cut-off year managed to accurately predict 4 of the 5 non-bankruptcy cases.
- The non-bankruptcy situation is meant if the **∑Xi.Fi ≥ 2.99.**
- This resembled an 80% failure prediction accuracy rate.
- There was a type II error of 20% (misclassifying non-bankrupt firms as bankrupt). (1 out of the 5 non-bankrupt institutions was misclassified as bankrupt).

Bankruptcy cases

- The z-scores computed one year prior to bankruptcy managed to accurately predict all the 5 bankruptcy cases as shown on the table.
- The bankruptcy situation is meant if the **∑Xi.Fi≤ 1.81**
- There was 100% failure prediction accuracy.

Z-score Results interpretation

The above findings seem to suggest that the failure prediction accuracy of the z-score model improves as we approach the actual bankruptcy or failure time. In the above cases, the prediction accuracy of the z-score model regarding the bankruptcy cases was 80% two years prior to bankruptcy and unbelievably improved to 100% one year prior to failure. On the same note, the prediction accuracy regarding non-bankruptcy cases was 60% two years in advance and significantly improved to 80% when computed one year in advance. These results agree with the z-score specifications that it should be capable of predicting risk of corporate failure within two years. The results of this study have also been supported by literature reviewed.

Awareness for and Utility of the Z-score model

The researcher issued 35 questionnaires to 35 risk managers of the 35 selected financial institutions including some of the ones whose financials were consulted. This was done in order to establish whether the financial institutions were aware of the z-score model and also to establish if they were using the model in management of risk of failure. Surprisingly, all the 35 financial institutions did not mention utilization of the z-score model though some mentioned awareness for the model. The responses from the questionnaires showed that 29 out of 35 institutions used a risk management model known as Basel II whist only six mentioned distinguished models for risk management purposes. Such responses suggested that the z-score model was not being utilized as a risk mitigation model.

V. CONCLUSIONS AND RECOMMENDATIONS

The results of the study showed that Altman's z-score model can successfully be used to predict risk of corporate failure within two years. It had also been established that the predictive value of the model depends on how earlier the model has been used to predict risk of failure. The results had indicated that the model can predict risk of failure with high accuracy when it has been used one year prior to bankruptcy. The study also revealed that the degree of prediction accuracy decreases as the prediction time horizon increases. This fact had been clarified when the z-score model had predicted risk of failure regarding the bankruptcy cases with 100% accuracy one year prior to failure and with 80% accuracy two years prior to failure giving rise to 20% misclassification error for the latter. It is important to note here that the degree of accuracy has decreased with prediction time horizon. In the same context, the model's predictive accuracy regarding the non-bankruptcy cases was 60% two years in advance and 80% a year earlier with misclassification errors of 40% and 20% respectively.

Finally, the study also revealed that the financial institutions in Zimbabwe were not making use of Altman's z-score model to predict risk of failure.

In the light of the research findings, the following research conclusions were drawn:

- Altman's z-score model can predict risk of failure on Zimbabwe's financial institutions with higher accuracy one year prior to failure or bankruptcy.
- When Altman's z-score model is used to predict risk of failure two years prior to failure or bankruptcy, the degree of accuracy decreases but without significantly affecting the predictive value of the model.
- The predictive value of Altman's z-score model gets distorted as the prediction time horizon increases.
- Financial institutions in Zimbabwe had not been using Altman's z-score model in predicting risk of failure. Most of the institutions had been depending upon the Basel II model as the major risk management tool.

The study therefore recommends that;

- Financial institutions in Zimbabwe should also employ Altman's z-score model as a tool in aiding failure prediction as an aspect of risk management.
- In the light of the research findings, it is also recommended that when using the z-score model, it should be frequently applied so as not to miss out the likely impending danger of bankruptcy.
- If possible, the z-score model should be employed on annual basis to make sure that risk of failure is not missed out.

This study recommends that further research be conducted on a comparative analysis of the quantitative and qualitative failure prediction models in order to determine the best failure prediction model(s) relevant to Zimbabwean firms.

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