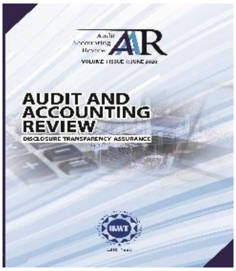

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Financial Ratios: A Tool used for Computing the Probability of Corporate Default

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Abstract

Financial institutions want to draw upon a pool of borrowers having a high capacity of making repayments to ensure a smooth lending process. Before lending, financial institutions can assess their prospective customers using various tools such as customer interviews, visits, ratings from external credit rating agencies, financial analysis, and internal ratings along with risk mitigation through securities and collateral, as guided by the regulators and Basel committee. Basel accord suggests an internal rating-based approach where banks are allowed to estimate the borrower's probability of default, internally. Multivariate statistical approaches such as logistic models is widely used for finding the probability of default models by banks. The current study covers the development of probability of default model after using financial ratios as predictors. Results reveals that financial ratios have a significant impact on the firm's probability of default, except cash flow ratios. Fitted probability of default model can be utilized in any corporate lending firm for the assessment of its strength and its ability to pay back the loan. Probability of default model meets the State Bank of Pakistan (SBP) and Basel requirements for the implementation of internal rating based approaches in the case of conventional Pakistani banks. Credit risk rating and expected credit losses can be calculated using fitted probability of default model. This study was executed only based on financial ratios because of the availability of financial data only. Conventional banks use managerial, business and economic factors along with financial ratios to construct better predictive models. The current study was conducted on limited data adopted from financial statements analysis published by SBP. The developed model in this study is suitable for all non-financial

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corporates. Future researchers may develop different models for different industries, for instance, manufacturing and trading.

Keywords: financial ratios, default, Basel, internal rating

Introduction

Financial institutions may follow Standardized approach or internal rating-based approach for its minimum capital requirement measurement. There are two approaches for estimating minimum capital requirements; Standardized Approach and Internal Rating Based Approach. Standardized approach is simple and straightforward where financial institutions use estimates from external rating agencies for its capital requirement calculations whereas when using Internal Rating based approach, financial institutions may compute credit ratings of its borrowers internally. There are two major categories of IRB (Internal Rating Based) approach; Foundation IRB approach and Advanced IRB approach. In foundation–IRB (F-IRB) approach a single component i.e. Probability of Default is internally estimated while in Advanced –IRB approach, financial Institutions have to internally estimate the Exposure at Default (EAD) and Loss Given Default (LGD) along with Probability of Default (PD). (State Bank of Pakistan, 2007)

Financial ratio analysis is a powerful tool to access financial health of any corporation because Financial Analysis helps companies, banks and investors in making their business decisions. Logit and probit models are most widely used in the identification of factors affecting probability of default (Karacula, 2009).

Main factor for predicting corporate's default rate is financial ratios belonging to liquidity, profitability, leverage, solvency, and activity. Most commonly used liquidity ratios are working capital to total assets, current assets to current liabilities and cash to current liabilities. Profitability ratios include net income to sales and net income to total assets. Leverage ratios include EBIT to total assets and total debt to total equity. Solvency ratios include EBIT to interest and equity to total debt whereas Activity Ratio includes sales to total assets.

There are two types of profitability ratios: the one in which revenues and expenses in the income statement are compared e.g., Net profit margin and contribution margin, etc. The other type of these ratios is in which results on the income statement are matched with that on the balance sheet. The ratios of this type are return on assets and return on equity etc. (Accounting Tools, 2018).

Liquidity ratios are those which reveal the ability of a firm's current assets to pay off its debts at the time when their payment is to be made. It is also a tool to find out the possible ways to collect cash or switch assets into cash. The examples of liquidity ratios are current ratio, quick ratio and working capital etc.

Cash flow ratios evaluate the similarities and differences of cash flows to other features of financial statements of a firm. When cash flows are in excess, it reveals that the firm can tolerate the low performing operations and can pay the dividends. These are necessary for the firms whose cash flows deviate from their profits. Current liability coverage ratio, Cash flow coverage ratio, cash flow margin ratio etc. are the examples of cash flow ratios. (Accounting Tools, 2018).

Solvency ratios assess the possibility of paying off its debts that are to be paid after a year from the date of borrowing. These ratios help to know, depending on the firm's cash flow, whether the firm can survive in the long run, for example, total debt to total assets ratio, Equity ratio and Interest earned ratio, etc. (Peavler, 2019)

In a research study in India, logistic regression (Al-Saati, #18) and other financial ratios were used as independent variables to study indicators that affect the performance of shares on the Indian stock exchange. They selected ratios of 30 large firms for 4 years. They classified eight ratios that showed that selected firms can be 74.6% correctly divided into "defaulted" or "non-defaulted" groups depending on their profit rates. This study paper examined the effects of using the LR method to predict the probability. (Dutta et al., 2012)

Review of Related Literature

There are multiple ways used in the past researches for bankruptcy prediction. Abbas & Ahmad (2011) has identified ratios relating to bankruptcy for sample firms bankrupted from 1996-2006 in Pakistan. The data of five years before bankruptcy were used. They have used Multivariate Discriminant Analysis (MDA) for bankruptcy prediction. In a study Ahmadi et al., (2012) has attempted to predict the bankruptcy of companies using the Logit model in Iran. Based on the research results, Logit model with variables of net profit to total assets ratio have shown that the ratio of retained earnings to total assets and debt ratio have more power to predict corporate bankruptcy in Iran.

Financial statements are a vital part of a company performance; these are also used for the analysis of a firm possible bankruptcy. Mohammed (2016) researched to analyze the financial situation of an Omani company. Secondary sources i.e. published financial statements of 8 years from 2007-2014 were used for the analysis. Jiming & Weiwei (2011) used non-financial indicators in the financial distress prediction model. They studied 50 manufacturing companies listed in Shenzhen and Shanghai stock exchange during 2005 and 2007 using logistic model that consisted of two models with financial indicators only and a mix of both financial and non-financial indicators.

A research was done in Sri Lanka using data from annual reports of a sample of 70 defaulted and non-defaulted companies listed on Colombo stock market from 2002-2008 by applying logistic regression. 15 financial ratios were used as variables. Results showed that model can predict exact true results for three years before default. Three financial ratios i.e. working capital to total assets, Debt ratio and cash flow from operating activities to total assets have more ability to predict financial distress (Lakshan & Wijekoon, 2013).

A study has revealed different areas that influence the financial performance of Pakistan Stock Exchange. The researchers has tried to find out the features among different divisions that have an impact predicting default. Independent variables like financial ratios were analyzed to study their connection with dependent variable using logit model. (Ramakrishnan et al., 2016).

Accounting ratios are also used in the previous studies for predicting bankruptcy of a firm. Almansour (2015) studied the linkage between accounting ratios and bankruptcy in Jordanian context and to see whether these ratios useful in bankruptcy prediction. 22 bankrupt and non-bankrupt Jordanian public listed companies had been used to apply a bankruptcy prediction model from the year 2000-2003. He has used Logit model to for studying the relationship bankruptcy probability and variables; through this a multiple regression model is adapted. The results show that five ratios remained significant which are WC/TA, CL/CA, RE/TA, MCE/BVD and S/TA.

Different models have been used worldwide to detect the probability of bankruptcy with assuming additional data as dummy to the existing study. Volk (2016) incorporated multiple models for his study on Slovenian non-financial firms from 2007-2010. In which the results revealed the model with dummy years has better results to predict credit risk than the others.

A study differentiated between two default forecasting models, i.e., multiple discriminant analysis (MDA) and logistic regression (Logit) to find out the effect of financial ratios that in prediction of default and to most relevant ratios for UK's firms. They have suggested a suitable model to predict the probability of default. Return on total assets, Solvency ratio, Gearing ratio and Interest cover were proved to be the most relevant in predicting default.(Bunyaminu & Issah, 2012)

Charalambakis and Garrett (2019) studied a huge number of Greek private sector firms. They included around 31,000 firms and ran multi period logit model on the data to find out factors that caused default in Greek industry. They found out profitability, leverage, liquidity ratio, etc., are considered as detectors of bankruptcy in Greek private market.

A study has focused on verifying the effect of fundamental factors that consist of financial ratio and management capability to financial distress. This paper added upper echelon theory as the new one. The method of analysis used was logit regression. The findings show that model as a whole results in goodness and fit and the sign of each independent variables show consistently to existing and new theory (Ahmad, 2013).

Altman (1968) suggested that liquidity, leverage, growth and profitability are the bases for firm's default. So, these ratios with link to financial failure of non-financial companies listed in Nairobi Stock Market were examined. The data were collected from 2007-10 using univariate and multivariate accounting based default predicting methods. The Pearson product moment correlation and regression analysis were employed to study the link between factors of failures and failure itself. Results showed that liquidity and leverage has no impact in finding default while growth and profitability had a major impact. The Altman Z score model had a major impact in predicting default model (Baimwera & Muriuki, 2014).

González-Aguado & Moral-Benito (2013) explained that understanding which variables are more relevant in assuming default risk at the firm level is more important in credit risk behavior. Quarterly data set from year 1980 to 2005, for 4367 US firms and 593 defaulted firms was being used. Results revealed that four variables were the main determinants of default i.e. the standard deviation of the firm stock return, working capital to total assets, retained earnings to total assets and total liabilities to total assets.

Li (2006) discussed Proc Discrim and Proc Logistic use in credit industry. He concluded that overall Generalized Logit Regression is better than Discriminant Analysis, but only this cannot conclude that Logit is good than Discrim because a detailed study is required for choosing the most appropriate method.

In an effort to forecast defaulted firms in the Malaysia, Defaulted firms were selected as dependent variable and ratios as independent. Logit had been used for the study. They concluded that independent variables that could be selected predict default firms were debt ratio, total assets turnover ratio and working capital ratio. It can be said that there is 50% probability that the model can predict for five years before default. (Alifiah et al., 2013)

Bartual Sanfeliu et al. (2013) applied logistic regression on Spanish companies and checked corporate default. They did research on 2783 firms. The results show that logit model is more successful than naïve model with more than 88% accuracy.

Baltaev & Chavdarov (2014) in their paper named as “Predicting Corporate default rates: Evaluating Moody’s Credit rating” estimated PD model by using Merton model and logistic regression since these models accurately predict default rate in corporate sector where logistic regression performed far better than Merton mode

De (2011) researched to find out less number of financial ratios that can be used to get the required information. They have used factor analysis on financials of 38 iron and steel companies for 10 years (1999-2000 to 2008-2009) using 44 financial ratios divided into 8 categories. They applied Multiple Regression Analysis to get rid incorrect variables. To further enhance the results factor analysis results are applied Cluster Analysis. The results came to introduce 8 new categories of financial ratios.

Two financial default predicting models, multivariate discriminant analysis and logit were examined with their pros and cons. They found out that logit regression model (LRM)has more benefits than multivariate discriminant analysis (MDA) for better assessment of default (ul Hassan et al., 2017).

In Indonesia, a study was done to find the most appropriate default prediction model for firms. They selected the listed firms from 2006-15. Owing to the use of independent variables other than ratios, variable corporate governance with ownership structure and macro-economic variables were also used for the conditions of the firms in Indonesia. They used Logit Model for the analysis. The result came that default determinants were Working Capital to Total Assets, Current Ratio, Book value of equity to total liabilities, Total Debt to Total Assets, EBIT to Current Liabilities, and Institutional Ownership (Dewi & Hadri, 2017).

Khan and Khokhar (2015) did a research to find out the profitability of listed cement companies of Kingdom of Saudi Arabia (KSA) from 2008-12. The results reveal that Debt to Equity Ratio (Baltaev, #21), Inventory Turnover Ratio (ITR) and Creditors’ Velocity (CRSV) have positive relationship with profitability of the companies.

Frade (2008) did the research to build a model to find out the probability of a debt to be defaulted in a year in US. He used logistic regression for this purpose. The results showed that profit margins, leverage position and company's competition with others are important factors that can decide a firms' probability of default.

Information value is very helpful and most widely used technique for accessing predictor power of the variable and is a very useful tool for variable reduction in binary logistic regression modeling (Regmi et al, 2014). Following criteria were used to access the predictor power of variable. Predictors with Information value below 2% have no predictor power in estimating classification category. Predictors with Information value between 2% to 10% have week predictor power in estimating classification category. Predictors with Information value between 10% to 30% have medium predictor power in estimating classification category. Predictors with Information value between 30% to 50% have strong predictor power in estimating classification category. Predictors with Information value above 50% have very strong predictor power in estimating classification category while they are suspicious and used with care.

Methodology

All non-financial companies of Pakistan were the target population of the study as any corporate can be a prospective customer of any bank for ending. According to Pakistan Stock Exchange (www.psx.com.pk) over 900 corporations are listed. Financial data (FY 14 to FY 19) of 456 of these companies are readily and publically available with SBP. Total companies comprised the population of the study.

In this study, data from financial statements (Balance sheet, Income Statement, Cash Flow) of corporate were gathered and compiled. A pool of defaulted companies was included in the sample as they were low in proportion to population. Financial statements of 355 corporations are included in the final sample chosen randomly. As each sampled corporate possessed data of at least 6 years of latest financials (2014 to 2019), total data points were 2022 financial statements with 1998 regular and 132 negative cases.

Twenty-seven ratios, belonging to categories like Liquidity, Profitability, Solvency, Valuation and Cash flows were initially selected. The ratios were chosen because they are commonly used in company financial performance forecasts. The figure 1 below presents the list of financial ratios to be used for predictive modeling purpose along with their categories and calculation formulas.

Figure 1

Formulas for Ratio Analysis

Category	Financial Ratio/ Calculation formula
Profitability Ratios	Net Profit Margin = *Netprofit / Sale*
	Asset Turnover Ratio = *Sales /Average total asset*
	Return on Assets =*Net income / Average total asset*
	Financial Leverage = *Average total assets/ Average Shareholder equity*
	Return on Equity =*Netincome / AverageShareholders' equity*
	Gross Profit Margin = *Grossprofit / Sale*
	Operating Return on Assets = *EBIT / Average total asset*
	Return on Capital Employed = *EBIT / Capitalemploye*
	Retained Earnings to Total Assets = Retained Earnings / Total Assets
Liquidity Ratios	Current Ratio= *Currentassets / Current liabilities*
	Quick (Acid Test) Ratio=(*Cash + Account receivable + Short term investments*)/ *Current liabilities*
	Cash Ratio= *Cash and cash equivalents / Current liabilities*
Activity Ratios	Inventory Turnover= *Sales / Inventory*
	No. of days Inventory = 365 / *Inventory turnover*
	Receivables Turnover Ratio = *Net credit sales / Average account receivable*
	No. of days Receivables= 365 / *Receivable turnover*
	Working Capital Turnover= *Sales / Working capital*
Cash Flow Ratios	Cash Flow from Operating Activities to Sales = *Net Cash flowfrom operations / Net sales*
	Cash Return on Assets = *Net Cash flow from operations /Average total assets*
	Cash Return on Equity = *Net Operations cash flow/ Average equity*
	Cash to Income= *Net Operationscash flow / Net income*
	Debt coverage ratio= *Net Cash flowfrom operations / Total debt*
Valuation ratios	Basic earnings per share
Solvency Ratios	Debt to Equity Ratio= *Total liabilities / Shareholders' equity*
	Debt to Asset Ratio= *Total debt (liabilities) / Average total assets*
	Debt to Capital Ratio= *Total debt (liabilities) / Total capital*
	Interest Cover Ratio= *EBIT / Interest expenses*

The ratios were grouped under five main categories to illustrate and represent the companies' short-term liquidity and cash positions, Profitability performance, Solvency and leverage status and the efficient utilization of the company's assets.

As binary logistic regression model is applied to the collected data, following equation presents the statistical model of the study

$$Z = b_0 + b_1 X_1 + b_2 X_2 + b_3 X_3 + \ldots\ldots\ldots\ldots + b_n X_n$$

Where Z is the log odds ln (p/1-p) and b_0 is the model constant, b_1, b_2, ---- b_n are regression weights of the independent variables, and X_1,X_2, ……X_n are independent variables (financial Ratios). N is the number of independent variable in the final model. Industry of the company is also included in the model as qualitative variable.

After fitting above model probability of default was calculated using following model

PD = 1 / (1 + EXP (-Z)), Where PD is probability of default and EXP is exponent function

A number of statistical methods are available to predict probability of default, like discriminant function analysis, logit and probit models, and neural networks. Selection of statistical method was made on the basis of nature of collected data and availability of statistical tools. All statistical methods mentioned above require certain statistical assumptions met before their application, however logistic regression is a candidate which requires less set of distributional assumptions. In this study binary logistic regression is applied by taking default status (0 = non-default, 1 = default) as dependent variable and all above mentioned financial ratios and industry as independent variables.

IBM SPSS was acquired for statistical analysis where logistic regression was applied to form probability of default equation. Probability of default of the all cases in the dataset was calculated.

Upon successful data collection, Data were cleaned, outliers were identified and treated and necessary set of financial ratios were computed using formulas presented in the previous section.

Data Analysis

As a first step data of financial statements of both defaulted and non-defaulted firms were collected and 27 different financial ratios were computed. Descriptive analysis were conducted to compare the logical behavior of financial ratios. Datasets were divided into 70% and30% split for the purpose of training and testing sample. The Model was developed on the basis of training dataset and validated on out of sample data set called validation sample. Basic descriptive analysis was carried out to judge the behavior of financial ratios in both the default and non-default groups.

Calculation of Financial Ratios

As discussed in methodology section of the document, 27 financial ratios were computed from financial statements of sample corporates. Financial ratios were categorized into five categories namely Profitability, Liquidity, Valuation, Cash flow and Solvency. Industry classification as categorical dummy variable was also added in the list of independent variable. Following table presents the list of financial ratios computed as candidates for independent variables along with their computational formulae.

Model Development

Binary logistic model was developed after short listing financial ratios using information value for all predictors. Return on assets, return on equity, operating return on assets, and return on capital are the financial ratios with information value below 30% were excluded from the analysis. Dataset is divided into training and testing samples for model training and possible out of sample model validation. At different model development iterations some of the financial ratios are excluded from the model based on following two reasons.

1. Ratios are not significantly based on their wald statistic (P-value was highly insignificant)

2. Understanding of the financial ratios in respect with default status like debt ratios have direct or positive impact on probability of default while profitability ratios have indirect or negative impact on financial ratios.

Seven financial ratios are found to be significant at 5% level of significance except inventory turnover (P-vaues = .19). Industry/sector of the borrower is included in the mode as dummy variable. Below table shows the results of regression model based on training dataset.

Table 2

Variables in the Equation

Variables in the Equation	β	S.E.	Wald	Sig.
Receivables turnover ratio	-3.719	0.535	48.35	0
Cash to income	-0.714	0.261	7.5	0.01
Quick ratio	-1.374	0.653	4.425	0.04
Inventory turnover	-0.02	0.015	1.743	0.19
Debt to assets	1.076	0.2	28.91	0
Debt to capital	0.069	0.019	13.83	0
Financial leverage	0.036	0.007	26.34	0
Industry (Dummy Variable)			66.43	0
Industry (1) Chemicals & Pharmaceuticals	3.735	0.798	21.91	0
Industry (2) Coke & Refined Petroleum Products	1.736	0.901	3.707	0.05
Industry (3) Electrical Machinery & Apparatus	-14.74	4375.67	0	1
Industry (4) Food Products	-14.61	5510.98	0	1
Industry (5) Fuel & Energy	-13.51	3808.16	0	1
Industry (6) Information, Comm. & Transport	4.477	0.836	28.71	0
Industry (7) Manufacturing	-15.14	4069.49	0	1
Industry (8) Mineral Products	0.697	1.147	0.369	0.54
Industry (9) Motor Vehicles, Trailers & Autoparts	-14.44	4222.56	0	1
Industry (10) Other Services Activities	-15.12	3090.68	0	1
Industry (11) Paper, Paperboard & Products	0.025	1.508	0	0.99
Industry (12) Sugar	4.78	1.165	16.85	0
Industry (13) Textile - Other Textiles	-0.531	1.194	0.198	0.66
Industry (14) Textile - Made-up Textile articles	4.354	0.666	42.67	0
Industry (15) Textile - Spinning, Weaving, Finishing	4.951	1.051	22.19	0
Constant	-3.601	0.544	43.78	0

Receivable turnover ratio is highly significant in predicting probability of default (*Wald=48.35, df=1, p<.001).* The regression weight coefficient (b = -3.72) is significant and negative as expected; indicating that increasing receivable turnover of a firm is associated with decreased odds of firm's default.

Cash to income is significant in predicting probability of default (Wald=7.5, df = 1, p<.05). The regression weight coefficient (b = -0.714) is significant and negative as expected; indicating that increasing Cash to income of a firm is associated with decreased odds of firm's default. Quick ratio is significant in predicting probability of default (Wald=4.425, df = 1, p<.05). The regression weight coefficient (b = -1.374) is significant and negative as expected; indicating that increasing Quick ratio of a firm is associated with decreased odds of firm's default.

Inventory turnover is only variable which is not significant in the model in predicting probability of default (Wald=1.743, df = 1, p<.001). The regression weight coefficient (b = -0.02) is significant and negative as expected; indicating that increasing Inventory turnover of a firm is associated with decreased odds of firm's default. Debt to assets is highly significant in predicting probability of default (Wald=28.91, df = 1, p<.001). The regression weight coefficient (b = 1.076) is significant and positive as expected; indicating that increasing Debt to assets of a firm is associated with increase odds of firm's default.

Debt to capital is highly significant in predicting probability of default (Wald=13.83, df = 1, p<.001). The regression weight coefficient (b = 0.069) is significant and positive as expected; indicating that increasing Debt to capital of a firm is associated with increase odds of firm's default. The odds ratio Exp (B) = 1.072 tells us that with one unit increase in Debt to capital, probability of default will decrease by 1.072.

Financial leverage is highly significant in predicting probability of default (Wald=26.34, df = 1, p<.001). The regression weight coefficient (b = 0.036) is significant and positive as expected; indicating that increasing Financial leverage of a firm is associated with increase odds of firm's default. Industry (Dummy Variable with 16 industries) is highly significant in predicting probability of default (Wald=66.43, df = 15, p<.001).

The rest of the coefficients represent different categories of industry variable by taking cement industry as reference category. Each industry has impact on probability of default in reference with cement industry. After explaining roles and significance of model predictors, following probability of default equation can be developed.

Probability of Default = 1/ (1+EXP (-z)) Where

z = -3.13+
-3.468 x Receivables turnover ratio
-0.415 x Cash to income
-0.896 x Quick ratio
-0.094 x Inventory turnover
0.894 x Debt to assets
0.062 x Debt to capital
0.062 x Financial leverage
3.546 x Dummy variable code of IndustryCode(1) – Cement
1.087 x Dummy variable code of IndustryCode(2) - Chemicals & Pharmaceuticals
-14.864 x Dummy variable code of IndustryCode(3) - Coke & Refined Petroleum Products
-15.017 x Dummy variable code of IndustryCode(4) - Electrical Machinery & Apparatus
-14.047 x Dummy variable code of IndustryCode(5) - Food Products
4.088 x Dummy variable code of IndustryCode(6) - Fuel & Energy
-15.597 x Dummy variable code of IndustryCode(7) - Information, Comm. & Transport
0.733 x Dummy variable code of IndustryCode(8) – Manufacturing
-14.32 x Dummy variable code of IndustryCode(9) - Mineral Products
-15.766 x Dummy variable code of IndustryCode(10) - Motor Vehicles, Trailers & Autoparts
0.319 x Dummy variable code of IndustryCode(11) - Other Services Activities
4.204 x Dummy variable code of IndustryCode(12) - Paper, Paperboard & Products
-1.023 x Dummy variable code of IndustryCode(13) – Sugar
3.939 x Dummy variable code of IndustryCode(14) - Textile - Other Textiles
4.835 x Dummy variable code of IndustryCode(15) - Textile - Made-up Textile articles

Above model showed positive prediction value is 59.57% and negative prediction value is 99.48% while overall accuracy is 98.15% which seems a good model.

Using the same model, probability of default was computed for testing sample, presenting positive prediction value by 76.4% and negative prediction value by 99.5% with overall prediction accuracy by 98.87%. Following table summarizes the above findings.

Table 3

Predicted Category for Testing Sample

Data Division	Predicted Category				Model fit/validation Statistics	
	Actual Category	Non-Default	Default	*Total*		
Training	Non-Default	1349	7	1356	True negative rate	99.48%
	Default	19	28	47	True positive rate	59.57%
Training Total		1368	35	1403	Overall prediction accuracy	98.15%
Testing	Non-Default	599	3	602	True negative rate	99.50%
	Default	4	13	17	True positive rate	76.47%
Testing Total		603	16	619	Overall prediction accuracy	98.87%

Results of both training and testing datasets are consistent.

Conclusion

Financial institutions want to draw upon a pool of borrowers having a high capacity of making repayments to ensure a smooth lending process. Before lending, financial institutions assess their prospective customers using various tools such as customer interviews, visits, ratings from external credit rating agencies, financial analysis and internal ratings along with risk mitigation through securities and collateral as guided by the regulators and Basel committee. Logistic regression model was developed to measure the probability of default of non-financial Pakistani firms. For this purpose, financial statements data of 358 firms from the financial years 2014 to 2019 was collected. Binary logistic regression model was applied to calculate 27 ratios from activity, cash flow, liquidity, profitability, and valuation category. Final model was fitted on three liquidity ratios, one valuation ratio, two solvency ratios, and one profitability ratio, all of which have a significant impact on a firm's probability of default. Financial ratios in the above specified categories are given below.

Valuation ratios (receivable turnover, inventory turnover and quick ratio) have a significant impact on a firm's probability of default. The *p*-value, which is below 5%, indicates that the above mentioned ratio has a significant relationship with the probability of corporate default. Profitability ratios (financial leverage) have a significant impact on a firm's probability of default. The *p*-value, which is below 5%, indicates that profitability ratios have a significant relationship with the probability of corporate default. Solvency ratios (debt to capital and debt to assets) have a significant impact on a firm's probability of default. The *p*-value, which is below 5%, concludes that solvency ratios have a significant relationship with the probability of corporate default.

Valuation ratios (cash to income) have a significant impact on a firm's probability of default. The *p*-value, which is below 5%, indicates that valuation ratios have a significant relationship with the probability of corporate default. Ratios from all groups have a significant impact on a firm’s probability of default except cash flow ratios.

The default model for the probability could be utilized for any lending institution to assess the ability of the customer about repayment of loan. Moreover as the model meet the SBP and Basel requirement thus can also be used internal rating purpose as well as to judge the credit risk rating and their probable losses.

Current study has been conducted on limited data taken from the financial statements being published by SBP and only single model was developed and used, propective researchers could enhance the scope of the research by incorporating more data as well more than one models of probability of default.

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