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Predicting Corporate Failure in Nigeria: A Case for Cadbury Nigeria Plc.

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Abstract

The main thrust of this paper is to use several corporate failure (bankruptcy) prediction models to test the ability and accuracy of the models to verify if the firm will fail shortly. Using a case study of a publicly quoted manufacturing firm (Cadbury Nigeria PLC) from the Nigerien Stock Exchange with data from 2011 to 2018.The four corporate failure prediction models tested were the Altman-Z, Almamy-Z, Taffler-Z, and Ohlson–Z scores. The Multiple Linear Discriminant Analysis (DLMA), the Logistic Regression Analysis were used to justify each of the model's claim of their power of prediction and hence finding which of the model is more accurate and germane to predict corporate failure in Nigeria. The study's findings were that all four models predicted no failure (bankruptcy) for Cadbury Nigeria PLC shortly. Further findings were that Altman Z topped in the ranking of predictive power amongst the other models z scores. Additionally, from the result of the study, fourteen (14) potent variables from the models tested were negative thus having the ability to predicting corporate failure. The other variables that are not too significant in predicting the firm's failure were the ratios of working capital-to-total assets, revenue-to-total assets, retained earnings-to-total assets, current assets-to-current liabilities, current liabilities-to-total assets, and log of total assets-to-GDP price level index. The potent variables can be re-estimated and used for further studies as a new corporate failure model in the manufacturing industries.

Keywords: *Altman-Z, Almamy Z, Taffler-Z, Ohlson-O, MLDA, Logit, Bankruptcy.*

INTRODUCTION

The pioneering work of Beaver (1966) on bankruptcy prediction using single financial ratios has sparked renewed interest in finance literature on corporate business failure predictions amongst academics and practitioners. He used a single equation model whereby classifications were made for each ratio separately and an optimal cut-off mark identified where the percentage of classifications to either failing or non-failing. A misclassification can either be made when they classify a failing firm as non-failing (called Type one (I) error), or a non-failing firm as failing (called Type two (II) error). A total of 79 companies were chosen as failed firms and another 79 companies as non-failing firms. The selected firms were then investigated using the predictive power of 30 ratios applied five years before failure. This univariate approach was quite simple and appealing, but this had several potential issues, and problems such as (1) classification based on one ratio at a time, may give inconsistent and conflicting results if the wrong classification is used for different ratios on the same company. (2) It contradicts reality, in that the financial status of a company is complex and cannot be captured by a single ratio. (3) The optimal cut-off point is chosen on an ex-post basis, i.e. when the actual failure status of each company is known. As a result, the cut-off points may be sample-specific and the classification accuracy may be much lower when applied on a predictive basis.

These controversies, called for the logical selection in a combination of ratios, thus the multivariate approach, which attempt to provide a more comprehensive picture of the financial status of a company. Following Beaver, Altman (1968) proposed a 'multiple discriminant analysis' (MDA) or 'multiple linear discriminant analysis' (MLDA). An additive model that provided a linear combination of ratios that best distinguished between groups of failing and non-failing firms. This technique dominated the literature on corporate failure models until the 1980s and was commonly used as the baseline for comparative studies when Ohlson (1980) introduced a new multiple linear discriminant model juxtaposing it with the logistic regression model (logit).

The major prompting and motivation of this paper were to make a threefold objective: first is to test the validity of the discriminant analysis on a renowned manufacturing company in Nigeria with Cadbury Nigerian Plc. as a case study is a household name and a company that produces a wide range and variety of consumer goods across the country. The second reason for the study is to test as many as four different corporate failure models to determine their predictive potency and power of detecting a corporate organizational failure in Nigeria. Finally, to adduce a possible alternative model that can best fit the Nigerian economy instead of the generalized models developed for the developed economies. This study will be organized and structured into five sections. Section one is the introduction of the paper, section two is the Theoretical framework and Empirical review, section three data, and methodology, section four is an interpretation of empirical results and section five is conclusion and recommendations.

THEORETICAL FRAMEWORK AND EMPIRICAL REVIEW

Theoretical Framework

The proponents of corporate business failure and bankruptcy prediction models did not provide an underpinning theory for their models hence the dearth in the literature on corporate business and bankruptcy theory. However, a few theories have been proposed such as (1) Cash Flow Theory, (2) Gamblers Ruin Theory (3) Merton Model (4) Liquidity, Profitability, and wealth Theory. For more details on these theories, see (Thian, Lim, Siwei, and Haaozhe, 2012). In this study, I hence propose a theory called The Financial Ratio Theory of Bankruptcy Prediction which shall be briefly discussed as follows.

Financial Ratio Theory

The proposed financial ratio theory of corporate business failure and bankruptcy prediction draws strongly from the fact that most early corporate failure models made use of financial data to gauge failure. Starting with (FitzPatrick, 1932; Smith and Winakor, 1935;

Beaver, 1966 and Altman, 1968), this theory hinges on the fact that financial ratios have been a source of measuring the financial health of the firm. When a firm is in "good" standing that is an indication of the healthiness of the business and when it is "bad" is an indication the business is likely going to default or go bankrupt in not too distant future. These ratios can either be found in the income statement or balance sheet of the firm's financial statement and annual report. So these ratios can be classified as Liquidity Ratios, Solvency Ratios, Profitability Ratios, and Working Capital Ratios. Hence determining corporate business failure and bankruptcy can come from a combination of these ratios.

Empirical Review

In this section, we review literature that either makes use of MLDA, Logit, and Probit methodology to assess a company's survival or failure profile. Models that have received much attention by researchers in the literature of corporate credit risk modeling include the univariate model of Beaver, the multiple linear discriminate analysis (MLDA) model of Altman (1968), Altman, Haldeman, and Narayanan (1977), Almamy, Aston and Ngwa (2015) model, Taffler and Tishaw's model (1977), Ohlson (1980) model and another powerful alternative model too numerous to be listed in this study. We now take a chronological look at past and recent literature on corporate failure (bankruptcy).Literature suggests that Crosbie and Bohn (2003) were one of the most comprehensive papers that are dedicated to the methodology model construct for the assessment of bankruptcy risk (or equivalently default risk). Beyond their paper, academic literature has provided a preponderance of empirical studies about model performance. Some evidence include Altman (1968), Taffler and Tishaw(1977), Ohlson (1980), Ezzamel, Brodie and Mar-Molinero (1987), Shisia, William, Waitindi, and Okibo(2014), Almamy (2015), Kihooto, Job, Muturi, and Emojong(2016), Alaminos, Castillo and Fernandez (2016), Taoushianis, Charalambous and Martzoukos (2016), Nelissen (2018), Arroyave (2018)

Almamy et al (2015) investigate the possible extension of the Altman Z score model to predict the financial health condition of UK firms by applying the discriminant analysis and performing ratio analysis to ascertain the statistical significance of the health position of firms operating in the UK from 2000 to 2013. They intended to further enhance the Altman Z model by adding a variable to the original five variables. The additional variable which is the ratio of cash flow from operations to total asset forms the new model which is believed to add predictive power of forecasting a firm financial health condition. When the model was applied, it yielded a predictive power of 82.9% which was consistent with Taffler's (1983) UK model. Furthermore, the Almamy J-UK model was tested for periods before, during, and after the financial crises, and a higher level of accuracy as par the model was achieved hence the model is seen to be a better predictive model than the original Z model. This may not be necessarily true in all cases as it is one cap that fits all situations. In conclusion, the authors recommended that the model will aid researchers, regulators, managers, and other practitioners to manage their risk profiles more effectively.

Ezzamel et al (1987) briefly reviewed the earlier research and reported their UK study of financial ratios using factor analysis. 53 ratios were used fragmented into five broad patterns: capital intensiveness, profitability expressed as earnings, or cash flows as related to assets or funds, working capital position, liquidity position, and asset turnover. They concluded that these patterns were not stable during the period of their study, even when considering the same group of companies. However, their general conclusions were that it was possible to identify distinct financial patterns and that these could be used to reduce the number of ratios being studied, but that the long-term instability of the patterns made their application to different periods or countries difficult.

Purbanngsih (2013) assessed the financial situation of some Indonesian listed stocks using the AltmanZ score and the current ratio techniques. A study population of 33 Consumer goods company from 2009-2010 with data collected from the Indonesia Stock Exchange. Their finding was that there is no significant difference between the Altman Z and the current ratio method applied in the test as they both found financial distress in the consumer goods industry. They recommended that the current ratio method and Altman Z-score are useful prediction tools for measuring financial distress in Indonesia.

Another study that used the traditional Altman's model was Shisia et al. (2014),who in their study on financial distress, argued that company distress had become a significant global issue after the 2008 global financial crisis, which resulted in increased business failure. Business failure was associated with bankruptcy as well as insolvency. The Altman Z corporate failure prediction model was used to test if Uchumia major supermarket in Kenya was financially distressed or sound. The study scope spanned for a five-year period from 2001 to 2006.The company's financial data was obtained from its secretariat. Important predictor ratios included total assets, retained earnings, current assets and liabilities, the book value of the equity and sales, and earnings before interest and taxes. The study used a multivariate discriminant analysis (MDA) statistical technique based on the Altman failure prediction model. The model was fundamental and relevant to Uchumi supermarket as it recorded declining Z-score values, indicating the company's real experience in financial distress, backing up the reasons Uchumi supermarket was de-listed from the NSE in 2006. The study suggests to the potential investors in companies to use the Altman failure prediction model as an assessment tool for predicting bankruptcy. Declining Z-score values depict a failing company.

Kihooto et al. (2016) sought to predict for bankruptcy among companies in the commercial and services sector, listed at the Nairobi Securities Exchange (NSE). The main objective of the study was to establish if companies in that sector are prone to bankruptcy. Secondary data over five years (2009 to the year 2013) were used in this study and the Altman Z-score model's finding indicated that on average, the companies' Z-scores lay between 1.88 and 3.5, which is an indication that the companies are relatively not in danger of bankruptcy.

Alaminos et al(2016) researched a global model for bankruptcy prediction using logistic regression to construct predictive models for Asia, Europe, and America and other global models for the whole world to build a predictive model with the level of predictability of bankruptcy in any region of the world. Their model was able to show a high level of superiority compared to another model over up to three years before the bankruptcy.

Taoushianis et al (2016) used the Leland and Toft model in a more recent study to extend the empirical accounting-based measure of bankruptcy, Z-score of (Altman, 1968), by incorporating bankruptcy probabilities a structural model with additional explanatory variables, with whose performance improved significantly. Their model which they call market-based Z-scores to yields the most powerful models at in-sample and out-of-sample forecasts amongst several alternative specifications. Even though the literature has generated numerous models that aim to forecast firms' bankruptcy risk, Taoushian is et al (2016) had to take a slightly different approach by constructing a dynamic structural model of a class of models designed and built upon some extract of the works of Merton (1974).

Fito et al (2017) on a survey to determine the model with greater predictive Z score in the Spanish economy, employed the Altman and Amat et al models. The research was to answer four basic questions of (i) is Altman scoring model better than Amat el (ii) is the timing of the economic cycle a condition of the gap (pre-crisis, crises, and post-crisis period) in the models proposed by Altman and Amat et al, (iii) is the business sector a condition of the temporary gap in the model and (iv) is the gap conditioned by the size of the company in both scoring models. To answer the above questions, data was sourced from the SABI database for the period 2005 to 2015. The finding was that Amat et al's model was more effective in the early detection of financial problems.

Gavurova, Packova, Misankova, and Smrcka (2017) focused on the assessment of four bankruptcy prediction models to find out the most appropriate model based on the conditions of the Slovak business environment. The four models set up were Ohlson (1980), Altman (1983), Indexes IN01, and IN05 which were validated on a sample of700 Slovak firms. Previous studies in Slovak show that IN01 and Inx05 were superior to Ohlson and Altman. After a careful and thorough examination of the models, they found exactly what previous studies observed that the Ohlson model was not applicable in their economy and that IN05 was a more superior model to predict bankruptcy than Ohlson and Altman in the Slovak economy.

Nelissen (2018) tested two famous bankruptcy prediction models (the Altman Z-score and the U.K. based J-UK model) intending to find which model serves as a better predictor of bankruptcy when applied to US companies. Expectations were that Altman's Z-score would have a lower predictive ability due to its focus on manufacturing firms and lower significance compared to when it was first revealed in 1968. It was also expected that the J-UK model would have a higher predictive power due to the additional cash flow variable. The models were tested based on a multiple discriminant analysis (MDA) which revealed that the discriminating ability of the J-UK model was significantly higher. However, both models had a high classification ability which is likely due to the sample size and availability of data which was not the case when the J-UK model was initially applied in the UK.

Arroyave (2018) commented that Logit and discriminant analyses have been used for corporate bankruptcy prediction in several studies since the last century, and also probit, artificial neural networks, support vector machines, among others. For the first time in Colombia, his paper presents a comparative analysis of the effectiveness of several models predicting corporate bankruptcy. Such models have previously been mostly used about European and North American markets, whereas in Colombia they are applied to the financial ratios of three firms. The main objective is to corroborate the validity of these models in terms of their ability to predict firm failure in the Latin American context, specifically for two bankrupt Colombian firms and one healthy one. The analysis is conducted using bankruptcy forecasting models widely proposed in the literature and used systematically in developed countries: the multiple discriminant analysis Z-Altman model, Korol's two-function model, and Prusak's P2 model. Besides, the logit and decision tree models developed by T. Korol are tested. The study showed that the Logit and the two-function model by Korol gave a better forecast of companies in Colombia.

DATA AND METHODOLOGY

Data for this study was collected from the annual financial statement of Cadbury Nigerian PLC and the CBN statistical bulletin of the 2018 edition. We proposed four models in this study. We proposed at least four models as it is important to note that no one model is superior or superlatively excellent, each model is bound to have one shortcoming or another. Some of the pitfalls are that a single model cannot be best for all countries in the world, modifications need to be made in a few cases. Secondly, it could also not be best for every sector or industry so adjustments to the models are therefore imperative. In the MLDA model, the ratios are combined into a single discriminant score, termed a 'Z score', with a low score usually indicating poor financial health. Altman's study involved 66 manufacturing companies with equal numbers of failures and survivors, and a total of 22 ratios from five categories, namely liquidity, profitability, leverage, solvency, and activity. From this set of ratios, five were finally chosen based on their predictive ability. Altman's original Z score equation was:

ALTMAN Z SCORE (1968)

$$Z = 1.2X_1 + 1.4X_2 + 3.33X_3 + 0.6X_4 + 0.999X_5$$

Where the variables in the equation are fully defined in table 2. The pass mark for Altman's Z score was2.99, above which companies would be considered relatively safe. Companies with Z scores below 1.81 would be classified as potential failures; Z scores between 1.81 and less than 2.99 were in a grey area. This we codify in the table below.

Table 1a: Threshold Calculation Altman Z-Score

Firm's condition	Benchmark Value
The company with High risk	if the value of Z<1.81
The company still has a risk of bankruptcy(gray area)	if the value of Z=1.81&Z<2.99
The company safe from bankruptcy	if the value of Z>2.99

ALMAMY, ASTON AND NGWA MODEL (2015) $AZ = A_1, A_2, A_3, A_4, A_5, A_6$

The Almamy et al model is an augmented Altman Z model. It extends Altman's model by including the A_6 variable. All other variables A_1-A_5 remains the same except X_6 which is defined as the ratio of cash flow from operation to total assets. Because Almamy is a replica model of Altman, the threshold (cut off point) is the same as Altman above. See details in table 2 below. The Almamy et al (2015) model we used is a special case and a bit different from their original submission. We modified it to mimic more like the Altman model.

Taffler Model (1977)

In the UK, a similar methodology was employed by Taffler and Tishaw (1977) based on a sample of 92 manufacturing companies. The resulting Z score equation was based on a combination of four ratios, albeit with undisclosed coefficients:

$$TZ = C_0 + C_1T_1 + C_2T_2 + C_3T_3 + C_4T_4$$

For industrial firms, Taffler gave the following as coefficients for the X variables in the model as below:

$$TZ=3.2+12.18T_1 +2.5T_2-10.68.T_3+0.029T_4$$

The percentages assigned to each variable $T_1$to T_4depicts the relative weight of each financial ratio to the overall discriminate power of the model (measured with the Mosteller-Wallace Criterion). The four ratios chosen (identified by factor analysis) correspond to the firm's financial profiles: Profitability, Working Capital Position, Financial Liability, and Liquidity. Taffler and Tishaw claimed a 99% successful classification based on the original 92 companies from which the model was derived. However, when the model was tested by Taffler (1983) on a sample of 825 companies, the results were less convincing. The equation then classified 115 out of the 825 quoted industrial companies as being at risk. In the following four years, 35% went bankrupt and a further 27% were still at risk. The decision criteria for the Taffler Z is that ZT scores less than 0 the firm is regarded as bankrupt and TZ score greater than 0 for non-bankruptcy positions. See details in table 4 below.

Table 1b: Threshold Calculation Taffler Z-Score

Firm's condition	Benchmark Value
The company is creditworthy	value of TZ (= 0.3, Z ∞)
The company is in the gray area	value of TZ (= 0.2, Z < 0.3)
The company is bankrupt	value of TZ (-∞, Z < 0.2)

Ohlson Model (1980)

Ohlson (1980) first applied the logistic regression as a way of incorporating conditional probabilities into financial bankruptcy (distress) models. He used nine (9) financial ratios in other to predict the probability of bankrupt companies.

$OZ = -1.33-0.407O_1+6.03O_2-1.43O_3+0.076O_4-2.37O_5-1.83O_6-0.285O_7-1.72O_8-0.521O_9.$ Find the description of the O_{1-9} variables in the table, see table5.

Table 1c: Threshold Calculation Ohlson Z-Score

Firm's condition	Benchmark Value
The company is creditworthy	value of OZ(Z <0.38)
The company is in the gray area	value of OZ (Z = 0.38)
The company is bankrupt	value of OZ(Z >0.38)

Table 2: Altman Z (Variables, Ratios, Code, and Weights)

Model's Variables	Ratios	Codes	Weight
Current Assets minus current liabilities/total assets	WC/TA	X_1	1.2
Retained Earnings/Total Assets	RE/TA	X_2	1.4
Profit Before Interest and Tax/Total Assets	PBIT/TA	X_3	3.33
Market Value of Equity/Book Value of Debt	MVE/BVD	X_4	0.6
Sales/Total Assets	SALES/ TA	X_5	0.999

Table 3: Almamy Z (Variables, Ratios, Code, and Weights)

Model's Variables	Ratios	Codes	Weight
Current Assets minus current liabilities/total assets	WC/TA	A_1	1.2
Retained Earnings/Total Assets	RE/TA	A_2	1.4
Profit Before Interest and Tax/Total Assets	PBIT/TA	A_3	3.33
Market Value of Equity/Book Value of Debt	MVE/BVD	A_4	0.6
Sales/Total Assets	SALES/ TA	A_5	0.999
The cash flow of Operation/Total Assets	CFO/TA	A_6	0.75

Table 4: Taffler Zt (Variables, Ratios, Code, and Weights)

Model's variables and Ratios	Ratios	Code	Weight
Profit before tax/Current Assets	PBT/CA	T_1	12.18
Current assets/current liabilities	CA/CL	T_2	2.5
Current liabilities/total assets	CL/TA	T_3	10.68
(Quick assets-liabilities)/Daily Operating Expenses (Sales-PBT-Depreciation)/365 - no credit interval	(QA-L)/CI	T_4	0.0029

Table 5 Ohlson O (Variables, Ratios, Code, and Weights)

Model's variables and ratios	Ratios	Code	Weight
Log(Total Assets/GNP Price Level Index)	In (TA/GDP)	O_1	-0.407
Total Liabilities/Total Assets	TL/TA	O_2	6.03
Working Capital/Total Assets	WC/TA	O_3	-1.43
Current Liabilities/Current Assets	CL/CA	O_4	0.076
Net Income/Total Assets	NI/TA	O_5	-2.37

Operational Cash flow/Total Liabilities	OPF/TL	O_6	-1.83
1 if Net Income was negative for the last two years and 0 otherwise	Dummy	O_7	+0.285
1 if Total Liabilities > Total Assets and 0 otherwise	Dummy	O_8	-1.72
Current Net Income(CNI)-Last Net Income(LNI)/Absolute(CNI+LNI)	CNI-LNI/ABS(CNI +LNI	O_9	-0.521

Logistic Modelling

The Logit regression analysis is essential in this study because it provides for probabilities of occurrence of the outcome. The study was guided by the following logistic regression model described below:

$$Yi= \alpha + \beta 1X1 + \beta 2X2 + \mu I \quad (1)$$

Where,

X1, X2…Xn is the independent or explanatory variables in the Altman, Almamy, Taffler, and Ohlson that are effective in predicting bankruptcy in the various models.

Yi = dependent variable (the bankruptcy scores from the different models recodify as below);

Yi = 1 if a company is financially distressed;

Yi = 0 if a company is not financially distressed.

The first equation based on logistic regression can be denoted as

$$\ln(P/1-P) = \alpha + \beta 1 \times 1 + \beta 2 \times 2 + \mu I \quad (2)$$

Therefore, the probability of a company becoming financially distressed will be given by

$$P = 1/1 + e^{-(\alpha + \beta 1X1 + \beta 1X2 + \beta nXn)} \quad (3)$$

Values with a figure of 0.5 and above denote that the company is financially distressed; while numbers below 0.5 show that a company is not economically distressed. A value of 0 indicates an indifferent state of the company. On the other hand, a negative coefficient reduces the probability of financial distress, while positive factors increase the chance of occurrence of bankruptcy prediction.

Hypothesis

Four hypotheses were tested separately to identify their predictive power on Cadbury Nigeria PLC a multinational manufacturing company in Nigeria. The four hypotheses are computed for Altman Z in hypothesis one, Almamy Z for hypothesis two, Taffler Z test for hypothesis three, and Ohlson Z test for hypothesis four.

Ho1: Firm will not go bankrupt shortly applying Altman Z scores
Ho2: Firm will not go bankruptshortly applying Almamy Z scores
Ho3: Firm will not go bankruptshortly applying Taffler Z scores
Ho4: Firm will not go bankruptshortly applying Ohlson Z scores.

Empirical Result

Descriptive Statistics

VARIABLES	ALTMAN Z		VARIABLES	ALMAMY Z	
	MEAN	STD DEV		MEAN	STD DEV
X_1	0.1367	0.13655	A_1	0.1367	0.13655
X_2	0.2758	0.14338	A_2	0.2758	0.14338
X_3	0.5553	0.33942	A_3	0.5553	0.33942
X_4	1.6824	1.82386	A_4	1.6824	1.82386
X_5	1.0105	0.17381	A_5	1.0105	0.17381
Z	3.6606	1.80000	A_6	0.0758	0.081493
			AZ	3.7364	1.81493

Source: SPSS 25 Computation

Descriptive Statistics

VARIABLES	TAFFLER Z		VARIABLES	OHLSON Z	
	MEAN	STD DEV		MEAN	STD DEV
T_1	1.8406	1.46947	O_1	2.1821	0.05581
T_2	3.3241	0.77943	O_2	3.3147	0.42347
T_3	4.3108	0.44092	O_3	0.1630	0.16273
T_4	0.5437	2.29006	O_4	0.0614	0.01455
TZ	4.5975	4.60713	O_5	0.1936	0.16896
			O_6	0.3066	0.39063
			O_7	0.0356	0.10076
			O_8	0.0000	0.00000
			O_9	0.0021	0.31943
			OZ	0.7556	1.30381

Source: SPSS 25 Computation

From the descriptive statistics report, the Taffler model generated the highest and highest standard deviation of 4.5975 and 4.60713 respectively. Whereas Ohlson's model with more variables produced the lowest mean score and standard deviation of 0.7556 and 1.30381 respectively while Almamy and Altman are considered second and third place in terms of their mean and standard deviation rating.

Altman Correlation Matrix

SPECIFICATION	CODE	X_1	X_2	X_3	X_4	X_5	Z
WC/TA	X_1	1					
RE/TA	X_2	-0.643	1				
PBIT/TA	X_3	0.235	0.201	1			
MVE/BVD	X_4	0.304	-0.053	-0.123	1		
SALES/ TA	X_5	-0.521	0.679	0.289	-0.475	1	
	Z	0.326	0.081	0.125	0.963	-0.316	1

**.correlation is significant at the 0.05 level (2-tailed). **.correlation is significant at the 0.01 level (2-tailed).*
Source: SPSS 25 Computation

There is a strong positive correlation between X_2 and X_5 (67.9%) and a strong positive correlation between X_4 and Z that is about (96.3%). Other variables in the matrices are either having a negative correlation or a low positive correlation.

Almamy Correlation Matrix

SPECIFICATION	CODE	A_1	A_2	A_3	A_4	A_5	A_6	AZ

WC/TA	**A_1**	1						
RE/TA	**A_2**	-0.643	1					
PBIT/TA	**A_3**	0.235	0.201	1				
MVE/BVD	**A_4**	0.304	-0.053	0.123	1			
SALES/ TA	**A_5**	-0.521	0.679	0.289	-0.475	1		
CFO/TA	**A_6**	0.611	-0.293	0.520	0.052	-0.189	1	
	AZ	0.352	0.066	0.149	0.957	-0.322	0.200	1

**.correlation is significant at the 0.05 level (2-tailed). **.correlation is significant at the 0.01 level (2-tailed).*
Source: SPSS 25 Computation

There is a strong positive correlation between A_1 and A_6 (61.1%), a strong positive correlation between A_2 and A_5 (67.9%), there is a strong positive correlation between A_3 and A_5 (52.0%), and a strong positive correlation between A_4 and AZ (95.7%).

Taffler Correlation Matrix

SPECIFICATION	**CODE**	T_1	T_2	T_3	T_4	TZ
PBT/CA	**T_1**	1				
CA/CL	**T_2**	0.651	1			
CL/TA	**T_3**	-0.584	-0.816*	1		
(QA-L)/CI	**T_4**	0.808*	0.929**	-0.720*	1	
	TZ	0.887**	0.917**	-0.778*	0.981**	1

*.correlation is significant at the 0.05 level (2-tailed). **.correlation is significant at the 0.01 level (2-tailed).
Source: SPSS 25 Computation

There is a strong positive correlation between T_1 and T_2 (65.1%), a strong positive correlation between T_1 and T_4 (80.8%), there is a strong positive correlation between T_1 and TZ (88.7%), there is a strong positive correlation between T_2 and T_4 (92.9%), a strong positive correlation between T_2 and TZ (91.7%) and lastly, there is a strong positive correlation between T_4 and TZ (98.1%).

Ohlson Correlation Matrix

SPEC	CODE	O_1	O_2	O_3	O_4	O_5	O_6	O_7	O_8	O_9	OZ
In (TA/GDP)	O_1	1									
TL/TA	O_2	-0.861**	1								
WC/TA	O_3	0.654	-0.853**	1							
CL/CA	O_4	-0.553	0.785*	-0.990**	1						
NI/TA	O_5	0.899**	-0.967**	0.718*	-0.630	1					
OPF/TL	O_6	0.862**	-0.905**	0.671	-0.606	0.929**	1				
(NI) 1 ELSE 0	O_7	-0.243	0.509	-0.280	0.255	-0.575	-0.519	1			
Dummy	O_8	0	0	0	0	0	0	0	1		
CNI-LNI/ABS(CNI+LNI	O_9	-0.160	-0.196	0.352	-0.401	0.105	0.017	-0.662	-0.420	1	
	OZ	-0.765*	0.961**	0.392	0.794*	-0.927**	-0.885**	0.683	0	-0.420	1

**.correlation is significant at the 0.05 level (2-tailed). **.correlation is significant at the 0.01 level (2-tailed).*
Source: SPSS 25 Computation

There is a high correlation between O_1 and O_3 (65.4%), between O_1 and O_5 (89.9%), and O_1 and O_6 (86.2%). A strong positive correlation exists between O_2 and O_4 (78.5%), between O_2 and O_7 (50.9%), between O_2 and OZ (96.1%). A strong positive correlation between O_3 and O_5 (71.8%), between O_3 and O_6 (67.1%). The strong correlation between

O_4 and OZ (79.4%). A strong positive correlation between O_5 and O_6 (92.9%) and a strong correlation between O_7 and OZ (68.3%).

Logistic Regression Result

Altman Logistic Regression Test Result

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	8.492	5	.131
	Block	8.492	5	.131
	Model	8.492	5	.131

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	2.599[a]	.654	.872

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	X_1	12.945	14.156	.836	1	.360	418553.750
	X_2	-1.252	14.438	.008	1	.931	.286
	X_3	-3.896	4.537	.738	1	.390	.020
	X_4	-.896	.880	1.037	1	.309	.408
	X_5	4.017	11.528	.121	1	.727	55.538
	Constant	-1.812	10.516	.030	1	.863	.163

a. Variable(s) entered on step 1: X_1, X_2, X_3, X_4, X_5.

The result from the logistic regression shows that the Altman Z is a good predictor model for corporate failure predictions. The model summary showed that the Nagelkerke R Square of 0.872 meaning that the model was capable of explaining 87.2% as to whether Cadbury Nigerian PLC will go bankrupt or not using the giving variables X_1, X_2, X_3, X_4, and X_5. Furthermore, the most important variables in the model were X_3, X_4, X_5 with negative coefficients indicating that they have the power of reducing the bankruptcy rate of the firm. The least important variables are X_1 and X_2 with a positive coefficient of 12.945 and 4.017 respectively. All five variables in the model were however seen to be not significant an indication that supports the stated hypothesis that the firm will not go bankrupt shortly. Cadbury Nigerian PLC, therefore, seems to be financially strong and will continue to function as a viable manufacturing firm in the Nigerian economy.

Almamy Logistic Regression Test Result

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	6.913	6	.329
	Block	6.898	6	.330
	Model	6.898	6	.330

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	2.099[a]	.578	.856

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	A_1	12.136	15.894	.583	1	.445	186506.055
	A_2	11.518	14.952	.593	1	.441	100515.162
	A_3	-4.257	4.996	.726	1	.394	.014
	A_4	-1.026	.850	1.456	1	.228	.359
	A_5	-8.226	10.907	.569	1	.451	.000
	A_6	-4.740	21.342	.049	1	.824	.009
	Constant	6.925	10.069	.473	1	.492	1017.463

a. Variable(s) entered on step 1: A_1, A_2, A_3, A_4, A_5, A_6.

The omnibus Chi-Square model statistics of 0.330 shows the result is not significant, also, the result from the logistic regression shows that the Almamy Z score model is a good predictor model for corporate failure predictions. The model summary showed that the Nagelkerke R Square of 0.856 meaning that the model was capable of explaining 85.6% as to whether Cadbury Nigerian PLC will go bankrupt or not using the giving variables A_1, A_2, A_3, A_4, A_5, and A_6. Results indicated that the least important variables in this model were A_1 and A_2since they have positive coefficients of 12.136 and 11.518 respectively. The other four variables A_3, A_4, A_5, and A_6 tends to reduce the firm's bankruptcy level because they have negative coefficients All six variables in the model were also seen to be not significant supporting the stated hypothesis that the firm will not go bankrupt shortly. Cadbury Nigerian PLC, therefore, seems to be financially strong and will continue to function as a viable manufacturing firm in the Nigerian economy.

Taffler Logistic Regression Test Result

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	6.098	4	.192
	Block	6.083	4	.193
	Model	6.083	4	.193

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	2.914[a]	.533	.789

Variables in the Equation

		B	S.E.	Wald	Df	Sig.	Exp(B)
Step 1[a]	T_1	-1.053	1.481	.506	1	.477	.349
	T_2	1.721	5.131	.112	1	.737	5.588
	T_3	2.967	4.312	.474	1	.491	19.437
	T_4	-.039	1.794	.000	1	.983	.962
	Constant	-17.551	33.111	.281	1	.596	.000

a. Variable(s) entered on step 1: T_1, T_2, T_3, T_4.

The result from the logistic regression shows that the Altman Z is a good predictor model for corporate failure predictions. The model summary showed that the Nagelkerke R Square of 0.789 meaning that the model was capable of explaining 78.9% as to whether Cadbury Nigerian PLC will go bankrupt or not using the giving variables T_1, T_2, T_3, and T_4. Furthermore, important variables in the model were T_2 and T_3 with a positive coefficient of 1.721 and 2.967 respectively. All four variables in the model were also seen to be not significant an indication that supports the stated hypothesis that the firm will not go bankrupt shortly. Cadbury Nigerian PLC, therefore, seems to be financially strong and will continue to function as a viable manufacturing firm in the Nigerian economy.

Ohlson Logistic Regression Test Result

Omnibus Tests of Model Coefficients

		Chi-square	Df	Sig.
Step 1	Step	3.513	6	.742
	Block	3.319	6	.768
	Model	3.319	6	.768

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	2.710[a]	.340	.641

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	O_1	47.281	105.246	.202	1	.653	341899604067184 100000.000
	O_2	-8.147	30.472	.071	1	.789	.000
	O_3	-22.291	227.281	.010	1	.922	.000
	O_4	-176.316	2145.479	.007	1	.935	.000

O_5	-28.414	52.970	.288	1	.592	.000
O_6	-2.027	15.090	.018	1	.893	.132
Constant	-57.093	139.568	.167	1	.682	.000

a. Variable(s) entered on step 1: O_1, O_2, O_3, O_4, O_5, O_6.

The result from the logistic regression shows that Ohlson Z is a good predictor model for corporate failure predictions. Although some variables were dropped from the model due to redundancy, the model summary never-the-less showed that the Nagelkerke R Square of 0.641 meaning that the model was capable of explaining 64.1% as to whether Cadbury Nigerian PLC will go bankrupt or not using the giving variables O_1, O_2, O_3, O_4, O_5, and O_6. All the variables with negative coefficients are important to reduce the firm's bankruptcy level except O_1which has a positive coefficient of 47.28. All six variables in the model were also seen to be not significant an indication that supports the stated hypothesis that the firm will not go bankrupt shortly. Cadbury Nigerian PLC, therefore, seems to be financially strong and will continue to function as a viable manufacturing firm in the Nigerian economy.

Model Summary Statistics

Model	Cox and Snell R^2	Nagelkerke R^2	Rank
Altman Z	0.654	0.872	1
Almamy Z	0.578	0.856	2
Taffler Z	0.533	0.789	3
Ohlson Z	0.340	0.641	4

Source: *Author's computation from SPSS 25*

The result from the model summary shows that the Altman Z topped the list of a model for predicting bankruptcy ranking first position with a Nagelkerke Rsquare of 87.2% and least in the model prediction is the Ohlson Z with a Negelkerke R square of 64.1%.

Summary of Most Potent Ratios from the Models

Model Name	Potent variables (Code)	Remarks
Altman Z model	X_2, X_3, and X_4	$\mathbf{X_2}$ $\mathbf{X_3}$and$\mathbf{X_4}$ are more important variables in the model.
Almamy Z model	A_3, A_4, A_5, and A_6	$\mathbf{A_3}$, $\mathbf{A_4}$, $\mathbf{A_5}$, and$\mathbf{A_6}$ are more important variables in the model.
Taffler Z model	T_1 and T_4	$\mathbf{T_1}$ and $\mathbf{T_2}$are important variables in the model.
Ohlson Z model	O_2, O_3, O_4, O_5, and O_6	$\mathbf{O_2}$ $\mathbf{O_3}$ $\mathbf{O_4}$ $\mathbf{O_5}$and $\mathbf{O_6}$ are important variables in the model

Source: Author's compilation

A summary of the non-potent variables from the various models is the Altman Z model with two non-potent variables X_1 and X_5, Almamy Z model produced two non-potent variables namely A_1 and A_2, Taffler Z model also generated two non-potent variables T_2 and T_3 while Ohlson Z model has one non-potent variable O_1. A total of 14 ratios were potent in the study as in the summary table. These potent variables when combined are likely to produce a more parsimonious corporate failure model for the manufacturing industry in Nigeria and other developing countries. However since the variables are so many, we can conduct a stepwise linear regression to select a few of the variables for further studies?

CONCLUSION AND RECOMMENDATIONS

The model summary was able to rank the various model tested on Cadbury Nigeria Plc. to show that the Altman Z model ranked first. The Altman Z model has proved superior to other models in this study, it is not to say that Altman Z is a better predictive model than others depending on the result obtained from one study to the other as in other studies Ohlson, Almamy and Taffler have yielded better predictive power. Since there is no one model with absolute superiority, we, therefore, recommend that for future works one can make use of those ratios we have identified as potent variables to gauge the bankruptcy prediction model in the manufacturing industry in Nigeria.

The model summary table revealed the strength of the bankruptcy models tested using Nagelkerke R Square from the binary logistic regression analysis. The Alman Z rank first (1^{st}) with an R^2 of 87.7%, Almamy Z (modified) ranked second (2^{nd}) with an R^2 of 85.6%, Taffler Z turns out third (3^{rd}) with R^2 78.9%, and lastly, Ohlson Z ranked the fourth (4^{th}) with R^2 of 64.1%. The four hypotheses were all not significant, indicating that the models were able to predict bankruptcy shortly. Conclusively, the Altman Z model was best for conducting and predicting bankruptcy tests for Cadbury Nigerian PLC followed by Almamy, Taffler, and OhlsonZ models.

It is advised that the 14 potent variables can be carefully selected and used as potent ratios for further studies in the Nigerian manufacturing sector as predictors for corporate and business failure predictions.

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