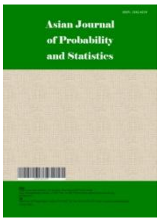

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An Analysis of the Predictors of Financial Distress for Zimbabwe Listed Corporates

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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Case Study

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Abstract

This study brings novelty to the area of corporate distress modelling in Zimbabwe by exploring company-specific indicators of corporate distress, unlike most of the previous studies, which used financial performance indicators. Using a binary logistic regression on a time series dataset collated between 2010 and 2017, this study establishes book value, book value per share, average debt to equity and equity per share as very significant determinants of corporate distress on the Zimbabwe Stock Exchange (ZSE). Future studies incorporating artificial intelligence and a combination of both the traditional financial ratios and market-based indicators is recommended to expand the scope of the study.

Keywords: Financial distress; logit; listed corporates.

1 Introduction

Large corporates are an integral part to economic growth. The existence of Stock exchanges could also be considered a pivotal aspect in sustainable economic growth. This is so because companies that list on a stock exchange are regulated and operate under good corporate governance [1]. The healthier the large corporates that

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are listed on the stock exchanges the more are the chances of advancing in economic growth. A corporate's levels of liquidity influences how far it is from bankruptcy and gives a good measure the financial health of a corporation [2]. Healthy listed corporates do attract Foreign Direct Investments that are very instrumental in economic development [3]. Financial distress is there for a phenomena that needs early detection in any economy to avoid corporate failures that lead to economic downturns due to liquidations and filing for bankruptcy [4].

The history of corporate failures dates back to centuries ago and continues to be a topical area of research globally. The World War 1 saw the Great depression that came as a result of the after war poor credit risk management, the energy crisis of 1970s , the dot com bubble of year 2000 after the introduction of the internet and the 2007-2009 famous global financial crisis are some of the well-known recorded in history financial distress occurrences. These resulted in companies filing for bankruptcy protection and in some cases closure. At the wake Covid-19 pandemic, we are seized with the "Great lockdown" financial crisis resulting from lockdowns affecting businesses and reduced capacity utilisation.

The definition of financial distress can be complex, depending on the industrial, geographical or regional norms. In general, financial distress is understood to occur when a company is unable to meet its financial obligations. According to (Hayes, 2020), this phenomenon is usually a result of high fixed costs, a large degree of illiquid assets or revenues sensitive to economic downturns. This forces a company to negotiate payment plans with its creditors. Failure of the restructuring may lead to corporate failure. The costs of restructuring is also unbearably high to corporates making it impossible for a corporate to come back to life again [5].

According to (Altman, 1968) corporate failure is defined by a case of a company that filed for bankruptcy protection under Chapter 11 of the Bankruptcy Act of 1938 in America .This paper seeks to determine and analyse the variables that drive a corporate into financial distress. This study looks at historically distressed and non-distressed corporates listed on the Zimbabwe Stock Exchange (ZSE) between the years 2010 and 2017.

The significance of this study is to enhance early warning signals for corporate institutions to monitor potential distress parameters and metrics in advance, which will trigger mitigatory measures. This enhanced risk monitoring and management framework might play a pivotal in promoting economic growth.

2 Literature Review

2.1 Corporate distress and listed companies

According to (Business insider, 2019) globally, over 20 000 companies filed for bankruptcy in an annual basis. With the current global COVID 19 pandemic, several firms in the world are likely to face some forms of financial distress due to mandatory lockdowns that have resulted in loss of production times and reduced capacity utilisations. Canada's Cirque du Soleil on the 29th of June 2020 filed for bankruptcy protection, the company owes over USD 900 million in debt and the pandemic has affected its operations in the entertainment industry (Reuters, 2020).

The number of distressed companies in South Africa increased from zero distressed corporates in April 2020 to 195 distressed corporates by May 2020 due to the effects of the Covid-19 pandemic. A projection into 2021 suggested about 220 bankruptcies would be reported (Bowmans, 2020).

For an economy to thrive there has to be a lot more listed companies to attract investors to a wider pool of potential corporates to invest. Early Warning Systems (EWS) are necessary to hedge against delisting due to bankruptcy [6,7].

The history of the ZSE dates back to 1896 although it has only been open to foreign investment since 1993. As at 2019, the exchange had about 17 stock broking members, and listing 63 corporate equities. The main indexes are ZSE industrial index, ZSE Mining index, ZSE Top 10 index, ZSE All share index. [1]

[1]*https://www.zse.co.zw/about-us/*

According to a report by African markets [8], over 15 companies had delisted from ZSE due to bankruptcy related problems between the years 2009 and 2015. Some of the reasons were due to the economic downturn experienced by the country while some of these where bankruptcy related to other business challenges. The number of listed companies fell from 78 to 63 listed counters. Then in 2015, some market watchers predicted that further delisting was to occur as the ZSE maintained stringent requirements not cognisant of the economy. Currently there are 68 listed counters on the ZSE from various sectors of the economy, including mining, agriculture, banking, retail and services industries (Chronicle, 2015).

Performance data of listed stocks in some of the SADC regions was also collected [2]for comparison purposes as at 2020 third quarter and is summarised in figure 1 below. The ZSE recorded a huge loss of 35.50% in the period under observations compared to other countries, which averaged 1.1% gains. This further qualifies the need for this research in order to investigate some of the causes of such huge variance as they relate to corporate distress.

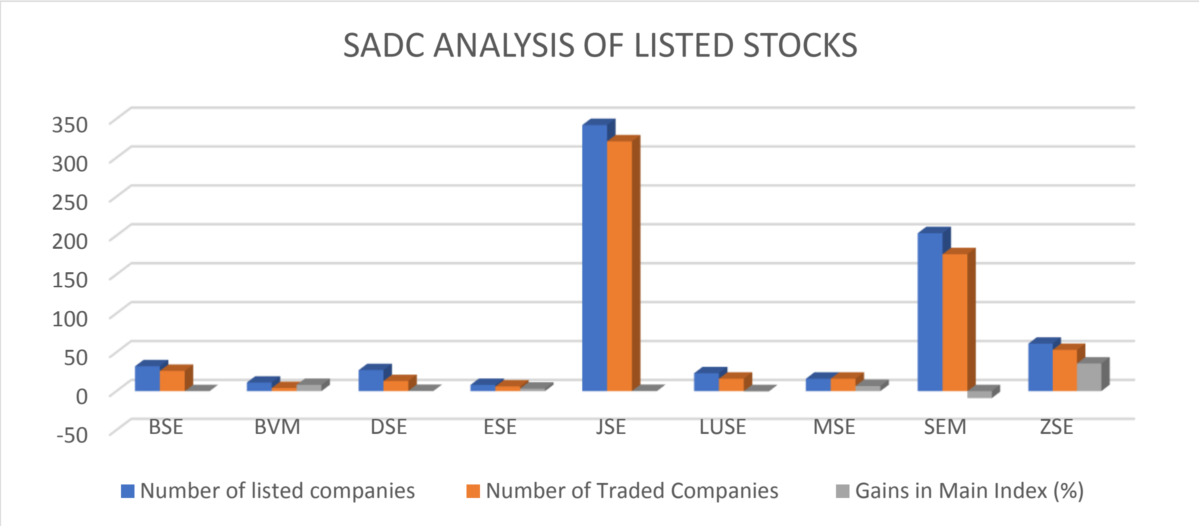

Fig. 1. Quarter 3, 2020 SADC Listed Stocks Analysis

Key: *BSE: Botswana Stock Exchange, BVM: Mozambique Stock Exchange, DSE: Dar es Salaam Stock Exchange, ESE: Eswatini Stock Exchange, JSE:Johannesburg Stock Exchange,LUSE: Lusaka Securities Exchange, MSE: Malawi Stock Exchange, SEM: Stock Exchange of Mauritius Limited*

On a regional perspective, between 1998 and 2004, 273 companies delisted from the Johannesburg Stock Exchange (JSE) to end with 396 (JSE, 2004). According to a report by (Business live, 2019) a crisis on continued delisting on the JSE daily was reported. While some delisting was a result of mergers and acquisitions meant to grow the business, some of these where due to bankruptcy (Business live, 2019).

2.2 Empirical review

According to Altman et al. [9], a comparison of statistical methods versus Neural Networks (NN) was done. In their study, which was carried on over 1000 corporates at various stages of distress, the results proved that both methods had good predictive strength of over 90%. However, the NN suffered over-fitting on the training sample and use of illogical weights. The authors recommended the use of a combined methodology using both statistical and artificial intelligent methodologies. From their study, it was noted that combining both Neural Networks and traditional statistical methods can yield a more robust model that capitalises on the strengths of both methodologies in predicting corporate failures.

Another research by Lee and Choi, [10] focused on building different distress prediction models by sector. Retail, Manufacturing and Construction industries were used from companies in Korea. The different models from each sector proved to be accurate by 6 to 12% as compared to a single model that predicts for all

[2]*https://www.cosse.africa/wp-content/uploads/2020/12/CONSOLIDATED-DATA-SADC-STOCK-EXCHANGES-AS-OF-Q3-2020.pdf*

companies without splitting per sector. This study used backward propagation Neural Networks (BNN) that is a branch of artificial intelligence. Compared with traditional statistical method of multivariate discriminant analysis, the BNN proved to be more accurate than the latter. Industry-specific modelling was therefore suggested to be a better measure of distress prediction in their study.

Wang et al. [11] had some deviations from the conventional methods that focused on financial ratios only to predict distress disregarding non-financial data. Data from China Security Market Accounting Research Database (CSMARD) was used to build a model that focused on the quality of the non-financial parameters in distress prediction. The methodology used was a regularized sparse-based random subspace with Evidential Reasoning Rule stemming from Artificial Intelligence. This method proved to be superior to traditional statistical methods. From their study, we see that non-financial data matters in building accurate models. It carries significant information that depicts behaviour that is crucial for distress prediction that may not be evident from purely financial data.

In a study by Mousavi and Ouenniche, [12] the aim was to establish a fair assessment of different methodologies used in predicting corporate distress. Statistical models, survival analysis and contingent claim analysis models using slacks-based context-dependent DEA (SBM-CDEA) framework were used. The methods were first categorised into original, refitted and new models. The evaluation criteria used was calibration accuracy, information content, the correctness of categorical prediction, and discriminatory power. Analysis of the performance of these models was carried out on UK companies listed on the London Stock Exchange. Building models that take into account macro-economic factors was proposed as it may increase the model accuracy.

Another frequently used methodology for distress prediction is Logistic regression. Several studies worldwide have chosen the methodology based on its simplicity and straight forwardness in presenting binary outcomes. The model development does not assume normality of the indicators and equal proportions for the binary outcomes of the response variable. In a study carried out by Brozyna, Mentel and Pisula, [13] the predictions and classifications that came out from a logistic regression model proved to be of high quality. Logistic regression is there for preferred for its robustness in classification and distress prediction [14] across the world.

Various distress prediction models have been explored for various economic zones (UK, US, Europe, India and Pakistan). A model in the context of Zimbabwe will be the main objective of this study. Country specific modelling using country specific data presents a more accurate model that can help investors and decision makers make well-informed decisions. This model will also inform governments on when to offer bailout packages to those large corporates that require some financial assistance while restructuring efforts are being implemented for recovery [15]. Argenti, [16] also agrees that economic and geographic differences make the models developed for a specific country more accurate predictors of distress as they use country specific data. (Brigham & Gapenski, 1994) in turn cite that industry specific data produces more accurate results in predicting distress.

2.3 Theoretical framework review

A lot of research exists in the subject of corporate distress. In some cases, it is viewed in a negative sense as lack of liquidity while in some cases companies moved from insolvent state to solvency, distress therefore is viewed as an integral process of any business. Early work started with Edward Altman in 1968 through the Z Score model that challenged the compromise on the quality of predictions using the univariate model developed by Beaver who carried out a Multi-discriminant analysis of predictors. The model was a linear combination of all the financial ratios that might be considered as strong indicators of corporate distress. The overall model had an accuracy of 95%.

3 Methodology

Logistic Regression (Logit) analysis is the methodology of choice for this paper. In several studies such as [15], the methodology has proven to yield high levels of accuracy in determining the drivers of corporate distress. This is a method used for investigating the relationship of binary outcomes such as pass/fail or distress/non-distress with explanatory variables [17]. In bankruptcy prediction, this model was first introduced in economics by Ohlson in 1980. For bankruptcy prediction, the binary response probability is usually the distress probability and the explanatory variables are the different financial ratios and other categorical data. Unlike Multi Discriminant Analysis (MDA), this method does not assume multivariate normality and equal covariance from the two samples of failed and passed companies [18]. In this study, however we used company-specific indicators for the listed counters on the ZSE [19]. The model estimates the significant indicators by finding the values of the coefficients of regression for each of the independent variables. The Logit function is presented by the equations below:

$$Z = \sum_{i=1}^{n} \beta_i X_i + \varepsilon \tag{1}$$

$$\ln\left(\frac{P}{1-P}\right) = Z = \sum_{i=1}^{n} \beta_i X_i + \varepsilon \tag{2}$$

$$Odds\ ratio = \frac{P}{1-P} = exp\ (Z) = exp\ \left(\sum_{i=1}^{n} \beta_i X_i + \varepsilon\right) \tag{3}$$

P- Probability of distress
X_i - The value of k-th distress indicator,
β_i - Coefficients of individual indicators, which represent their weights towards contribution to distress
Z- is the linear combination of the indicators and the estimated weights

The maximum likelihood method will be used to estimate the coefficients of the indicators.

3.1 Data used

Annual Time series data from ZSE[3] were collected between the years 2010 and 2017. The data comprised of 216 observations from 27 companies listed on ZSE. Twelve independent variables were identified from stock market observed data. As seen in the descriptive statistics on table 1, the variability of the dataset was too wide and division by a factor was necessary for some variables to reduce the dimension variability. Book value was divided by a factor of ten million while total debt was divided by a factor of one hundred million. As previous studies have proved, variable transformation is not always mandatory for all observations as Logit transformation does not assume normality of the independent variables. This is done to improve model predictive accuracy and reduce skewness on data due to wide variability [20]. According to Okereke, [21], independent variable transformation by different constants produced a slope estimates that were a function of the divisor. What this means is the same divisor used in the transformation should be used in the estimation using the model so as to eliminate bias that may result from using the untransformed inputs in a model developed using transformed variables [22]. Further to that [23] agree that the coefficients are not affected by the transformation but the interpretation of the model should take into account the different transformations carried out on each independent variable [24]. The Augmented Dickey Fuller test for the existence of unit roots was carried out and the output showed that the variables were stationery at level.

Table 1. Descriptive statistics

Variable	Observations	Mean	Standard Deviation	Min	Max
bkvalue	216	154 million	576 million	-2.98 million	7.47 billion
eps	216	0.109	0.482	-0.715	3.59
bvps	216	0.382	0.695	-0.00555	4.69
tdebt	216	353 million	1.59 billion	527 000	12.8 billion
avrgdebteq	216	3.30E	5.59	0.170	23.8

3.2 Variables

Multi-collinearity tests, Weight of Evidence(WoE) and Information Value(IV) as mentioned by Nehrebecka, [25] were calculated for each independent variable and out of the twelve variables, five values with the highest IVs where chosen for estimating the model parameters. According to Brozyna, Mentel and Pisula, [13] the

[3]*https://www.zse.co.zw/market-statistics/*

higher the IV the higher the predictive strength of the indicator in determining the response, a cut off of 0.3 and above is said to be a good IV coefficient (see Appendix). These are the book value, the book value per share, equity per share, total debt and average debt to equity. The Fig. 2 describes the expected effects of the variables based on research done by other scholars like [26].

Table 2. Variables used

Indicator Name	Short code	Type	Description	A priori
Distress/Not Distress	Distress	Dependent	The presence of financial bankruptcy =1 No financial bankruptcy=0	Not applicable
Market capitalisation	mktcap	Explanatory	A product of share price and the number of shares outstanding.	+
Share price	sharepr		The price of a single share	+/-
Book value	bkvalue		Net worth of a company	+
Operating income	opincome		Net income realised after deducting Cost of goods	+
Equity per share	eps		Ratio of net profit/number of shares	+
Book value per share	bvps		Ratio of net worth of a company to the number of outstanding shares	+
Free Cash Flow to Equity	FCFE		Amount of cash available=Cash from Operating Activities – Capital Expenditures + Net Debt Issued (Repaid)	+/-
Accruals	accruals		The net effect of what is owed to the company by its debtors and what the company owes its creditors.	+/-
Total Debt	tdebt		Total amount owed by the company	-
Debt to Equity	debteq		Ratio of total debt to Total Equity	-
Number of shares	sharesno		Total number of shares held by a company	+/-

Source: Author

3.3 Causality tests

In order to ascertain that there exists a causal relationship between the independent variables and the dependent variables, three causal conditions have to be met. This data will be tested for association, temporal precedence and spuriousness.

3.3.1 Association test

In causal relationships, we want to establish if there is association between the independent variable and the dependent variable. This will be done using the Pearson Correlation Matrix.

3.3.2 Temporal precedence

If there exists a causal relationship between the dependent variable and the independent variable, there must be evidence that the independent variable causes the dependent variable; i.e a change in the independent variable occurs first to trigger a change in the dependent variable. In our case for example taking the variable book value we have the null hypothesis:

H_0: book value has causal effect on distress.

The Wald coefficient test will be used as a comparable statistic for the Granger Causality test for binary outcomes. It will be carried out on all the indicators.

3.3.3 Spuriousness test

The spuriousness condition is to establish if the causal effect on the dependent variable is indeed from the independent variable and no other factors. Individual logistic regressions will be carried out for each variable.

4 Results and Discussion

Book value, total debt, book value per share and equity per were found to be significant at 1% level as shown in Table 2.

Table 3. Logistic Regression output

Variables	Distress
bkvalueo10mil	-0.307***
	(0.0932)
Bvps	5.977***
	(1.950)
tdebto100mil	0.0748***
	(0.0202)
avrgdebteq	0.216***
	(0.0664)
eps	-38.26***
	(9.182)
Constant	-0.530*
	(0.287)
Observations	216

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 4. Association test results

	Distress	markca~l	bkvalu~l	bvps	tdebto~l	avrgde~q	eps
Distress	1.0000						
markcapo10~l	-0.1812	1.0000					
bkvalueo10~l	-0.1533	0.7229	1.0000				
bvps	0.0310	0.5544	0.6685	1.0000			
tdebto100mil	-0.1493	0.7630	0.7697	0.7101	1.0000		
avrgdebteq	0.5243	-0.1031	-0.0927	0.0137	-0.0776	1.0000	
eps	-0.1937	0.8487	0.4228	0.4883	0.7522	-0.1090	1.0000

4.1 Model Diagnostics

The model obtained in Table 6 had to be tested to satisfy all the conditions for causality as detailed below.

4.1.1 Association test

From the Pearson's correlation coefficient Table 4, it is evident that there exists a negative association between distress and book value, equity per share and total debt. An increase in these has a negative effect on distress, i.e reduction chances of distress. On the other hand, book value per share has a positive association implying an increase in book value per share yields an increase in the chances of distress.

4.1.2 Temporal precedence

From the Wald coefficient statistic shown in Table 5 below, we fail to reject the null hypothesis at 1% level of significance and conclude that book value has causal effect on distress. We also fail to reject the null hypothesis for book value per share, equity per share and total debt as all these coefficients are significant at 1% leve. Hence, these parameters have exerted a causal effect on distress.

Table 5. Temporal precedence test results

Variables	Wald Coefficient P Value
bkvalueo10mil	0.0010
bvps	0.0022
avrgdebteq	0.0003
eps	0.0001

4.1.3 Spuriousness test

From the individual logistic regressions carried out for each variable, the variable for total debt proved to be spurious as shown by the insignificant coefficient in Table 5 below.

Table 6. Spuriousness test results

	(1)	(2)	(3)	(4)	(5)
Variables	**Distress**	**Distress**	**Distress**	**Distress**	**Distress**
bkvalueo10mil	-0.0893***				
	(0.0272)				
bvps		0.0905***			
		(0.199)			
tdebto100mil			-0.0289		
			(0.0190)		
avrgdebteq				0.410***	
				(0.0720)	
eps					-17.61***
					(4.169)
Constant	0.0567	-0.566***	-0.317*	-1.590***	-0.153
	(0.195)	(0.161)	(0.171)	(0.217)	(0.163)
Observations	216	216	216	216	216

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

The variable for total debt had to be eliminated from the model and the resultant model is as shown in Table 7 below. The output shows that distress is a function of book value, equity per share, book value per share and average debt to equity for corporates listed on the ZSE.

The fitted model from equation 1 is as below.

Z = -0.605 +0.244*average debt to equity-0.228*book value+5.471* book value per share-35.563*equity per share

The results show that at 1% level of significance, book value, book value per share, total debt, average debt to equity and equity per share are all significant determinants of corporate distress in the ZSE. At 1% level of significance, we can see that companies listed on the ZSE are generally not distressed as evidenced by the significant negative coefficient of -0.605. This could be a result of the economic reforms being implemented by the government in the past couple of the years.

Table 7. Non-Spurious Model Results

variables	**Distress**
bkvalueo10mil	-0.228***
	(0.0756)
bvps	5.471***
	(1.860)
avrgdebteq	0.244***
	(0.0670)
eps	-35.54***
	(8.828)
Constant	-0.605**
	(0.285)
Observations	216

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Companies with a larger book value are less likely to get into financial distress as seen by the negative coefficient of -0.228. However, the higher the book value per share the higher the chance of a company getting into financial distress as the coefficient is positive and significant with a value of 5.471. This is against a-priori as we expected to have an increase in book value per share to result in a reduced effect to get into financial distress. For Zimbabwean listed companies this could mean that listed companies are holding on to shares of less value which are not enticing to the market leading to low interest and trading on these. Hence a company is more likely to get into financial distress despite having a high book value per share.

Companies with high levels of total debt seem to be more likely to get into financial distress which is consistent with the work of [27], as they are likely to be over borrowed as reflected also by the average debt to equity, which suggest that companies with a higher average debt to equity have higher chances of getting into default. The effect of equity per share on the likelihood of distress is consistent with a-priori where the higher the ratio the less likely is a company to get into financial distress.

A unit increase in book value has a 0.228 increase in the likelihood of distress holding other variables constant. Equity per share has the highest magnitude contribution towards financial distress with a unit increase in Equity per share resulting in 35.563 decreases in the likelihood of distress. This makes equity the strongest determinant of financial health of any institution, which is consistent with a-priori. Book value per share ratio is 22 times stronger in determining the effect on financial distress as compared to average debt to equity ratio.

5 Conclusion

The main aim of this study was to analyse the predictors of corporate distress for ZSE listed companies. The objective was to determine the factors that drive a ZSE listed company to get into financial distress from a Zimbabwean perspective as evidence of limited study by Matenda, Sibanda et al. [27]. From this study, there is evidence that book value per share and average debt to equity contribute towards a company getting into financial distress amongst ZSE listed corporates. A company that aims at reducing its borrowing while increasing its equity will be able to reduce the chances of getting into financial distress. This is the evidence of high costs of debt that corporates in Zimbabwe suffer due to the current economic challenge. Currently the minimum lending rate is set by the central bank at 35%, which is extremely high making corporates very sensitive to debt which is different from the observation by Cortina et al. [28] of increase in low interest rates which make debt enticing.

On the other hand, book value and equity per share tend to reduce the risk of getting into financial distress, thus a company that maintains high cash reserves has high chances of maintaining a healthy financial system that will support business and economic growth. This is normally the case with blue chip companies who have sufficient equity and do not have to borrow and hence maintain less finance costs. These companies are characterised by high liquidity and ability to achieve greater business flexibility, as they do not face the current liquidity challenges and the high costs of borrowing in the country.

Companies listed on the ZSE are therefore encouraged to keep a close eye monitoring on the movement of these indicators to guard against financial distress well on time through early reaction. As more research is being done, future studies should use a combination of corporate governance, macro-economic factors and other financial ratios not incorporated in this study due to data challenges and limited times frames.

As the ZSE has a wide variety of economic sectors, sector based models would in turn yield more accurate determinants of financial distress according to the Korean study by Lee & Choi, [10]. Other methodologies mentioned in this research will be explored further for comparison of model adequacy. Implementation of country –specific risk based models for identifying determinants of financial distress is a pivotal instrument in guiding investors and economic development in Zimbabwe and Africa at large.

This captures the idiosyncratic factors for the country under study [27] thereby invariably improving the accuracy of models than off the shelve models. Embracing of international standards by furthering this research through developing Probability of Distress model will also aid corporates to be trusted in the global space and get foreign investments for further development and maintaining healthy financial positions that promotes corporate expansions and economic growth. Early warning signs will definitely benefit corporates in making early decisions and carrying out remedial actions to avoid financial distress.

Competing Interests

Authors have declared that no competing interests exist.

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APPENDIX

Table 8. Information Value Coefficients

Variable	Information value
avrgdebteq	4.22
bvps	1.94
eps	1.79
debteq	1.61
bkvalue	1.39
sharesno	1.2
opincome	1.15
sharepr	0.77
tdebt	0.49
mktcap	0.45
FCFE	0
accruals	0

Table 9. Spurious model

```
Logistic regression                             Number of obs     =        216
                                                LR chi2(5)        =     132.35
                                                Prob > chi2       =     0.0000
Log likelihood =  -76.20251                     Pseudo R2         =     0.4648
```

Distress	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
eps	-38.26316	9.181985	-4.17	0.000	-56.25952	-20.2668
avrgdebteq	.2160063	.0664227	3.25	0.001	.0858202	.3461924
bkvalueo10mil	-.3074352	.0931522	-3.30	0.001	-.4900102	-.1248601
tdebto100mil	.0748325	.0202088	3.70	0.000	.0352239	.1144411
bvps	5.976844	1.950314	3.06	0.002	2.154298	9.79939
_cons	-.5296095	.2865401	-1.85	0.065	-1.091218	.0319988

Table 10. Spurious variable regression

```
Logistic regression                             Number of obs     =        216
                                                LR chi2(1)        =      10.36
                                                Prob > chi2       =     0.0013
Log likelihood = -137.19679                     Pseudo R2         =     0.0364
```

Distress	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
tdebto100mil	-.0289163	.0190334	-1.52	0.129	-.066221	.0083885
_cons	-.3165732	.1706138	-1.86	0.064	-.6509701	.0178237

Table 11. Non-Spurious model

```
Logistic regression                             Number of obs     =        216
                                                LR chi2(4)        =     127.92
                                                Prob > chi2       =     0.0000
Log likelihood = -78.416617                     Pseudo R2         =     0.4492
```

Distress	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
eps	-35.53623	8.827557	-4.03	0.000	-52.83792	-18.23453
avrgdebteq	.2441076	.0670176	3.64	0.000	.1127554	.3754598
bkvalueo10mil	-.2278244	.0755633	-3.02	0.003	-.3759256	-.0797231
bvps	5.471418	1.859629	2.94	0.003	1.826613	9.116224
_cons	-.6046277	.2849593	-2.12	0.034	-1.163138	-.0461178

Table 12. Augmented Dickey Fuller Tests

```
Augmented Dickey-Fuller test for unit root         Number of obs   =       214

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -6.730            -3.472            -2.882            -2.572
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

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.
.
. dfuller bvps , lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =       214

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -4.021            -3.472            -2.882            -2.572
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0013

.
. dfuller eps , lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =       214

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -4.127            -3.472            -2.882            -2.572
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0009

.
. dfuller avrgdebteq  , lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =       214

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -4.258            -3.472            -2.882            -2.572
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0005
```


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