Predicting Financial Bankruptcy of Five Manufacturing Sectors in Pakistan Using Logistic Regression

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Abstract

Financial distress is a debatable issue among the researchers especially in developing economies. This study investigates the significant financial indicators for five manufacturing sectors listed on Pakistan Stock Exchange (PSX). Sample consists of 35 bankrupt and 156 non-bankrupt companies from textile, cement, sugar, technology and communication and power generation and distribution sectors. Study uses two data sets from 2005 to 2013 for estimation sample and 2014 to 2016 for holdout sample. Logistic regression analysis comprises of sixteen financial ratios under respective indicators i.e. profitability, liquidity, leverage, asset efficiency and size. Findings of the study reveal six significant financial ratios for each indicator i.e. return on equity (ROE), quick ratio, current ratio, shareholder's equity to total assets, sales to current assets and natural log of total assets. Results show overall model accuracy of 89.6 percent for estimation sample while 92.2 percent for holdout sample which indicates model consistency with better financial distress prediction power in the context of Pakistan.

Keywords: *Financial Distress Prediction, Pakistan Stock Exchange, Bankruptcy, Financial Soundness, Logistic Regression.*

Introduction

Over the decades predicting financial distress has become an interesting topic because it is very crucial for stakeholders, listed companies and even for country's economy (Wanke, Barros & Faria, 2015). If financial distress can be accurately predicted, companies' managers can take precautions to avoid any catastrophic effects. Additionally, investors can also judge the company's profitability condition and devise strategies which can minimize expected losses related to their investments. However, due to integration of global economy and fast development in the capital market, the number of companies facing financial distress has been increasing over the years (cite any source saying this).

Different models have been developed to predict the probability of company's default. Several studies have been conducted for both small and large nonfinancial companies to predict business failures. A pioneer study was conducted by Beaver (1966) using univariate analysis with thirty financial ratios and then improved with multiple discriminant analysis (MDA) developing Zeta model by Altman et al. (1977). After mid 1970's, researchers had continuously put efforts focusing on the problems related to the prevailing methods (refer to Moyer, 1977; Mensah, 1984; Zmijewski, 1984). Ohlson (1980) and Zavgren (1985) found financial ratios quite significant in the prediction of financial distress. However, the continuous efforts of researchers on overcoming the methodological problems like strictness in implementation of linearity assumptions related to MDA resulted in shifting the focus to logit analysis (Ohlson, 1980; Zavgren, 1985). The logit analysis is not limited to strict statistical assumptions of linearity as compared to MDA to provide best estimations of likelihood of financial distress (Mihalovic, 2016).

To cope with the problem of financial distress researchers used univariate and multivariate models like MDA and logit for financial bankruptcy prediction. It is observed that these models have different prediction power for different companies as well for different economies (Altman, 2014). The reason behind is the problems associated with financial structure of companies which contributes to the financial bankruptcy (Bongini, Ferri & Hahm, 2000). Moreover, the findings of previous researches for developed economies are not applicable in developing and underdeveloped economies. However, developing and underdeveloped economies have different socioeconomic factors, market structures and provisions and implementation of law and the accounting standards; due to which their financial reporting standards also differ from that of developed countries (Her & Choe, 1999).

Pakistan, which is also one of the developing countries, is facing financial failures in both small and large corporations. Over the last decade, large numbers of business failures have occurred in Pakistan (Sneha, 2015). It was reported that 103 companies; which is quite higher than previous years, had been delisted from the Pakistan Stock Exchange (PSX) under Liquidation /Winding up under court from the year 2012 to 2016 (KSE, 2016). This issue drives the need to study and propose a bankruptcy model for the early prediction of financial distress in Pakistan.

Social and economic environment of Pakistan has been adversely affected by such business failures (Rashid & Abbas, 2011). Acosta-Gonzalez, Fernandez-Rodriguez, and Ganga (2017) described that the corporate sector of any country is very sensitive towards its economic conditions. This sensitivity towards economic environment can increase financial shocks into the country. Additionally, such shocks can weaken the countries macroeconomic environment and it also increases the stress level in the economy. Therefore, the developing economies face the problem of bankruptcy due to instable economic conditions, political structure and inefficient market conditions (Geng, Bose & Chen, 2015).

In the context of Pakistan, there are only limited numbers of studies available in the area of financial distress and its early prediction. These researches incorporated two or three sectors only (cement, sugar and textile) in the analysis of their respective studies (Rashid & Abbas, 2011; Ijaz, Hunjra, Hameed & Maqbool, 2013). Additionally, most of the models used in previous studies in Pakistan predict financial distress only one year prior to bankruptcy. Furthermore, no research has been found to use the logit model for bankruptcy prediction in Pakistan. Therefore, current study proposes that there is a need to develop a bankruptcy model using logistic regression which could predict financial distress at least three to five years prior to its actual occurrence of bankruptcy in Pakistan.

Literature Review

Predicting firm's bankruptcy is very important in corporate governance. Firms' failures are very common problem for developed and developing economies (Altman et al., 1979). The first study that used multivariate data analysis for bankruptcy prediction was conducted by Altman (1968) in which he used the economic and financial ratios which can possibly determine the firm's failure. The study incorporated sixty-six firms from the manufacturing sector including both bankrupt and non-bankrupt firms and it incorporated twenty-two ratios of these categories: leverage, profitability, solvency, liquidity and activity.

Five ratios were finally selected because of their performance in predicting firms' bankruptcy and the model derived from the findings accurately categorized 95 percent of the selected sample (accurately categorizing 94 percent as bankrupt and 97 percent as non-bankrupt firms) a year before bankruptcy. However, the accuracy percentage decreases with the increase in number of years prior to bankruptcy.

Beaver (1966) used various empirical methodologies to examine companies' financial problems. He disclosed that the ratio of cash flow to total debt can best explain the financial distress of any company after that come the total debt to total asset ratio, net income to total assets ratio, working capital to total assets ratio and the current ratio. Altman (1968) included renowned z-score model. He incorporated 22 financial ratios multiple discriminating analysis to extract five financial ratios having accurate explanatory ability. The ratios extracted are retained earnings /total assets, working capital /total assets, earnings before interest and taxes / total assets, sales / total assets and market value equity / book value of total debt.

Altman et al. (1977) suggested a zeta model for improving z-score model. The results of the study clearly indicated that as compare to other variable, seven variables could accurately provide explanation regarding the firm's bankruptcy prediction and those are liquidity, capitalization, cumulative profitability, stability of earnings, return on assets, size and debt service. Altman et al. (1977) used neural network for identifying firms' failure by the Italian central bank. It included the total sample of 1000 firms and ten financial ratios as independent variables, the study found that the categorization of neural networks was quite similar to that attained by the discriminant analysis. It concluded that neural network is not a clearly dominating mathematical technique as compare to the previously used statistical techniques.

Ohlson (1980) used logit analysis which overcomes various issues related to the MDA approach such as the assumption that bankrupt and non-bankrupt company's financial ratios are both normally distributed and both have same variance covariance matrix (Maddala, 1983). In a study Hamer (1983) compares logit analysis with MDA. He concluded that both models are comparable while predicting firm's failure. However, in another study Begley et al. (1986) stated that Ohlson (1980) model is more effective than Altman (1968) model.

Begley et al. (1980) used the time "bias" factor in the classical model for predicting firm's failure. They applied the models of Altman (1968) and Ohlson's (1980) to a sample of bankrupt and non-bankrupt of firms of 1980's, the study found that accuracy of the model of Altman for predicting company's failure has decreased when applied on the data of 1980's companies. The findings of the study elaborated the importance of including time factor in the traditional models for predicting business failure.

Ou (1990) stated that the nonprofit data in annual financial statements of firms contains information which indicate the direction in which company's profit will change in the upcoming year. In his study Ou first created set of 61 independent variables in two steps, in first step he used single variable Logit model by which 13 variables were selected which were significant at the 10% level of significance, in the second step he used multi-variable Logit model to get estimation regarding these 13 variables, and then he kept those significant at the level of 10%. In the final step he selected last eight variables: percentage growth in the net sales / total assets, change in rate of return relative to the previous year's rate of return, the accounting rate of return, percentage growth in the inventory / total assets, percentage growth in the capital expenditure/ total assets ratio, with a 1-year lag, percentage growth in depreciation expense and percentage growth in the inventory / total assets.

Li, Zhou and Sun (2011) stated that multiple classifiers are far better than single classifiers in terms of prediction accuracy and returns on investment. Authors stated that there is no major difference between bagging and majority voting while predicting accuracy, but the multivariate classifiers predict stock returns more accurately than single classifiers. The two classical statistical models logit and MDA are considered to have an important role in predicting business failures.

Chen (2011) conducted a study in which the initial sample collected was the data of 100 companies listed on Taiwan Stock Exchange Corporation, the aim of the study was to bring improvement in the accuracy of failure prediction model. In empirical research he used 37 financial and nonfinancial ratios and included principal component analysis to find out the suitable variables. Other models incorporated for predicting financial failure are decision tree, classification methods and the logistic regression techniques. The research results were quite beneficial and also verified the possibility and validity of the method proposed for predicting financial distress of the listed companies.

As per the literature available on prediction of financial distress, limited number of studies are available in the context of Pakistan's economy (Rashid & Abbas, 2011; Khurshid, 2013). Available studies were limited to only two individual sectors,Sugar sector and the textile sector for finding out the financial soundness by using different financial ratios. Rashid and Abbas (2011) stated in their research that the most significant financial ratios to predict business failures are cash flow ratio, earnings before interest and taxes to current liabilities and sales to total assets ratio. Moreover, Khurshid (2013) included the data of companies of nonfinancial sector of Pakistan from the year 2003 to 2010 and used financial ratios to predict financial distress by implementing Z-score model. His study concluded that the profitability, leverage, current ratio and solvency are negatively correlated however efficiency ratio is positively correlated with the other. The present study however highlights the significance of conducting additional research to contribute in the available literature on predicting financial failure in the context of Pakistan.

Data and Methodology

Present study uses sixteen financial ratios for logit analysis. Sample for the study consists of five manufacturing sectors of Pakistan Stock Exchange (PSX) which possess enormous number of bankruptcies in previous years. Manufacturing sectors include textile, sugar, cement, technology and communication and power generation and distribution. Data is collected for 35 bankrupt and 156 non-bankrupt companies. Period of the study is from year 2005 to 2016 in which estimation sample includes observations from 2005-2013 and three-year holdout sample is from 2014 to 2016 to check the robustness of results. The reason of three-year period of holdout sample is that the general government elections were held on 11th May, 2013 in Pakistan. Six months are left for political movement adjustments and then it is decided to take period of 2014 to 2016 for holdout sample in the analysis current study.

Accounting procedures and rules usually vary from country to country and findings of developed economies are different for developing and underdeveloped economies (Altman, 2014; Geng, Bose and Chen, 2015). As Scott (1981) stated that financial ratios used in most of the empirical work do not belong to any strong underlying theory, hence use of these ratios is acceptable for the current study.

The reason for selected ratios is their frequent use and popularity in the literature for financial bankruptcy prediction purpose. The data of the variables for the proposed study is taken from the financial statements of non-financial companies listed on PSX. The ratios are classified into five categories. profitability, liquidity, leverage, asset efficiency and size. Each indicator is further categorized into its own group of ratios, which are efficiently significant for its own indicator. Table 1 depicts the ratios of five indicators (profitability, liquidity, leverage, asset efficiency and size) which are frequently used in the previous empirical studies.

Table 1 illustrates the sixteen individual financial ratios with their symbols and four respective categories of indicators. After reviewing the available literature in Pakistan, it is observed that no recent research is found which used the logit model (logistic regression) for the prediction of bankruptcy. Hence, the current study uses of logistic regression for the financial distress prediction for five manufacturing sectors in Pakistan.

Table 1: Ratios for each category of financial indicator

Label	Ratio	Symbol	Indicator	Source
X_1	(Gross Profit / Sales)	GPS	Profitability	Kumar and Ravi (2007)
X_2	(Net Profit / Sales)	NPS	Profitability	Rashid and Abbas (2011)
X_3	(Net Profit / Shareholder's Equity)	NPSE	Profitability	Her and Choe (1999)
X_4	(Earnings Before Interest & Taxes / Total Assets)	EBITTA	Profitability	Altman et al. (2014)
X_5	(Earnings Before Interest & Taxes / Total Liabilities)	EBITTL	Profitability	Trujillo-Ponce, Samaniego-Medina and Cardone-Riportella (2014)
X_6	(Current Assets – Inventories) / Current Liabilities	QR	Liquidity	Allayannis, Brown and Klapper (2003)
X_7	(Current Assets / Total Assets)	CATA	Liquidity	Urgurlu and Aksoy (2006)
X_8	(Long term Debt / Total Assets)	LTDTA	Leverage	Agarwal and Bauer (2014)
X_9	(Shareholder's Equity/ Total Assets)	SETA	Leverage	Urgurlu and Aksoy (2006)
X_{10}	(Fixed Assets / Shareholder's Equity)	FASE	Leverage	Eljelly and Mansour (2001)
X_{11}	(Shareholder's Equity/ Long term Debt)	SELTD	Leverage	Altman et al. (2014)
X_{12}	(Sales /Current Assets)	SCA	Asset Efficiency	Urgurlu and Aksoy (2006)
X_{13}	(Sales / Fixed Assets)	SFA	Asset Efficien cy	Eljelly and Mansour (2001)
X_{14}	(Sales / Total Assets)	STA	Asset Efficiency	Bandyopadhyay (2006)
X_{15}	(Net Profit$_t$-Net Profit$_{t-1}$)/ Net Profit$_{t-1}$	NPG	Growth	Nam, Kim, Park and Lee (2008)
X_{16}	log [(Total Assets) $_t$]	LnTA	Size	Altman et al. (2014)

Ohlson (1980) implies logit analysis in order to find out the likelihood of bankruptcy. If we consider *yi* as the occurrence of bankruptcy of a firm *i*, which will be equal to 1 if a firm goes bankrupt and 0 otherwise. In this case the probability that the firm *i* go bankrupt will be shown as:

$$P\ (yi = 1|Xi\ ) = \exp(\beta1X1i + \beta2X2i +\cdot\ \cdot\ \cdot+\beta ki\ Xki\ ) \ /\ 1 + \exp(\beta1X1i + \beta2X2i +\cdot\ \cdot\ \cdot+\beta ki\ Xki\ )$$

In the above equation $\{\beta 1, . . ., \beta k\}$ are k parameters which are to be estimated, $\{X1, . . ., Xk\}$ are variables which will determine bankruptcy, and the errors are logistically distributed. Following equation is estimated to run the logit regression,

$$P(Y_i = 1) = \alpha + \beta_i NPSE_i + \beta_i QR_i + \beta_i CATA_i + \beta_i SETA_i + \beta_i SCA_i + \beta_i LnTA_i$$

Results and Discussion

This section describes the descriptive and empirical results of the study. Table 2 illustrates below the descriptive results of the mean values of independent variables for bankrupt and non-bankrupt companies. It also depicts the significant probability values mean differences between bankrupt and non-bankrupt companies for each financial ratio.

Table 2 shows the values for means and significant differences for both bankrupt and non-bankrupt companies. Profitability ratios for non-bankrupt companies shows of -0.6716 while it is 0.6046 for bankrupt companies. Another profitability ratio EBITTA shows mean value of 0.0614 for non-bankrupt companies while -.0369 for bankrupt companies. Liquidity ratios include quick ratio and current ration with mean value of .9640 and .4151 for non-bankrupt companies and 7.4467 and .3280 for bankrupt companies respectively. Long term debt to total asset ratio is used to measure the leverage capacity of the company with mean values of .1021 and .3062 for non-bankrupt and bankrupt companies respectively.

Table 2: Descriptive statistics and mean differences for bankrupt and non-bankrupt companies

	Means		Mean Differences	
	Non-Bankrupt Companies	Bankrupt Companies	Difference	Significance
GPS	-.1921	-.1360	-0.0561	.892
NPS	-.5768	-.4527	-0.1241	.861
NPSE	-0.6716	0.6046	-1.2763	.051
EBITTA	.0614	-.0369	0.0982	.000
EBITTL	.1380	2.1946	-2.0566	.314
QR	.9640	7.4467	-6.4826	.000
CATA	.4151	.3280	0.0871	.000
LTDTA	.1021	.3062	-0.2041	.000
SETA	.4315	-.0737	0.5052	.000
FASE	3.7474	-4.9485	8.6959	.005
SELTD	15.8118	2.2820	13.5298	.234
SCA	2.7594	2.1681	0.5912	.000
SFA	6.4995	3.0186	3.4808	.701
STA	1.0347	.6387	0.3960	.000
NPG	.6220	-1.7454	2.3674	.214
LnTA	14.8637	14.1151	0.7487	.000

Asset efficiency ratios include SETA, FASE, SCA and STA with mean values of .4315, 3.7474, 2.7594 and 1.0347 for non-bankrupt and -.0737, -4.9485, 2.1681, and .6387 for bankrupt companies. Bankrupt companies express negative growth rate and in contrast non-bankrupt companies show higher growth rate. Size of the non-bankrupt companies illustrates mean value of 14.8637 which is slightly greater than bankrupt companies with 14.1151 of its mean value. Table 2 also illustrates the mean differences values with their significant probability value of .000 for EBITTA, QR, CATA, LTDTA, SETA, SCA, STA, LnTA and 0.005 for FASE respectively.

Table 3: Collinearity Statistics

	Tolerance	**VIF**
GPS	.568	1.760
NPS	.568	1.760
NPSE	.837	1.194
EBITTA	.250	3.997
EBITTL	.618	1.618
QR	.949	1.053
CATA	.559	1.788
LTDTA	.685	1.461
SETA	.681	1.469
FASE	.873	1.145
SELTD	.997	1.003
SCA	.390	2.567
SFA	.998	1.002
STA	.356	2.812
NPG	.991	1.009
LnTA	.870	1.150

Above table 3 depicts the results of collinearity diagnostic test. To treat with the problem of multicollinearity variance inflation factor is considered. Researchers suggested that value of VIF must be less than 10 (Abdullah, Halim, Ahmad & Rus, 2008). Values higher than 10 signals the existence of multicollinearity in the data. However, the results of VIF in table 3 shows all values are less than 10 which shows no concerns of multicollinearity in the data. Results of logistic regression are illustrated below in table 4.

Table 4: Logistic regression

Variable	Coefficients	Significance
NPSE	.050	.041
QR	.191	.000
CATA	-2.950	.000
SETA	-7.223	.000
SCA	-.149	.000
LnTA	-.246	.000
Constant	5.437	.000

*Significant at $\alpha = 0.05$

Table 4 shows the results of logistic regression with the significant financial ratios NPSE, QR, CATA, SETA, SCA and LnTA and their regression coefficients. All ratios are highly significant with their probability value 0.000 which is less than alpha 0.05 except NPSE with its probability value of 0.041. NPSE shows a positive relationship with probability of financial distress. This finding is aligned with previous studies (Her & Choe, 1999; Abdullah, Halim, Ahmad & Rus, 2008; Chancharat, Tian, Davy, McCrae, & Lodh, S., 2010). Bankrupt companies can also generate more profits as compared to non-bankrupt companies. However risky companies are not favorable for creditors because it increases the chances of company's value to decrease further which is unfavorable for creditors because they will receive less profit share then. QR shows positive relation with the probability of financial distress that bankrupt firms are not using their current assets efficiently as documented by (Chancharat, Tian, Davy, McCrae & Lodh, 2010: Allayannis, Brown and Klapper, 2003). CATA is revealing negative relationship with financial distress. Moreover, SETA shows negative sign as expected. As shareholder's equity decreases it assures the increase of debt in capital structure causes increase in probability of financial distress (Urgurlu and Aksoy, 2006). For asset efficiency SCA is demonstrating negative relationship with financial distress (Urgurlu and Aksoy, 2006). In the last, decrease in natural log of total assets (LnTA) leads to high probability of financial distress with negative sign of its coefficient. The reason behind this small size companies bear elevated risk of financial bankruptcy (Ohlson, 1980; Beaver, 1996; Altman, 2014).

Table 5: Model Accuracy

Accuracy Percentage	Estimation sample	Holdout Sample
Bankrupt	49.3	66.3
Non-bankrupt	98.8	98.3
Total	89.6	92.2

Table 5 shows the accuracy percentage for estimation sample and hold out sample of the study. For estimation model 98.8 percentage accuracy is correctly reported companies as non-bankrupt companies. Similarly, 49.3 percent bankrupt companies are predicted correctly. On the other hand, for holdout sample model accuracy remained 66.3 and 98.3 percent for bankrupt and non-bankrupt companies respectively. The overall accuracy for the estimation model is 89.6 percent that is higher than the overall accuracy of Ohlson (1980). In addition to this hold out sample shows higher overall percentage of model accuracy with 92.2 percent notably.

Conclusion

The empirical results of the study confirm that it is worthwhile to investigate the predictors of financial distress for five manufacturing sectors listed at PSX. Sectors include textile, cement, sugar, technology and communication and power generation and distribution. Study employs logistic regression using estimation sample from 2005 to 2013 and three years of holdout sample from 2014 to 2016. Results of logistic analysis gives six significant financial ratios i.e. net profit to shareholder's equity (ROE), quick ratio, current ratio, shareholder's equity to total assets, sales to current assets and natural log of total assets. Overall model accuracy of estimation sample is reported as 89.6 percent while for holdout sample it becomes higher with 92.2 percent. This confirms model consistency with considerable increase in percentage of model accuracy.

Study also contributes into the literature on predicting bankruptcy by finding out significant financial predictors for five manufacturing sectors of PSX. An early prediction model regarding the company's bankruptcy could help the management of to develop strategies to avoid such failures. Senior management, creditors and shareholders all have keen interest in bankruptcy prediction of the company as they all have stake in the respective company. Suitable selection of bankruptcy model can help the auditor to identify the auditor's knowledge regarding the going concern concept of the company.

Bankruptcy prediction models also help the auditors in understanding the auditor's biases. It is beneficial for the auditors not having full knowledge about company because due to this it becomes difficult for them to make appropriate judgments regarding various conditions of company's going concern. Finally, a proper bankruptcy prediction model can also help the investors to identify the chances of firm's failure and devise trading strategies to get abnormal returns from the company in the context of Pakistan. Last but not the least it is suggested that if future research, using logistic regression researchers can estimate models one to five years prior to bankruptcy. It will help to predict financial bankruptcy as early as possible before its actual occurrence.

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