

Credit Default Modeling: a Logit Approach

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Abstract
This paper aims at developing a credit scoring model that can best be used to ascertain the credit score and predict probability of default of firms seeking credit. The study subsequently aspires to find the financial ratios that can best be used to successfully construct the credit score and predict default risk. To achieve these purposes, the paper applied the logit model. Performance of the model was assessed using the percentage correctly classified (PCC) and the area under the receiver operating characteristic curve (AUC). The results show that the logit model yield very good performance rate for credit scoring and risk assessment. Further empirical evidence indicates that ratios bordering on: interest coverage, liquidity, activity, and firm size are those that can be significantly helpful in scoring credit applicants and assessing credit risk. Practically, the model can aid in reducing the time spent on evaluating credit applicants, and can give an exact default-risk intensity of each firm subjected to the model as well as serve as an early warning system. The multiplier effect will be a significant improvement in loan portfolio quality of the model user which is in accordance with the Basel II framework.
Keywords: Credit default modeling, logit, Ghana

1. Introduction

Credit risk management (CRM) has become a key factor in today's banking business environment. Embedded in this management structure, is the risk identification, measurement, and assessment process of borrowers (Santomero, 1997). These aspects of the CRM system are deemed crucial in view of the fact that credit risk emanates from default probability (default risk) of borrowers (Doumpos et al., 2002). This is the risk of loss due to a debtor's non-payment of a loan or other line of credit (either the principal or interest or both) (Chen et al., 2010). This therefore places a major task on the credit granting decision process (creditworthy assessment) which requires a distinct attention in order to properly segregate creditworthy borrowers from unworthy ones (Abdou and Pointon, 2009). According to Matoussi and Abdelmoula (2010), most credit analysis in developing nations are done using traditional approaches which focuses mainly on the borrower's capacity, character, condition, capital, and collateral (the 5C's) and in some cases reduced to 4C's and 3C's (Yap et al., 2011). Nevertheless, such creditworthy assessment routine does not allow for objective decision making and also for the computation of a single performance score in the creditworthy assessment process (Emel et al., 2001; Derban et al., 2005; Abdou and Pointon, 2009). As a remedial measure, scholars have relied on a number of statistical methods to build quantitative credit assessment models. Some of these techniques include: multiple discriminant analysis (MDA), probit model, logit model, and artificial neural networks (ANN). Earlier distress prediction models (e.g. Altman, 1968; Zmijewski, 1984; Ohlson, 1980) used the term 'bankruptcy' as a measure of failure/distress or default criterion. Notwithstanding, default and bankruptcy cannot be mixed, in that, default does not necessarily lead to bankruptcy (Bhimani et al., 2010). In recent times however, researchers have focused on building and developing default specific creditworthy assessment and distress prediction tools (e.g. Altman and Sabato, 2007; Li et al. 2011; Chijoriga, 2011; Wu and Wang, 2000) as well as making use of bank specific data to build credit scoring models (see e.g. Lin, 2009; Chijoriga, 2011) because banking institutions themselves are investing in such internal models as they deliver a well-defined information set at less expense to the bank, and permit them to make faster and more accurate decisions on loan applications (De-Young et al., 2008). In this present paper, we aim to determine the predictive accuracy in terms of credit risk of the logit model and also to find the financial ratios that can offer the most predictive significance in determining credit worthiness of firms.

The rest of the paper is organized as follows. Section 2 provides an overview of the performance of credit scoring models and then a review on the financial ratios that significantly impact default risk is also presented. The methodology for constructing the credit scoring model is covered in Section 3 followed by discussion of the empirical results of the paper in section 4. The concluding aspect of the paper is presented in section 5.

2. Literature Review

2.1 Financial Ratios as Predictors of Default

It is well established that the effective use of screening technology greatly reduces the information asymmetry between borrowers and lenders, thereby enhancing the efficiency of the financial intermediation process (Psillaki et al., 2010). Over the past decades, a vast literature has emerged concerning the development of statistical models designed to predict default probability with the help of financial ratios. Based specific historical performance indicators in the form of ratios, a scoring model can be built or developed to ascertain future default risk (Yap et al., 2011). Although some skeptisms have been raised about the usefulness of financial and non-financial ratios as means of assessing creditworthiness, they have become useful and acknowledged in a variety of areas including credit lending (Beaver, 1966; Zavgren, 1985; Bhimani et al., 2010).

As it stands, one of the primary issues of credit scoring research has been to determine which variables significantly influence the probability of default (Marshall, 2010). In testing the usefulness of ratios as predictors of failure, Beaver (1966) independently tested a series of ratios (univariate analysis) including: Cash Flow Ratios, Net-Income Ratios, Debt to Total Asset Ratio, Liquid Asset to Total Asset Ratio, Liquid-Asset to Current Debt Ratio, and Turnover Ratios. The author found cash-flow to total-debt ratio to be the strongest in the ability to predict failure while the net-income to total assets ratio predicts second best followed by the total debt to total assets ratio while the liquid-asset ratios performed the least. In a similar study, Altman (1968) found Working capital/Total assets, Retained Earnings/Total assets, Earnings before interest and taxes/Total assets, Market value equity/Book value of total debt, and Sales/Total assets ratios as significant predictor variables for bankruptcy in his Z-score model. Amongst these ratios, the author found the profitability ratio to be the highest contributory factor to predict distress. Altman described this outcome as not surprising citing that, the incidence of bankruptcy in a firm that is earning profit is almost nil. On the contrary, profitability does not necessarily mean cash hence firms making/reporting profit still have a certain chance of failure. More especially when debts to creditors must be paid with cash and not profit (Appiah and Abor, 2009).

Altman and Sabato (2007) found ratios bordering on profitability, liquidity and leverage to be significant in predicting credit default risk in their SME risk model. Similarly, Ohlson (1980) showed that financial structure, profitability, and liquidity are essential ingredients for firm survival. Related findings on profitability, liquidity and leverage have been shown by Lin et al. (2011). Others have shown that accrual, cash flow and collateral variables are the best default indicators or predictors (see e.g. Matoussi and Abdelmoula, 2010). The result reiterates the significance of cash flow to a business. To buttress the importance of cash flow ratios to the health of a firm, Rujoub et al. (1995) extensively used only a wide array of cash flow ratios to predict financial failure. The empirical evidence of the paper revealed high performance of the ratios to predict default.

One other firm characteristic that has emerged as a factor in evaluating default risk is firm size. In a study by Chen et al. (2010), the authors indicated that asset size of a firm has a significant impact on its credit risk exposure indicating that, the probability of default is biggest among small sized firms and much lower in medium and large-sized ones. As identified by Ohlson (1980) also, the size of a firm significantly affects its failure probability. It is evident at this point that ratios covering a company's profitability, liquidity, leverage, size and general cash flow activities are necessary and key to the health and worth of a firm. These have dominated the empirical literature as far as the significant predictor variables in any credit scoring model are concerned. In all these assessments, profitability ratios appear to have the most dominance. Appiah and Abor (2009) have however raised concerns on the 'over reliance' on profitability as a measure of solvency, asserting further that following the events of this present era, profitability of a firm cannot be a concrete evidence of its good financial standing given the collapse of big profit making firms like Enron and WorldCom.

2.2 Performance of Default Prediction Models

In practice, there are numerous statistical methods for building credit scoring or distress models. For the purpose of managing credit risk, commercial banks use these various scoring methodologies to evaluate the financial performance of client firms (Emel et al., 2003). Traditionally, the logit, probit, and multiple discriminant analysis techniques have been in the fore front of prediction models. In recent times however, more quantitatively demanding and robust nonparametric approaches such as data envelopment analysis (DEA) (Psillaki et al., 2010), and case based reasoning (CBR) (Li and Sun, 2011) are being employed to predict distress, assess credit risk, and support the credit decision process.

Examining the predictive ability of the four most commonly used financial distress prediction models (MDA, probit, logit, and ANN), Lin (2009) revealed that the probit model possesses the best and stable performance. Kolari et al. (2002) used both the parametric method of logit analysis and the nonparametric approach of trait recognition to develop classification early warning systems (EWSs). The study found that both logit and trait recognition perform well in terms of in-sample classification results. However, with regards to holdout sample performance, trait recognition outperforms the logit model in terms of minimizing type I and II errors.

Huang et al. (2006) performed a comparative study between the logit model and the artificial neural network approach. Their empirical evidence indicate that the logit model perform well in terms of predictive accuracy than the one fitted by artificial neural network technique (ANN). Li et al. (2011) combined the classical models and random subspace binary logit (RSBL) model (or random subspace binary logistic regression analysis) to forecast corporate distress in China. The results indicate that the RSBL performs significantly better than the traditional models (i.e., MDA, logit, and probit models) in predicting corporate failure.

Following the Case-Based Reasoning (CBR) technique, Li and Sun (2008) showed that the nonparametric approach statistically outperforms MDA, and logit significantly in financial distress prediction 1 year prior to distress. In another comparative study, Lee et al. (2002) found that accuracies increase in terms of the neural networks and hence outperform traditional multiple discriminant and logistic regression approaches.

Odeh et al. (2010) examined the performance of the ANN, logistic regression and adaptive neuro-fuzzy inference system in predicting credit default. The empirical findings show that correct credit default predictions (in and out-of-sample) vary with model used. At this stage, it is clear that statistical models have their strengths and outperform each other under different circumstances such as regional differences and the nature of data used (see Kolari et al., 2002; Lin et al., 2007; Odeh et al., 2010).

A cursory look at the literature suggests that even though empirical proofs concerning the overall performance of prediction models exist, it will be difficult to generalize, meaning that models respond (in terms of predictive accuracy) differently to the kind of data used as well as the time the information is available (Ohlson, 1980; Mensah, 1984). Hence, using or applying existing classification models developed in different contexts as benchmarks for determining default can be misleading.

This paper contributes to the literature in many ways. First, instead of relying on existing classification accuracies as benchmark for accepting and validating the predictive strength of the logit model which could be misleading, this paper employs statistical means to test the validity of the model. In essence, the Press-Q statistic and the chance criterion were used to test the validity of the model instead of making comparisms to existing models. Secondly, we assess the marginal probability of default in relation to the predictors which is scarce in the literature. Finally, the study is in the emerging market context where studies like this are scanty. This goes a long way to inform financial institutions on the importance of internal credit rating instead of relying on traditional credit risk assessment which mostly leads to adverse selection and moral hazards.

3. Methodology

3.1 The Binary Dependent Variable

The two (binary) groups of interest in this paper are: defaulted and non-defaulted firms. It does not matter which group is assigned the value of 1 or 0 but the assignment must be noted for the purpose of interpretation of the results (Hair et al., 2006). The dependent variable (probability of default) in this paper is presented as:

$$Probability\ of\ default = \begin{cases} 1, if\ firm\ i\ defaulted \\ 0, if otherwise \end{cases}$$

3.2 The Logit Model

In the application of logistic regression model to credit scoring, the objective is to find the conditional probability of a good or bad loan, given the values of the independent variables pertaining to a particular credit applicant (Lee and Chen, 2005).

The logit model (L_i) can be stated as:

$$L_i = \ln\left(\frac{P_i}{1-P_i}\right) = Z_i \tag{3.1}$$

Where: $Z_i = \beta_1 + \beta_2 X_1 + \cdots + \beta_k X_k$; $\frac{P_i}{1-P_i}$ is the odds ratio in favour of loan default, P_i is the probability of default; $Y = 1$ means firm i has defaulted; X_i are the set of predictor variables and $\beta_1, \ldots, \beta_k$ represents the coefficients of the explanatory variables.

For the purpose of estimation, we will state the logit model in this form:

$$L_i = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_1 + \beta_2 X_1 + \cdots + \beta_k X_k + \mu_i \tag{3.2}$$

where μ_i is the error term.

Table 1
Selected Ratios for the Default Prediction

Variables	Definition	Expected Sign on Default
X_1	$EBIT/Interest\ Expense$	-
X_2	$Total\ Liabilities/Total\ Assets$	+
X_3	$Cash/Total\ Assets$	-
X_4	$Net\ Working\ Capital/Total\ Assets$	-
X_5	$Current\ Assets/Current\ Liabilities$	-
X_6	$EBIT/Total\ Assets$	-
X_7	$Retained\ Earnings/Total\ Assets$	-
X_8	$Accounts\ Receivables/Total\ Liabilities$	-
X_9	$Operating\ Income/Total\ Assets$	-
X_{10}	*Logarithm of Total Assets*	-

3.3 Data Pool and Sample Size

In all, the financial statements of two hundred (200) firms who had sourced financing from a Ghanaian bank were randomly gathered to serve as the sample for the study. Out this number, one hundred and fifty (150) were used as the estimation sample and the remaining fifty (50) were used as the hold-out sample to validate the model.

4. Results and Discussions

4.1 Descriptive Statistics and Distribution of Variables

Table 2 presents descriptive statistics of the independent variables used in estimating the logit regression model as well as their distribution. The statistics covers mean values, standard deviation, and a two-sample t-test statistic to compare the group means of both defaulted and non-defaulted firms. The null hypothesis (H_0) in this test is that: "there is no statistical difference between the two groups". It must be emphasized here that the descriptive analysis is not a predictive test but rather, a convenient way of outlining the general relationships between the defaulted and non-defaulted firms per their financial ratios (see also Beaver, 1966).

It is clear from the table that the firms in their respective groups have significant differences in their mean values in terms of some ratios $(X_1, X_3, X_4, X_5, X_7, X_9)$ and in terms of others, they are not (X_2, X_6, X_8, X_{10}). It must be added however that, firms that face problems at some specific point in time have a gradual deterioration of their financial characteristics over the preceding years; therefore, it is possible that some of these firms may have similar financial characteristics to financially healthier ones few years prior to the occurrence of financial problems (Doumpos et al., 2002). More so, it is important to note that simple mean comparison such as the one in this paper, is not exhaustive in itself since it provides little information on cause and effects implying that ratios may have little or no ability to predict distress or failure, in spite of the differences in their means (Beaver, 1966).

Table 2
Profile Analysis of Means and Standard Deviations of Firms and Distribution of Variables

	Default Status				Group Difference		t-value	*p*-value
	Defaulted firms		Non-defaulted firms					
Variables	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Err.		
X_1	-16.7140	86.1433	52.3824	125.5027	69.0965	20.1946	3.4215	0.0008
X_2	1.4138	3.3849	1.1667	2.6735	-0.2471	0.5128	-0.4819	0.6306
X_3	0.0808	0.1789	0.1475	0.0163	0.0667	0.0270	2.4671	0.0148
X_4	-0.0385	0.6474	0.0368	0.3738	0.3803	0.0837	4.5386	0.0000
X_5	2.2836	6.4436	6.6444	12.9518	4.3608	1.9955	2.1853	0.0304
X_6	-0.3572	36.0814	1.6623	5.2847	2.0196	3.6241	0.5573	0.5782
X_7	-4.4332	27.7589	0.8557	2.4775	5.2889	2.7481	1.9246	0.0562
X_8	0.1431	0.1732	0.8473	3.3603	0.7042	0.4913	1.4331	0.1539
X_9	-5.1126	27.4668	1.0212	2.3687	6.1337	2.7176	2.2570	0.0255
X_{10}	8.3632	5.1809	9.4997	5.0725	1.1364	0.8989	1.2643	0.2081

Notes: *p*-values are meant for testing the null hypothesis that there is no statistical difference between the two considered group of firms in relation to a particular ratio

4.2 Correlation Analysis

Below in table 3 is a Pearson correlation matrix for all the variables used in estimating the default risk models. Correlation analysis is a possible way of assessing the strength of a group of independent variables as against the dependent variable. It also offers a general idea of the inter-relationship between the regressors prior to estimation. This in a way provides an overview about possible multicollinearity problems. From the correlation matrix, all the predictor variables recorded their expected sings in relation to default probability. The X_2 ratio showed a positive expected relationship while the rest of the ratios ($X_1, X_3, X_4, X_5, X_6, X_7, X_8, X_9, X_{10}$) produced negative but expected relationship with the probability of default. Among these ratios, only the; X_1, X_3, X_4, X_5, X_9 ratios have statistical significant correlation with probability of default at the 0.05 significance level.

To test for the presence of any multicollinearity problem, we employed two tests. First, we used the variance inflation factor (VIF) criterion after estimating a linear probability model and secondly, performed a univariate analysis. Chatterjee and Price (1991) and Hair et al. (2006) suggest a maximum variance inflation factor (VIF) of 10 for any meaningful and unbiased estimation results. Carrying on with the VIF test, all the variables had VIF values below the maximum criteria except X_7 and X_9 which recorded very high VIF values above the. As a remedy, X_7 which recorded the highest VIF value was dropped and the test carried out once more. After eliminating X_7, it was found that all the regressors had VIF values below the maximum acceptance value. Further, by applying the univariate analysis to X_7 and X_9, the later showed a pseudo R^2 of 0.09 and was statistically significant in explaining the probability of default at the 0.05 significance level as against the insignificant X_7 ratio with a pseudo R^2 of 0.02. Hence, the X_9 ratio is superior and is worth including in the estimation.

Table 3: Correlation Matrix between Probability of Default and Financial Ratios

	Probability of default	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
Probability of default	1.0000										
X_1	-0.2707*	1.0000									
	(0.0008)										
X_2	0.0396	0.0258	1.0000								
	(0.6306)	(0.7542)									
X_3	-0.1987*	0.3262*	0.1792*	1.0000							
	(0.0148)	(0.0000)	(0.0282)								
X_4	-0.3495*	0.1691*	-0.0390	0.1209	1.0000						
	(0.0000)	(0.0386)	(0.6354)	(0.1404)							
X_5	-0.1768*	0.1667*	-0.0561	0.1105	0.3828*	1.0000					
	(0.0304)	(0.0414)	(0.4956)	(0.1781)	(0.0000)						
X_6	-0.0458	0.2935*	0.4928*	0.1934*	-0.0306	-0.0329	1.0000				
	(0.5782)	(0.0003)	(0.0000)	(0.0178)	(0.7099)	(0.6890)					
X_7	-0.1563	0.3601*	0.0680	0.0770	-0.0141	0.0009	0.7952*	1.0000			
	(0.0562)	(0.0000)	(0.4081)	(0.3488)	(0.8644)	(0.9909)	(0.0000)				
X_8	-0.1170	0.3373*	-0.0653	-0.0144	0.1464	0.2298*	-0.0078	0.0114	1.0000		
	(0.1539)	(0.0000)	(0.4275)	(0.8611)	(0.0737)	(0.0047)	(0.9241)	(0.8900)			
X_9	-0.1824*	0.3732*	0.0416	0.0958	0.0043	-0.0205	0.7716*	0.9875*	0.0162	1.0000	
	(0.0255)	(0.0000)	(0.6129)	(0.2438)	(0.9581)	(0.8034)	(0.0000)	(0.0000)	(0.8444)		
X_{10}	-0.1051	0.1426	-0.0283	-0.0733	0.0213	-0.0479	-0.0156	0.0167	-0.0468	0.0255	1.0000
	(0.2006)	(0.0817)	(0.7312)	(0.3726)	(0.7960)	(0.5606)	(0.8498)	(0.8395)	(0.5698)	(0.7564)	

Notes: *p*-values are in parenthesis; * denotes significance at the 5% α-level; X_1 stand for EBIT/Interest Expense ratio; X_2 is Total Liabilities/Total Assets ratio; X_3 represent Cash/Total Assets ratio; X_4 is Net Working Capital/Total Assets ratio; X_5 is Current ratio; X_6 indicate Return on Assets ratio; X_7 signify Retained Earnings/Total Assets ratio; X_8 imply Accounts Receivable/Total Liabilities; X_9 is Operating Income/Total Assets and; X_{10} is the log of Total Assets as a proxy for firm size.

4.3 Estimation Results

In credit risk modeling techniques such as the one employed in this study, predictions and evaluation of models are mainly based only on the function of the significant predictor variables. Therefore, for us to generate a reduced form of the model that contains only the significant variables at a respectable alpha-value, the backward elimination procedure was applied to arrive at the final credit risk model. In this present paper, variables were retained and/or eliminated at the 0.10 significance level. After four backward elimination processes, five statistically significant ratios were retained in the model. The ratios cover: financial leverage/coverage, liquidity, activity, and firm size. The result of the regression is summarized in table 4 below.

The interest coverage ratio (X_1) was found to be statistically significant at the 1% α-level with *p*-value of 0.005. The coefficient estimate of the logit model is traditionally interpreted using the odds ratio. However, an astute way of interpreting the logit results is through the marginal effects. From our results, X_1 recorded a marginal effect value of -0.1118, meaning that, a unit increase in the X_1 ratio reduces the probability of default by 0.1118 holding all else constant. The rest of our logit results are discussed using this approach.

In terms of liquidity, two ratios (X_3 and X_4) entered into the model were retained. The marginal effect associated with the X_3 ratio is -0.4208 signifying that a 1-unit increase in the ratio will result in a 42.08 percent reduction in the probability that a firm will enter into default all else constant. The second liquidity ratio is X_4. The probability value of -0.2014 suggests that, a 1-unit change in the ratio reduces the probability of default by 0.2014 holding other variables constant.

In this paper, the activity ratio was measured as accounts receivable to total liabilities (X_8). Accounts receivables are often seen as liquid assets which provide cash to make payments to creditors (Tucker and Moore, 2000). From our results, we found a negative rapport between the X_8 ratio and the probability of default. With a marginal effect of -0.3589, it means that a unit increase in the ratio (X_8) will result in a 35.89 percent lower probability of defaulting all else constant.

It is also suggested that firm size serves as a surrogate variable for numerous omitted variables in financial distress prediction and its inclusion increases model goodness of fit (Becker et al., 1998). In this paper, firm size is measured as the logarithm of total assets. The empirical results yielded a negative and statistically significant influence on the probability of default at the 5% α-level. The marginal effect value of -0.0166 proposes that a 1-unit change in the asset base of a firm decreases the probability of it defaulting by 0.0166 all other things being equal. The results imply that bigger firms are less likely to default (i.e. have lower default risk) as compared to small-sized ones.

In order to ascertain the fit of the model, the pseudo R^2, and the likelihood ratio (LR) statistic were used. A look at the pseudo R^2 values in table 4 reveals that the model recorded a value of 0.2435. Taking another look at the estimation results table, one can witness the LR statistic for the models. The LR statistic/index is an overall measure of the simultaneous significance of the ratios in our model. The LR value of 45.41 with a corresponding *p*-values of 0.000 ($p < 0.1$) demonstrates a strong significance at the 1% α-level. We hence fail to accept the null hypothesis of no joint significance and argue that there is a joint and strong statistical significance between the predictors and probability of default at the 0.01 significance level.

From the regression result (i.e. table 4), we can state our logit scoring and credit risk model as follows:

$$\boldsymbol{\hat{L} = 1.5238 - 0.7200X_1 - 2.7105X_3 - 1.2969X_4 - 2.3118X_8 - 0.1069X_{10}}$$

where $\hat{L}$ is the overall index/score. The overall index is then used to determine the probability of default (PD) based on a logistic function (i.e. represents the cumulative logistic distribution function) which is given as $\frac{e^{\hat{L}}}{1+e^{\hat{L}}}$ and $\hat{L}$ is the score from the model.

Table 4: Estimation Results

	Logit Model				
Variables	Coefficient	Odds Ratio	Standard Error	*p*-value	Marginal Effect
X_1	-0.7200	0.4868	0.2578	0.005	-0.1118
X_3	-2.7105	0.0665	1.1674	0.020	-0.4208
X_4	-1.2969	0.2734	0.5741	0.024	-0.2014
X_8	-2.3118	0.0991	1.1935	0.053	-0.3589
X_{10}	-0.1069	0.8986	0.0422	0.011	-0.0166
Constant	1.5238		0.5939	0.010	
LR	45.41			0.000	
Pseudo R^2	0.2435				

Notes: Dependent variable is probability of default; the values reported in the "Marginal Effect" column are average predicted probabilities; X_1 stand for EBIT/Interest Expense ratio; X_3 represents Cash/Total Assets ratio; X_4 is Net Working Capital/Total Assets ratio; X_8 imply Accounts Receivable/Total Liabilities ratio; X_{10} is the log of total assets as a proxy for firm size; LR is Likelihood Ratio statistic.

4.4 In-sample Performance Assessment

In order to judge the performance of the model, we used the percentage correctly classified (PCC) and the area under the receiver operating characteristic (ROC) curve (AUC). In this study, we assumed an equal misclassification cost (i.e. the costs of both type I error and type II errors are the same) and so, a 0.5 cutoff probability was used under the PCC. Table 5 provides the performance results. It is evident that the model recorded a PCC of 0.8000 (80.00%). What this means is that, the model was able to accurately classify 80 percent of the defaulted and non-defaulted firms in-sample.

The AUC value of 0.8171 or 81.71 percent signifies that, there is a 81.71 percent chance of a highly risky firm being classified as such by the model. It is well recognized that, in order to wholly evaluate the overall credit scoring capability of a designed model, it is important to factor in the misclassification costs (type I and type II errors). The type I error associated with the model means that, there is a 0.3617 probability of classifying high risk borrowers into a low risk group.

Table 5: In-Sample Model Performance

Sensitivity (%)	Specificity (%)	PCC (%)	AUC (%)	Type I Error (%)	Type II Error (%)
63.83	87.38	80.00	81.71	36.17	12.62

Notes: Predictions are based on 0.5 cutoff probability for the PCC

4.5 Model validation

In order to test the efficacy of our model, the paper subjected the results to a hold-out sample. The validation result is displayed in table 6 below. At this model validation stage, the predictive ability of the model is found to be 72.00%. The type I error rate of 15.38 percent imply that, there is a 15.38% chance that a highly risky and unworthy borrower will be accepted for credit.

As a standard or benchmark of testing and measuring the acceptability of the estimated model, the paper computed and used the Press-Q statistic and also utilized the proportional chance criterion (Hair et al., 2006) to ascertain how the model would have performed if left to chance or in the situation where borrowers are classified at random. The results are displayed in table 7 below.

The Press-Q test compares the results to a critical value (6.63) at the 0.01 significance level. From table 7, it can be observed that the in-sample Press-Q for the model is 54. Comparing this to the critical value, it can be concluded that the in-sample classification accuracy of the model is statistically acceptable and significant at the 0.01 significance level ($54 > 6.63$). Turning to the out-of-sample predictive performances, the model once again shows a robust performance ($9.68 > 6.63$) indicating that statistically, the model is externally valid at the 1% α-level.

Observing the results in table 7 once more, we can witness that by chance, our model could have achieved accuracy rate of 57.22% in the in-sample estimation. Comparing this accuracy rate to the 80.00% PCC in-sample rate, this paper can firmly say that the models have performed considerably well (in-sample) at least better than a random process.

Table 6: Out-of-Sample Model Performance

Sensitivity (%)	Specificity (%)	PCC (%)	AUC (%)	Type I Error (%)	Type II Error (%)
84.62	67.57	72.00	84.82	15.38	32.43

Notes: Predictions are based on 0.5 cutoff probability for the PCC

Table 7

Chance Criterion and Press's Q Statistical Results

In-sample		**Out-of-sample**	
Chance Criterion	Press's Q	Chance Criterion	Press's Q
57.22	54*	61.52	9.68*

Notes: * denotes significance at the 0.01 significance level; values in the chance criterion column are percentages

5. Summary and Conclusion

The paper aimed at developing a credit scoring and risk assessment model by applying the logit model. Subsequently, we purposed to find the financial ratios that can contribute significantly to the credit modeling process. In relation to trade-off between profit and loss, we found that the logit model has a good chance of reducing risk of loss and high chance of increasing profits because it produced a high sensitivity rate and also AUC out-of-sample thereby yielding a low type I error rate. Further, it was observed that the ratios that can effectively help score and subsequently predict the default risk of borrowers are: EBIT/Interest Expense ratio; Cash/Total Assets ratio; Net Working Capital/Total Assets ratio; Accounts Receivable/Total Liabilities ratio; and Total Assets. It is hence recommended that in ascertaining the credit worthiness of borrowers, financial institutions should critically examine the cash flow of firms and limit the over reliance on profit as an indication of good financial performance.

On the other hand, there is a limitation in this paper that call for further research. Data on diverse firms was used in the model analysis. Meanwhile it is eminent that sectorial differences exist. So, for the purpose of developing sector specific models, further research may put together an observation set of firms limited to a specific sector to develop a sector specific model.

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