Anticipating financial distress in monster sectors of Pakistan's economy: an application of logit

DOI: 10.35530/IT.074.03.2022105

EHSANUL HASSAN
MUHAMMAD AWAIS-E-YAZDAN
RAMONA BIRAU
LUCIA PALIU-POPA

ABSTRACT – REZUMAT

Anticipating financial distress in monster sectors of Pakistan's economy: an application of logit

It's always been worthwhile for companies to identify significant predictors of financial distress before its occurrence. This study intends to analyse the scenario of financial distress prediction by focusing on Pakistan. The sample of the study covers companies from the three biggest sectors (textile, sugar and cement)listed on the Pakistan stock exchange for the period of 2005 to 2020. The financial ratios are divided into four main categories of profitability, liquidity, leverage and asset efficiency with a total of 18 financial ratios. The results indicate that the financial ratio produced model accuracy rates of 90.11 percent for the first year prior to bankruptcy, 87.72 percent for the second year prior to bankruptcy, 85.32 percent for the third year prior to bankruptcy, 82.36 percent for the fourth year prior to bankruptcy and 79.57 percent for the fifth year prior to bankruptcy. The results also indicate that profitability, liquidity, leverage, and asset efficiency, are significant predictors of financial distress. The study provides a useful financial distress prediction model for policymakers, company managers, investors, lenders and creditors in the Pakistan stock exchange.

Keywords: *Pakistan stock exchange, financial distress, logistic regression, bankruptcy, non-financial companies, economic sustainability, financial obligations, textile industry*

Anticiparea dificultăților financiare în sectoarele majore ale economiei din Pakistan: un studiu privind aplicarea modelului logit

Întotdeauna a fost util ca firmele să identifice predictori semnificativi privind dificultățile financiare înainte de apariție. Acest studiu își propune să analizeze scenariul de predicție a dificultăților financiare concentrându-se pe economia din Pakistan. Eșantionul studiului acoperă companii din cele mai mari trei sectoare (textil, zahăr și ciment) listate la bursa din Pakistan pentru perioada 2005–2020. Indicatorii financiari sunt împărțiți în patru categorii principale de profitabilitate, lichiditate, efect de levier și eficiență a activelor, cu un total de 18 rate financiare. Rezultatele empirice indică faptul că raportul financiar a produs rate de acuratețe a modelului de 90,11 % pentru primul an anterior falimentului, 87,72 % pentru al doilea an înainte de faliment, 85,32 % pentru al treilea an anterior falimentului, 82,36 % pentru al patrulea an anterior falimentului și de 79,57 % pentru al cincilea an înainte de faliment. Studiul oferă un model util de predicție a dificultăților financiare pentru factorii de decizie, managerii de companii, investitorii și creditorii care vizează piața bursieră din Pakistan.

Cuvinte-cheie: *bursa din Pakistan, dificultăți financiare, regresie logistică, faliment, companii nefinanciare, sustenabilitate economică, obligații financiare, industria textilă*

INTRODUCTION

Financial distress is the failure of the companies to meet their financial obligations. This can be observed from the problems faced by the companies in maintaining their liquid assets and fulfilling their promises regarding credit. the forecast of financial distress of any organization plays a vital role in the decision-making for all stakeholders i.e. creditors, investors, financial institutions, owners (shareholders), suppliers, customers and regulators [1]. It is pertinent that each stakeholder would have different agendas based upon their roles, but the common objective would always be a company's growth. The company's ability to fulfil its obligations is always valuable for the customers [2].

Overall, the major concern of all stakeholders is the prediction for future success and failure of a company [3]. Therefore, it is critical to developing bankruptcy prediction models which help in forecasting business failure and its consequences at micro and macroeconomic levels [4]. These predictive models will help the stakeholders identify future business risks and develop strategies for dealing with risks. Bankruptcy prediction models are also used for the purpose of credit scoring and evaluation of the companies [5]. The models are continuously being enhanced with more prediction accuracy for financial distress [6].

As a developing country, Pakistan is also facing business failures in both small and large companies. A large number of bankruptcies have occurred in the last decade. Sneha [7] reported that the Pakistan Stock Exchange (PSX) is experiencing more delisting than a listing of companies. From 2012 to 2018, 138 companies had been delisted from the PSX under

Liquidation/Winding up under court (PSX, 2018). Pakistan's economy had been affected badly. Therefore, it is necessary to investigate the ratios which are beneficial for the prediction of the instability of companies. Due to the global financial crises of 2008–2009, a sudden shock was faced by the Pakistan stock exchange and companies started struggling for their survival [8]. In 2010 and 2011 there is an increasing trend in the percentage of delisting companies. It is noticed that after the adjustment period of post-financial crises (2010–2011), the percentage of delisted companies increases in 2012 drastically up to 17.89 percent. This increasing trend shows that the Pakistan stock exchange has experienced a high percentage of delisting after the financial crises.

Pakistan's economy has been adversely affected by the financial crises of 2008–2009 and the Pakistan stock exchange has experienced a high rate of bankruptcy following these financial crises. In this situation, it becomes more important to forecast financial distress with maximum accuracy and precision to avoid potential bankruptcy. Even though there is a vast literature on financial distress prediction, most of the studies in the literature have used individual ratios to predict financial distress.

In January 2020, the World Health Organization (WHO) initially declared COVID-19 a health emergency. The economy as a whole is highly unstable on a global level. Many areas and nations may attest to this. The severity, intensity, and long-term economic effects of this pandemic are all quite uncertain. These problems have led to financial market volatility, which has had a significant effect on how businesses make decisions in future years. Companies always try their best to survive in financially distressed markets. The completion of the financial distress cycle may take time and most of the time companies succeed to come out of their financial distress period to the normal business life cycle. Moreover, it is also not necessary for every company that it will be shut down right after any financial distress immediately. Notably, the current study is using the data from 2005 to 2020 and the aftereffects of COVID-19 may be observed or investigated well in the sample after a few years in future. Therefore, it is a limitation of the current study that the impact of COVID-19 in the current sample could not be addressed. Even though this study is an extension of previous studies, this study will strengthen past models through a comprehensive evaluation of financial ratios by focusing on Pakistan. There are very limited studies on predicting financial failure in Pakistan. Only three worth reading studies are found: a study by Rashid and Abbas [9] and a study by Khurshid [10] and a study by Ijaz, Hunjra, Hameed and Maqbool, [11]. Rashid and Abbas [9] conducted the first study in Pakistan in which they used only one model to predict bad financial health and instability. Khurshid [10] conducted a study to investigate the determinants of financial instability of non-financial companies in Pakistan, but the analysis was limited to only two sectors i.e. sugar and textile. As per available literature, no study is found which addressed the need for financial distress prediction model for enormous sectors in Pakistan and if some studies tried to address, they were lacking to address the core contribution of monster sectors independently in the Pakistani economy or cater only a few other sectors using other prediction models.

Moreover, the study comprises various sections. The subsequent section critically reviews the previous literature covering aspects of financial distress models used in past. 3rd section illustrates the methodology. 4th section discusses the results and findings and 5th section elaborates on the detailed discussion and finally 6th section concludes the whole study.

REVIEW OF LITERATURE

The phenomenon of bankruptcy is increasingly likely to happen in modern society, influenced by factors that are within and outside the company [12]. The market is extremely competitive, and it leads the business process by eliminating them unfit. Waqas and Md-Rus [13] conducted a study for the identification of predictors of financial distress in Pakistan. The sample data were obtained for the years 2007 to 2016 with 290 non-financial companies which were listed on the Karachi Stock Exchange of Pakistan. The study used an idiosyncratic sigma of previous returns as a market variable along with the use of financial ratios. However, the results of logistic regression revealed that market variables are not necessary to be significant in the prediction of financial distress in developing countries. On the other hand, financial ratios of profitability, liquidity, asset efficiency, leverage and cashflow indicators were reported as significant predictors of financial distress in Pakistan.

Alifiah and Tahir [14] developed financial distress prediction model in Malaysia. The study used manufacturing and non-manufacturing companies listed on Bursa Malaysia from January 2001 to December 2005. The macroeconomic variable money supply (M2) was also used as an independent variable with individual financial ratios. Logistic regression was used for the analysis. The study concluded that money supply (M2), total asset turnover ratio, net income to total assets and current ratio were the significant predictors of financial distress the for manufacturing sector. However, money supply (M2), net income to total asset ratio, working capital ratio and debt ratio were obtained as significant predictors for non-manufacturing sectors.

Luqman, Hassan, Tabasum, Khakwani and Irshad [15] conducted a study to analyse what role the voluntary adoption of corporate governance systems plays to alleviate financial distress. The study used the data of 52 companies from the non-financial sector listed on the Karachi Stock Exchange from the year 2006 to 2015. The study aimed to analyse the instruments that help the company to mitigate financial distress using logistic regression. The study concluded that the audit committee, block holder ownership and director ownership all are negatively correlated to the probability of financial distress. Moreover, the causal relationship showed that the companies which adopt corporate governance mechanisms face lower financial distress.

Altman et al. [16] conducted research to find out the usefulness of the Z-Score model to predict financial distress and bankruptcy. The focus of the study was on predicting financial distress among banks that operate internationally. The data was gathered from 31 European and three non-European countries. Most of the companies were from the non-financial sector and were primarily private except for the firms in China and the USA. The study concluded that the Z-score model outperformed the results with a prediction accuracy of 75 percent as compared to other market-based and hazard models.

Rashid and Abbas [9] conducted a study in Pakistan focusing only on the textile and sugar sectors. The authors used 24 financial ratios for 52 non-financial companies for the period of 1996 to 2006 and concluded that the most significant financial ratios to predict bankruptcy in Pakistan are earnings before interest and taxes to current liabilities, cash flow ratio and sales to total assets ratio. The model of the study secured a 76.9 percent of accuracy level for bankruptcy prediction.

Research studies compare the ability of such methods to predict bankruptcy and also give attention to building new and more detailed methods that can predict bankruptcy in a better way. After reviewing the above literature, we derive the following hypotheses.

H_1: *Profitability ratios have a significant negative influence on the financial distress prediction of non-financial listed companies in Pakistan.*

H_2: *Liquidity ratios have a significant negative influence on the financial distress prediction of non-financial listed companies in Pakistan.*

H_3: *Leverage ratios have a significant positive influence on the financial distress prediction of non-financial listed companies in Pakistan.*

H_4: *Asset efficiency ratios have a significant negative influence on the financial distress prediction of non-financial listed companies in Pakistan.*

RESEARCH DESIGN

The previous studies have discussed different approaches to measuring corporate insolvency. Enormous researchers have identified more than twenty-five methods (with little variations), widely used. Univariate and multivariate analysis is adopted in the 1960s and 1970s, probit and logit models in the 1980s, models of artificial learning in 1990sand the contingent claim models in the 2000s [17]. The present study has also used logistic regression analysis for obtaining significant financial ratios for non-financial sector companies listed in the PSX.

Selection of financial ratios variables

This study applies extensive ratio analysis of 18 financial ratios as independent variables which are categorized into four indicators of assets efficiency, leverage, profitability and liquidity. These financial ratios are important and selected based on their significance and popularity in the literature to measure financial distress [13, 14]. Each indicator has its group of ratios that will directly assess the significant of the indicator.

Data of the study

The study used the financial data of non-financial companies from three huge sectors namely textile, sugar and cement listed on the Pakistan stock exchange from year 2005 to 2020. Balance sheets of all companies were scanned thoroughly for selecting the companies which fulfilled this criterion of bankruptcy. The final data of 44 companies were selected as bankrupt while the remaining 153 companies were supposed to be non-bankrupt because they showed positive equity. For the selection of non-bankrupt companies' group against the criterion of matched industry and asset size to that of the bankrupt group is used. Meaning that these companies were taken on the basis that the company belonged to the same sector and industry as that of the respective bankrupt company, the company possessed positive equity in all years of the sample period and the company had the same asset size as that of the respective bankrupt company.

Methodology

The logit model is widely used in the literature [18]. Researchers give preference to the logit model because of its unique advantages over the MDA model as it does not assume the normality of predictive variables. Also, it provides a probabilistic output instead of the score which has to be converted to a probabilistic measure that ultimately leads to an additional source of error [19].

Logit model

The Logit model states that for any company, there is a given set of characteristics through which we can measure a definable probability of default. Therefore, the probability of default for a company is based on these conditional sets of characteristics. Statistically, this model can be equated as:

$$P(Y_i = 1) = \frac{1}{1 + \exp(-\alpha - \beta x_i)} \tag{1}$$

where Y_i will be 1 if the company is bankrupt, x_i is vector of the explanatory variable. When the probability of bankruptcy increases the value of $\alpha + \beta x_i$ also increases.

The simplified form of this equation is:

$$P_i = 1/(1 + e^{-Z}) \tag{2}$$

Here,

$$Z = \beta x_i + \mu \tag{3}$$

Equation 1 is showing the cumulative logistic distribution function. To apply the prediction model, we will estimate the weights of the financial ratios with the help of equation 3. Optimal β (weights) can be estimated where the likelihood value is maximized. If the probability of default calculated through the logit model is greater than 0.5 then the company will be considered as financially distressed otherwise it will be considered as a healthy company.

For logit analysis, the econometric model of our study can be written as:

$$P(Y_i = 1) = \alpha + \beta_i NPFA_i + \beta_i SCA_i + \beta_i SFA_i + \\ + \beta_i STA_i + \beta_i TLTA_i + \beta_i LTDTA_i + \beta_i FASE_i + \\ + \beta_i TDSE_i + \beta_i EBITCL_i + \beta_i NPS_i + \beta_i NPSE_i + \\ + \beta_i EBITTA_i + \beta_i RETA_i + \beta_i QR_i + \beta_i CACL_i + \\ + \beta_i CATA_i + \beta_i CCL_i + \beta_i CLTA_i$$

Sample specification for bankruptand non-bankrupt companies

The sample of the study must have the following criteria. For bankrupt companies, the company must belong to the non-financial sector. It is because the financial sector has a different bankruptcy procedure. The company must have at least five years of financial information. A company is considered bankrupt if it shows a negative book value of equity in any one of the years in the sample period. On the other hand, for non-bankrupt companies, the company must belong to the same industry as the other group of non-financial sectors. The company must have the closest asset size matched-with within the bankrupt group. The data for the non-bankrupt company is taken from the corresponding year in which the company went bankrupt in another group. Finally, the company possesses a positive book value of equity in all years of data in the sample period.

RESULTS AND FINDINGS

All ratios are entered using a stepwise logistic regression approach. Before using financial ratios in logistic regression analyses it was necessary to check the multicollinearity problem and whether it exists in the sample data or not. For this purpose, correlation analysis and collinearity diagnostics are done. The results of the correlation analysis are presented in table 1. Moreover, table 2 shows the values of tolerance and variance inflation factor (VIF) for each financial ratio used in the analysis given below.

According to Hair, Black, Babin and Anderson [20] and Waqas and Md-Rus [13] if the value of VIF is greater than 10, it depicts the existence of multicollinearity problem. Moreover, table 1 shows that all the values of VIF are less than 10 which also strengthens the results of correlation and confirms that there is no multicollinearity problem in the data. After multicollinearity diagnostics, the study used all these financial ratios as independent variables in regression analysis for financial distress prediction for each year prior to bankruptcy (YPB) (table 3).

Table 3 shows the results of logistic regression with the coefficient estimates and their significant p-values for the first YPB. P-values of QR and TDSE at alpha one percent, SCA and LTA at alpha 5 percent and NPSE at alpha 10 percent are statistically significant. The model obtained five statistically significant variables or financial ratios which can be developed as below:

$$\text{Logit Score} = 1/\left\{1 + e^{-[-8.03 + (-0.586 X_1) + (-11.478 X_2) + (-3.168 X_3) + (0.816 X_4) + (0.527 X_5)]}\right\}$$

or

$$= 1/\left\{1 + e^{-[-8.03 + (-0.586\, S/CA) + (-11.478\, QR) + (-3.168\, NP/E) + (0.816\, LTA) + (0.527\, TD/SE)]}\right\}$$

where SCA is the ratio of sales to current assets which measures the company's efficiency; (CA-IN)/CL is the ratio of quick assets to current liabilities which measures the company's liquidity; NPSE is the ratio of net profit to shareholders' equity which measures company's profitability and TDSE is the ratio total debt to shareholder equity which measures company's leverage.

The coefficient interpretation of logit estimation is a little bit different because it is a nonlinear estimation. These can be calculated in a spreadsheet and also these are called marginal effects. Marginal effects are calculated as per the suggestion of Brooks (2008). Brooks suggested that for the correct interpretation of coefficients in the logit model the mean value of each explanatory variable should be calculated. So, the mean values here are $\overline{X}_1$, $\overline{X}_2$, $\overline{X}_3$, $\overline{X}_4$ and $\overline{X}_5$ with values of 2.565, 0.726, –2.726, 14.213 and 22.369 respectively. The logit function is calculated as:

$$\hat{P}_{iYPB1} = 1/\left\{1 + e^{-[-8.03 + (-0.586*2.565) + (-11.478*0.726) + (-3.168*-2.726) + (0.816*14.213) + (0.527*22.369)]}\right\} = \\ = 1/\left(1 + e^{-14.137}\right) = 0.99$$

This shows that with every one-unit increase in the ratio of sales to Current Assets the case's probability to join the bankrupt group will be reduced by $-0.586 \times 0.999 = -0.586$ units. Similarly, one unit increase in quick assets to current liabilities ratio will decrease the probability of financial distress by $-11.478 \times 0.999 = -11.478$ units. The corresponding changes in the probabilities occur for net profit to shareholders equity, natural log of total assets, and total debt to shareholders equity are $-3.168 \times 0.999 = -3.167$ units; $0.816 \times 0.999 = 0.816$ units and $0.527 \times 0.999 = 0.527$ units, respectively. Also, all the coefficients are economically and statistically significant at a 10% level of significance. Furthermore, the same procedure is applied to the results of the second, third, fourth and fifth YPB (table 4).

Table 4 represents the percentages of models' accuracy concerning each year prior to bankruptcy. It is shown that precision percentages of the model are higher in the first YPB with 90.11 percent and 87.72 percent in the second YPB and 85.32, 82.36 and 79.57 in the third, fourth and fifth YPB respectively.

DISCUSSION

The study intents to identify the predictors of financial distress for the non-financial companies listed on the

Table 1

CORRELATION MATRIX

	EBITCL	NPS	NPSE	EBITTA	RETA	QR	CATA	CCL	CLTA	CACL	TLTA	LTDTA	FASE	TDSE	NPFA	SCA	SFA	STA
EBITCL	1																	
NPS	0.579^{**}	1																
NPSE	–0.003	0.003	1															
EBITTA	0.032	0.078^{*}	0.003	1														
RETA	0.001	0.002	0.019	0.444^{**}	1													
QR	0.006	0.006	0.003	0.087^{**}	0.165^{**}	1												
CATA	–0.005	0.009	–0.012	0.143^{**}	0.055	0.044	1											
CCL	0.006	0.001	0.017	0.423^{**}	0.592^{**}	0.308^{**}	0.137^{**}	1										
CLTA	-0.146^{**}	-0.083^{**}	–0.012	–0.006	–0.022	-0.108^{**}	0.237^{**}	-0.098^{**}	1									
CACL	–0.004	–0.003	0.001	–0.002	0.001	0.004	0.029	0.004	0.025	1								
TLTA	-0.064^{*}	–0.032	0.007	–0.051	–0.016	-0.079^{*}	0.081^{**}	-0.072^{*}	0.648^{**}	0.011	1							
LTDTA	0.003	0.002	–0.001	–0.002	0.000	–0.002	0.012	–0.002	–0.004	0.001	–0.001	1						
FASE	–0.002	–0.002	0.011	0.006	0.001	0.001	0.037	0.002	–0.020	–0.003	–0.012	–0.005	1					
TDSE	0.015	0.010	0.004	–0.001	–0.006	–0.007	0.037	–0.005	0.006	0.013	0.010	0.024	–0.002	1				
NPFA	0.002	0.002	–0.016	0.697^{**}	0.001	–0.003	0.069^{*}	0.000	0.180^{**}	0.001	0.081^{**}	–0.001	0.000	–0.005	1			
SCA	0.048	0.052	–0.018	0.007	–0.015	-0.062^{*}	–0.041	–0.030	-0.123^{**}	–0.034	-0.081^{**}	–0.007	0.031	0.016	–0.026	1		
SFA	0.010	0.008	–0.001	–0.011	–0.010	0.002	0.097^{**}	–0.001	–0.010	0.004	–0.013	0.000	0.000	0.021	0.001	0.034	1	
STA	0.048	0.044	–0.010	0.052	–0.013	–0.040	0.322^{**}	–0.014	-0.064^{*}	–0.001	-0.087^{**}	–0.002	0.019	0.024	–0.019	0.701^{**}	0.091^{**}	1

Note: Dependent variable: Financial Distress Proxy (Binary); Independent variables: EBITCL is earnings before interest and taxes to current liabilities, NPS is net profit to sales, NPSE is net profit to shareholders equity, EBITTA is earnings before interest and taxes to total assets, RETA is retained earnings to total assets, QR is quick ratio, CATA is current assets to total assets, CCL is cash to current liabilities, CLTA is current liabilities to total assets, CACL is current assets to current liabilities, TLTA is total liabilities to total assets, LTDTA is the long-term debt to total assets, FASE is fixed assets to shareholders equity, TDSE is total debt to shareholders equity, NPFA is net profit to fixed assets, SCA is sales to current assets, SFA is sales to fixed assets, STA is sales to total assets.

Table 2

MULTICOLLINEARITY ANALYSIS		
Financial ratios	**Collinearity statistics**	
	Tolerance	**VIF**
EBITCL	0.613	2.560
NPS	0.620	1.516
NPSE	0.913	4.033
EBITTA	0.216	4.060
RETA	0.558	1.930
QR	0.292	1.187
CATA	0.570	1.119
CCL	0.429	3.047
CLTA	0.180	2.082
CACL	0.488	1.127
TLTA	0.746	3.832
LTDTA	0.756	1.646
FASE	0.189	1.111
TDSE	0.921	1.086
NPFA	0.216	3.186
SCA	0.162	2.764
SFA	0.732	2.018
STA	0.370	2.019

Table 3

COEFFICIENT ESTIMATES FOR INDIVIDUAL FINANCIAL RATIOS MODELS				
Years prior to bankruptcy (YPB)	**Variables**	**Coefficient**	**ME**	**Prob.**
First YPB	C	–8.03	-	0.085
	SCA	–0.586	–0.586	0.040
	QR	–11.478	–11.478	0.002
	NPSE	–3.168	–3.168	0.080
	TDSE	0.527	0.527	0.003
Second YPB	C	–6.658	-	0.019
	FASE	0.273	0.236	0.026
	EBITCL	–4.485	–3.862	0.019
	QR	–2.073	–1.786	0.030
Third YPB	C	–2.496	-	0.265
	TDSE	0.625	0.323	0.000
	CATA	–4.465	–2.302	0.006
	SCA	–0.479	–0.247	0.038
Fourth YPB	C	–4.998	-	0.082
	LTDTA	5.319	2.293	0.090
	RETA	–1.207	–0.52	0.033
	CACL	–0.897	–0.387	0.048
Fifth YPB	C	–1.584	-	0.155
	EBITTA	–10.661	–5.245	0.031
	TLTA	2.931	1.442	0.087

Note: SCA is sales to current assets, QR is quick ratio, NPSE is net profit to shareholders equity, TDSE is total debt to shareholders equity, FASE is fixed assets to shareholders equity, EBITCL is earnings before interest and taxes to current liabilities, CATA is current assets to total assets, LTDTA is the long-term debt to total assets, RETA is retained earnings to total assets, CACL is current assets to current liabilities, EBITTA is earnings before interest and taxes to total assets, TLTA is total liabilities to total assets.

Table 4

MODEL ACCURACY	
Years prior to bankruptcy (YPB)	**Percentages of model accuracy (%)**
First YPB	90.11
Second YPB	87.72
Third YPB	85.32
Fourth YPB	82.36
Fifth YPB	79.57

PSX. The data analysis is done using logistic regression with 18 individual financial ratios. However, results of individual financial ratios show that EBITCL, NPSE, EBITTA and RETA are significant profitability ratios. The profitability ratios possess negative sign of coefficients which means that the higher the value of profitability ratios lesser will be the probability of financial distress. The results of profitability ratios align with previous studies like Cederburg and O'Doherty [21], Hu and Sathye [22], Altman et al. [16], Rashid and Abbas [9], Campbell et al. [23], Choe and Her [24] and Hotchkiss, Smith, and Stromberg [25].

In addition, liquidity ratios analysis is also worth important for a company. Basically, it is the ability of a company to fulfil its short-term liabilities. The ratios QR, CACL and CATA are significant liquidity ratios with the negative sign of coefficient values obtained for this study. The negative sign of coefficient estimates shows that an increase in a company's liquidity decreases the probability of financial distress. Past studies which articulated the same results for liquidity ratios are Chiaramonte and Casu [26], Ijaz et al. [11], Rashid and Abbas [9], Yap et al. [27], Campbell et al [23], Allayannis et al. [28], Ugurlu and Aksoy [29].

The rational introduction of debt in a company's capital structure is very important. The logistic regression results for leverage ratios show LTDTA, FASE, TDSE and TLTA are statistically significant. Leverage ratios exhibit positive sign of coefficient estimates which indicates the inverse relationship between leverage ratios and the probability of financial distress. The lower the unnecessary debt in capital structure, the lesser will be the probability of financial distress. Past studies like Agarwal and Bauer [30], Tinoco and Wilson [31], Abdullah et al. [32], Jones and Hensher [33], and Eljelly and Mansour [34].

The proper and efficient utilization of company assets is an important aspect of a running business. The findings of the study suggest only one asset efficiency ratio which is SCA. The ratio is statistically significant with a negative sign to predict financial distress. The inverse relationship shows that efficient utilization of assets reduces the probability of financial distress. Furthermore, the asset efficiency ratios' results are similar to the previous study like Ugurlu and Aksoy [29] and Eljelly and Mansour [34]. Spulbar et al. [35] have conducted a research study on the effects of tax revenue on the evolution of Gross domestic product (GDP) in the case of European Union member states. On the other hand, Sumera et al. [36] examined the implications of education on the dynamics of economic growth. Spulbar et al. [37] investigated the impact of digitalization on poverty alleviation and economic growth due to the COVID-19 pandemic.

CONCLUSION

The empirical findings of the study fulfil all the research objectives and answer all the research questions of the present study. The study reveals that significant profitability ratios are earnings before interest and taxes to current liabilities (EBITCL), net profit to shareholder's equity (NPSE), earnings before interest and taxes to total assets (EBITTA) and retained earnings to total assets (RETA). Additionally, the liquidity ratios which show significant results are quick ratio (QR), current assets to current liabilities (CACL) and current assets to total assets (CATA). The significant leverage ratios for financial distress prediction are a long-term debt to total assets (LTDTA), fixed assets to shareholders equity (FASE), total debt to shareholders equity (TDSE) and total liabilities to total assets (TLTA). Furthermore, the findings reveal that sales to current assets (SCA) are the only significant individual financial ratio as an asset efficiency ratio. Lastly, the highest precision rate of model accuracy produced in the study is 90.11 percent for the first YPB.

REFERENCES

[1] Garcia, C.J., Herrero, B., *Female directors, capital structure, and financial distress,* In: Journal of Business Research, 2021, 136, 592–601

[2] Macerinskiene, I., Mendelsonas, T., *Macroeconomic determinants of corporate insolvency*, In: KSI Transactions on Knowledge Society, 2013, 6, 3, 35–40

[3] Reinhart, C.M., *From health crisis to financial distress*, In: IMF Economic Review, 2022, 70, 1, 4–31

[4] Jardim, P.C., Pereira, T.E., *Corporate Bankruptcy of Portuguese Firms*, In: Zagreb International Review of Economics and Business, 2013, 16, 2, 39–56

[5] Altman, E.I., *An emerging market credit scoring system for corporate bonds,* In: Emerging Markets Review, 2005, 6, 4, 311–323

[6] Bharath, T., Shumway, T., *Forecasting Default with the Kmv-Merton Model*, AFA 2006 Boston Meetings Paper, 2004, Available at: https://ssrn.com/abstract=637342 [Accessed on September 2022]

[7] Sneha, P., *More delisting than new listings on bourses,* Business Standard, 2015, Available at: http://www.business-standard.com/article/markets/more-delisting-than-new-listings-on-bourses-115012000905_1.html [Accessed on September 2022]

[8] Liahmad, K.R., Utami, Y.P., Sitompul, S., *Financial Factors and Non-Financial to Financial Distress Insurance Companies That Listed in Indonesia Stock Exchange*, In: Humanities and Social Sciences, 2021, 4, 1, 1305–1312

[9] Rashid, A., Abbas, Q., *Predicting Bankruptcy in Pakistan*, In: Theoretical and Applied Economics, 2011, 18, 9, 103–128

[10] Khurshid, M.R., *Determinants of Financial Distress Evidence from KSE 100 Index*, In: Research Journal of The Institute of Business Administration Karachi-Pakistan, 2013, 8, 1, 7

[11] Ijaz, M.S., Hunjra, A.I., Hameed, Z., Maqbool, A., *Assessing the financial failure using z-score and current ratio: A case of sugar sector listed companies of Karachi stock exchange*, In: World Applied Sciences Journal, 2013, 23, 6, 863–870

[12] Alaminos, D., del Castillo, A., Fernandez, M.A., *A global model for bankruptcy prediction*, In: PloS one, 2016, 11, 11, 1–18

[13] Waqas, H., Md-Rus, R., *Predicting financial distress: Importance of accounting and firm-specific market variables for Pakistan's listed firms*, In: Cogent Economics & Finance, 2018, 6, 1, 1545739

[14] Alifiah, M.N., Tahir, M., *Predicting financial distress companies in the manufacturing and non-manufacturing sectors in Malaysia using macroeconomic variables,* In: Management Science Letters, 2018, 8, 6, 593–604

[15] Luqman, R., Hassan, U.M., Tabasum, S., Khakwani, M.S., Irshad, S., *Probability of financial distress and proposed adoption of corporate governance structures: Evidence from Pakistan,* In: Cogent Business & Management, 2018, 5, 1, 1–14

[16] Altman, E.I., Iwanicz-Drozdowska, M., Laitinen, E.K., Suvas, A., *Financial distress prediction in an international context: A review and empirical analysis of Altman's Z-score model*, In: Journal of International Financial Management & Accounting, 2017, 28, 2, 131–171

[17] Jackson, R.H., Wood, A., *The performance of insolvency prediction and credit risk models in the UK: A comparative study,* In: The British Accounting Review, 2013, 45, 3, 183–202

[18] Aziz, A.M., Dar, H.A., *Predicting corporate bankruptcy: where we stand?*, In: Corporate Governance: The International Journal of Business in Society, 2006, 6, 1, 18–33

[19] Ohlson, J.A., *Financial ratios and the probabilistic prediction of bankruptcy*, In: Journal of Accounting Research, 1980, 18, 1, 109–131

[20] Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., *Multivariate data analysis,* (7th ed). Prentice Hall, 2010

[21] Cederburg, S., O'Doherty, M.S., *Asset-pricing anomalies at the firm level*, In: Journal of Econometrics, 2015, 186, 1, 113–128

[22] Hu, H., Sathye, M., *Predicting financial distress in the Hong Kong growth enterprises market from the perspective of financial sustainability*, In: Sustainability, 2015, 7, 2, 1186–1200

[23] Campbell, J.Y., Hilscher, J., Szilagyi, J., *In search of distress risk*, In: The Journal of Finance, 2008, 63, 6, 2899–2939

[24] Choe, C., Her, Y.W., *A Comparative Study of Australian and Korean Accounting Data in Business Failure Prediction Models*, In: Journal of Accounting and Finance, 2002, 1, 41–68

[25] Hotchkiss, E.S., Smith, D.C., Stromberg, P., *Private equity and the resolution of financial distress*, In: The Review of Corporate Finance Studies, 2021, 10, 4, 694–747

[26] Chiaramonte, L., Casu, B., *Capital and liquidity ratios and financial distress. Evidence from the European banking industry*, In: The British Accounting Review, 2017, 49, 2, 138–161

[27] Yap, B.C.F., Yong, D.G.F., Poon, W.C., *How well do financial ratios and multiple discriminant analysis predict company failure in Malaysia,* In: International Research Journal of Finance and Economics, 2010, 54, 166–175

[28] Allayannis, G., Brown, G.W., Klapper, L.F., *Capital structure and financial risk: Evidence from foreign debt use in East Asia,* In: The Journal of Finance, 2003, 58, 6, 2667–2710

[29] Ugurlu, M., Aksoy, H., *Prediction of corporate financial distress in an emerging market: the case of Turkey,* In: Cross Cultural Management: An International Journal, 2006, 13, 4, 277–295

[30] Agarwal, V., Bauer, J., *Distress Risk and Stock Returns: The neglected Profitability Effect,* In: FMA Annual Meeting, Nashville, TN, 2014, 15–18

[31] Tinoco, M.H., Wilson, N., *Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables,* In: International Review of Financial Analysis, 2013, 30, 394–419

[32] Abdullah, N.A.H., Halim, A., Ahmad, H., Rus, R.M., *Predicting corporate failure of Malaysia's listed companies: Comparing multiple discriminant analysis, logistic regression and the hazard model*, In: International Research Journal of Finance and Economics, 2008, 15, 201–217

[33] Jones, S., Hensher, D.A., *Predicting firm financial distress: A mixed logit model*, In: The Accounting Review, 2004, 79, 4, 1011–1038

[34] Eljelly, A.M., Mansour, I.H.F., *Predicting private companies' failure in the Sudan*, In: Journal of African Business, 2001, 2, 2, 23–43

[35] Spulbar, C., Ehsanifar, M., Birau, R., Babaie, A., Doagă, D.I., *Advanced empirical research based on structural equation modeling (SEM) regarding the impact of tax revenue on GDP dynamics at EU-28 level*, In: Scientific Annals of Economics and Business, 2021, 68, 3, 285–307, https://doi.org/10.47743/saeb-2021-0017

[36] Sumera, A., Zahid Naeem, M., Spulbar, C., Birau, R., Ninulescu, P.V., *Impact of Education and Income Inequality on Per Capita Income Amid COVID-19 pandemic*, In: Revista de Științe Politice. Revue des Sciences Politiques, 2022, 76, 18–33

[37] Spulbar, C., Anghel, L.C., Birau, R., Ermiș, S.I., Treapăt, L.-M., Mitroi, A.T., *Digitalization as a Factor in Reducing Poverty and Its Implications in the Context of the COVID-19 Pandemic*, In: Sustainability, 2022, 14, 17, 10667, https://doi.org/10.3390/su 141710667

Authors:

EHSANUL HASSAN[1], MUHAMMAD AWAIS-E-YAZDAN[2], RAMONA BIRAU[3], LUCIA PALIU-POPA[3]

[1]National University of Sciences and Technology (NUST), Sector H-12, Islamabad, Pakistan
e-mail: ehsanul.hassan@seecs.edu.pk

[2]Faculty of Business and Management Sciences, The Superior University Lahore, Lahore, Pakistan
e-mail: awais.yazdan@gmail.com

[3]Faculty of Economic Science, University Constantin Brancusi, Tg-Jiu, Romania
e-mail: univers_cont@yahoo.com

Corresponding author:

RAMONA BIRAU
e-mail: ramona.f.birau@gmail.com