Peer-reviewed and Open access journal
ISSN: 1804-5006 | www.academicpublishingplatforms.com
The primary version of the journal is the on-line version

BEH - Business and Economic Horizons
Volume 14 | Issue 2 | 2018 |pp.389-401
DOI: http://dx.doi.org/10.15208/beh.2018.28

Predicting financial distress: Applicability of O-score and logit model for Pakistani firms

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Abstract: Predicting financial distress have significant importance in corporate finance as it serves as an effective early warning system for the related stakeholders. The study applies the most admired financial distress prediction O-score model and compares its predictive accuracy with estimated logit model. The study estimates logit model by including the profitability ratios, liquidity ratios, leverage ratios, and cash flow ratios. This study filled the gap by using the cash flow ratios to predict financial distress for Pakistani listed firms. The sample for the estimation model consists of 290 firms with 45 distressed and 245 healthy firms for the period 2006-2016 and covers all sectors of Pakistan Stock Exchange. The study provides important insights on the role of different financial ratio in predicting financial distress and shows that estimated logit model produces higher accuracy rate in predicting financial distress.

JEL Classifications: G01

Keywords: Financial distress, bankruptcy, logit regression, O-score model, financial distress, emerging market, Pakistan

Citation: Waqas, H., & Md-Rus, R. (2018). Predicting financial distress: Applicability of O-score and logit model for Pakistani firms. *Business and Economic Horizons, 14*(2), 389-401. http://dx.doi.org/10.15208/beh.2018.28

1. Introduction

The capital structure of firm contains some portion of debt which drives the risk of default and is reflected in its cash flow and profitability patterns. This risk can be dangerous if the debt of firm reaches beyond some certain limit. Furthermore, the consequences of financial distress are hazardous to firms; many firms are forced to windup their operations and this condition is worst in emerging economies. Asian markets are more fragile in nature and more prone to financial difficulties; e.g. in Pakistan 105 out of 570 listed firms got delisted during 2012-2016 due to default. Owing to this high rate of corporate default, the cumulative non-performing loans of the country reached to 9.04 billion dollars in 2017 (State Bank of Pakistan, 2017), which shows a worst situation of financial market of Pakistan. In such circumstances, banks and other financial institutions are more concerned about the financial soundness of the borowers. Need for measuring the financial health of the borrower to quantify the amount of default risk in a loan calls for using of default prediction models. These defaults models are termed as bankruptcy model, or financial distress models in literature and used alternatively (Dichev, 1998).

Different models were developed in the literature including univariate analysis (Beaver, 1966), multiple discriminated analysis (MDA) model (Altman, 1968), logit model (Ohlson, 1980), probit model (Zmijewski, 1984), hazard model (Shumway, 2001), and neural network model (Charitou, Neophytou, & Charalambous, 2004), etc. Despite there exist many models developed in literature yet, Z-score and O-score models are the most widely used models in the financial literature (Aziz & Dar, 2006). Furthermore, Agarwal & Taffler (2008), Altman (1968), Beaver (1966), Dichev (1998), Ohlson (1980), and Shumway (2001) develop the model by using data from developed countries like Australia, UK and US.

Developed countries have long equity market history with established financial policies and accounting standards, while the emerging economies face absence of standardized accounting practices, and systematic financial policies that may cause the high rate of bankruptcy. Likewise, Pakistan stock exchange is recognize as an emerging economic market by Bloomberg (Kim & Mangi, 2016), yet firms listed at Pakistan stock exchange face high rate of bankruptcy due to lack of standardized bankruptcy model developed by using the data of firms listed at Pakistan stock exchange. Although, few studies are conducted in Pakistan to predict the financial distress nonetheless, these studies are limited to small sample size, consists on specific sectors or other, such as Ijaz et al., (2013) taken only sugar sector, Malik (2013) focused on sugar and cement sectors, while other contributing sectors are ignored. Furthermore, despite the empirical importance of cash flow ratios, only few of studies has used cash flow ratios to predict the financial distress. Thus the objective this study is to fill the gap in literature by using the cash flow ratios along with other profitability, leverage, and liquidity ratios by using the large sample size of 290 firms listed on Pakistan stock exchange during the 2006 to 2016. The results are analyzed by using the large sample size that contain data from all the sectors of Pakistan stock exchange.

2. Literature review

Financial distress, bankruptcy, and defaults are inter-related terms which are used in literature as bankruptcy is regarded as the outcome of financial distress (Coats & Franklin, 1993). In earlier studies, the key financial ratios including the profitability ratios, leverage ratios, solvency ratios and cash flow ratios are used to predict the financial distress and these ratios frequently reported by firms in auditor's report and in internal financial reports. Financial ratios are considered as the primary source information to evaluate the firm performance as going concern. In early 1940's credit rating agencies use financial ratios to access the financial health of the firms while extending loans to clients. To provide the true picture and avoid the tempering of financial ratios, securities exchange commissions or other government regulating institutions appoint independent auditors to monitor the quality of these statements. Deakin (1972) highlights the importance of financial ratios to predict the financial distress. Literature provides the significance of profitability ratios, debt ratios, liquidity ratios and cash flow ratios in predicting the financial distress. In literature, Altman (1968), Altman, Iwanicz-Drozdowska, Laitinen, & Suvas (2014), Beaver (1966), Hill, Perry, & Andes (1996), Ohlson (1980), Shumway (2001), Xu, Xiao, Dang, Yang, & Yang (2014) document the importance of profitability ratios in predicting the financial distress. Liquidity ratios are the other set of accounting ratios which are vital in predicting the financial health of the firms. liquidity refers to firms ability to convert the assets of firms into cash, quickly and economically to pay off its financial obligations (Brealey, Myers, & Allen, 2011). Past studies of Campbell, Hilscher, & Szilagyi (2008), Chiaramonte & Casu (2016). Manab, Theng, & Rus, (2015), Ijaz et al. (2013), Zmijewski (1984) articulate the significant importance of liquidity ratios in predicting financial distress.

Leverage ratio is another important factor in studies of financial distress. Firms must trade-off between benefits and cost of capital by deciding the optimal level of leverage ratio in capital structure. The firm can increase the debt to minimize its cost of capital while the borrowing beyond some points increases the risk of bankruptcy as firms with high debt ratios are more prone to financial distress. Altman (1968), Bandyopadhyay (2013), Shumway (2001), and Xu et al. (2014) find the significance of leverage ratios in predicting financial distress. Another important set of financial ratios in predicting financial distress is cash flow ratios. Cash flow theory suggests, a firm will be healthier if it generates enough cash flow from its operations. Firms face financial distress when they fail to generate sufficient cash inflows (Wruck, 1990), whereas the firms with sufficient cash flows are in a position to pay off its financial obligations when it comes due. Arlove, Rankov, & Kotlica (2010), Beaver (1966), Biddle, Ma, & Song (2016). Gentry, Newbold, & Whitford (2016), Jones & Peat (2014), and Ohlson (1980) have stressed the importance of cash flow ratios in predicting the financial distress.

Importance of financial ratios is significant in literature and different researchers have analyzed these financial ratios by using different statistical models. A ground-breaking study of Beaver (1966) uses the univariate analysis to compare the ratios of failed and non-failed firms and present the significant difference between ratio of failed and non-failed firms. Furthermore, it is argued that the cash-flow to total debt is the strongest predictor of financial distress, followed by total debt to total asset ratio. Altman (1968) use the multiple discriminant analysis (MDA) technique to discriminate the healthy and defaulted firms. MDA is a statistical technique used to classify the observation into prior defined groups based on dependent's distinct characteristics. After establishing groups, MDA drives a linear relationship between the characteristics that discriminate the between the groups. This MDA model is regarded as the best techniques used to discriminate the one group with another (failed and healthy). Altman (1968) conclude that discriminant ratio analysis is an accurate measure of to differentiate the bankrupt and healthy firms with an accuracy rate of 94 percent.

Altman's Z-score was criticized based on its assumptions of normal distribution of explaining variables. Furthermore, Z-score provides a score on the basis of this score firms are ranked based on their financial health instead of the precise result on distressed or non-distressed. To avoid the problems associated with Z-score, Ohlson (1980) come with a new model based on logit regression that have binary outcomes. Logit regression provides a probabilistic model that establishes a non-linear maximum likelihood function and come up with a probability of firm's failure. By using the sample of 105 failed and 2058 healthy firms, Ohlson conclude that logit model is more useful in predicting the probability of financial distress for the firm. Another probabilistic bankruptcy model developed by Zmijewski (1984) that use the probit regression. Zmijewski (1984) use the probit regression on financial ratios e.g. liquidity, performance, and leverage. These two probabilistic models (logit and probit) are widely used in literature e.g Bandyopadhyay (2006), Bauer & Agarwal (2014), Duda & Schmidt (2010), and Shumway (2001), yet literature does not indicate the predictive power of these models affected by using the new data set over the original time and dataset used to develop these models. In addition, many other bankruptcy models are developed in literature including recursive partitioning (decision tree) analysis (RPA), neural network (NN), linear probability model (LPM), nevertheless Logit model remained the most used model for bankruptcy prediction after 2000 (Aziz & Dar, 2006).

3. Methodology

To calculate the financial ratios, data was collected from the annual reports published by State Bank of Pakistan (SBP) and Securities Exchange Commission of Pakistan (SECP). SECP regulates and monitors the financial and governance matters for the listed companies in Pakistan. Sample period for the study is from 2006 to 2016 for the 290 manufacturing firms. The study has excluded those firms having data for less than 5 years. Firms are considered as distressed if the firm is quoted below the 50 percent of its face value in the market or any firm with negative book value of equity.

The analysis of this study is carried out in three parts. In the first part, we estimate the logit model for Pakistani listed firms by using the financial ratios. These financial ratios are selected on the basis of their significance in prior literature. Data from 2006 to 2013 is used to estimate the model. In the second part, we use the Ohlson (1980) coefficient scores on Pakistani data to check the accuracy rate. The classification accuracy of O-score and estimated logit model is then compared. In the final part of the study, we run a regression on the hold-out sample using the data set from year 2014 to 2016.

Statistical equation for logit model is as follows:

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

In this equation, Y_i is to be equal to 1 for the bankrupt firm. x_{i-1} presents the value of vector of independent variable, and the higher the value of $\alpha+\beta x_{i-1}$ is the higher the probability of bankruptcy.

Ohlson (1980) used Size as the log of total assets to GNP price level index, total liabilities to total assets (TLTA), working capital to total assets (WCTA), current liabilities to current assets (CLCA), 1 if the value of liabilities exceeds to total assets, zero otherwise (OENEG), net income to total assets (NITA), funds provided by operations to total liabilities (FUTL), 1 if the net income is negative for last two year, otherwise zero (INTWO), and $(NI_t - NI_{t-1})/\langle NI_t| - |NI_{t-1}\rangle$ when NI is the net income for the most recent time period.

To estimate the distress model for Pakistan, this study uses the eight financial ratios that are significant in prior literature on financial distress. These ratios are net income to total assets (NITA), retained earnings to total assets (RETA), EBIT to total assets (ETA), current assets to current liabilities (CATL), working capital to total assets (WCTA), total liabilities to total asset (TLTA), cash flow from operations to total liabilities (CFOTL), and cash flow from operations to sales (CFOS).

Following equation is estimated to run the logit regression:

$$P(Y_i = 1) = \alpha + \beta_i NITA_i + \beta_i \text{RETA}_i + \beta_i \text{ETA}_i + \beta_i \text{CATL}_i + \beta_i \text{WCTA}_i + \beta_i \text{TLTA}_i + \beta_i \text{CFOTL}_i + \beta_i \text{CFOS}_i \tag{2}$$

Where $P(Y_i = 1)$ is probability of distress, NITA is net income to total assets, RETA is retained earnings to total assets, ETA is EBIT to total assets, CATL is current assets to current liabilities, WCTA is working capital to total assets, TLTA is total liabilities to total asset, CFOTL is cash flow from operations to total liabilities, and CFOS is cash flow from operations to sales.

We also analyses Ohlson (1980) coefficient score using Pakistani data. We uses the same variables as in Ohlson (1980) which includes size of the firms measure as the log of total assets to GNP price level index, total liabilities to total assets (TLTA), working capital to total assets (WCTA), current liabilities to current assets (CLCA), 1 if the value of liabilities exceeds to total assets, zero otherwise (OENEG), net income to total assets (NITA), funds provided by operations to total liabilities (FUTL), 1 if the net income is negative for last two year, otherwise zero (INTWO), and $(NI_t - NI_{t-1})/\langle NI_t| - |NI_{t-1}\rangle$ when NI is the net income for the most recent time period. The O-score equation is provided as follows.

$$O - Score = -1.32 - 0.407 \log\left(\frac{TA}{GNP}\right) + 6.03\left(\frac{TL}{TA}\right) - 1.43\left(\frac{WC}{TA}\right) + 0.0757\left(\frac{CL}{CA}\right) - 1.72 OENEG - 2.37\left(\frac{NI}{TA}\right) - 1.83\left(\frac{TUTL}{TL}\right) + 0.285 INTWO - 0.521\ \frac{NI_T - NI_{T-1}}{|NI_T| + NI_{T-1}|} \tag{3}$$

4. Results and analysis

The descriptive statistics are provided in Table 1 and the mean differences between distressed and healthy firms are shown in Table 2.

Descriptive statistics reveals that the profitability ratios (NITA, RETA) for the healthy firms are higher than the distressed firms. Furthermore, the net income to total assets (NITA) is higher for the healthy firms where it shows for each unit of total asset, the healthy firms are producing 0.57 unit of income. Retained earnings to total asset is positive for the healthy firms while this ratio shows negative sign for the distressed firms, implying that retained earnings is kept idle for the distressed firms. Earnings before interest and tax to total asset ratio (ETA) is positive for both group of data set, but the ETA ratio is higher for the healthy firms. All the profitability ratios indicate that the assets of the healthy firms are being used more effectively than the distressed firms.

Current asset to total liabilities ratio is used to measure the liquidity of the firm. Descriptive statistics demonstrate that the healthy firm possesses 3.265 units of current asset against each unit of liability. This implies that firm possesses more current assets than its liabilities. Although this ratio is 1.5 for the distressed firms, yet distressed firms also possess the ability to dispose-off its liabilities with current assets. Another liquidity ratio used in this analysis is working capital to total assets ratio that indicates whether a firm has enough current assets to cover its short-term debt. Results show a positive WCTA ratio of 0.08 for the healthy firms while this ratio is negative for the distressed firms. It indicates that distressed firms are not able to settle its short-term obligations with its working capital.

TABLE 1. DESCRIPTIVE STATISTICS FOR HEALTHY AND DISTRESSED FIRMS

VARIABLES	HEALTHY FIRMS		DISTRESSED FIRMS	
	MEAN	STD. DEVIATION	MEAN	STD. DEVIATION
NITA	0.057	0.121	0.028	0.218
RETA	0.247	0.274	-0.690	1.453
ETA	0.102	0.109	0.061	0.217
CATL	3.265	28.388	1.561	8.527
WCTA	0.080	0.226	-0.545	1.044
TLTA	0.561	0.205	1.268	0.996
CFOTL	0.288	0.800	0.217	2.961
CFOS	-0.084	8.245	-427.998	7325.262

Leverage ratio is used to analyze the amount of debt included in the capital structure of the firms. Higher debt ratio is often associated with high probability of financial distress. Total liabilities to total asset ratio is high for the distressed firms. It illustrates that distressed firms contains higher debt in their capital structure. This study also has used two cash flow ratios including cash flow from operations to sales and cash flow from operation to total liabilities. Cash flow to total liabilities ratio (CFOTL) is an estimate of how much time a firm needed to repay its total debt if all the cash flow is devoted to repayment of debt. CFOTL for the healthy and distressed firms are almost the same. Cash flow to sales ratio measures firm's ability to convert its sales into cash. This ratio is negative for both sample sets, yet this negative value is more for the distressed firms.

TABLE 2. MEAN DIFFERENCES BETWEEN DISTRESSED AND HEALTHY FIRMS

VARIABLES	MEANS		MEAN DIFFERENCES	
	HEALTHY FIRMS	DISTRESSED FIRMS	T-STATISTICS	SIG
NITA	0.057	0.028	4.013	0.000*
RETA	0.247	-0.691	29.447	0.000*
ETA	0.102	0.061	6.067	0.000*
CATL	3.265	1.561	1.260	0.208
WCTA	0.080	-0.545	26.653	0.000*
TLTA	0.561	1.268	31.642	0.000**
CFOTL	0.287	0.216	1.013	0.311
CFOS	-0.083	-427.998	2.921	0.004*

The univariate analysis identifies ratios that are significant and has highest ability to differentiate between healthy and distressed firms for the sample data set. Table 2 demonstrates the variables with mean difference. The variables that are significant at the 5 percent level are net income to total assets (NITA), retained earnings to total assets (RETA), EBIT to total assets (ETA), total liabilities to total assets (TLTA), working capital to total assets (WCTA) and cash flow from operation to sale (CFOS), while current asset to total liabilities and cash flows from operations to total liabilities have not shown significant differences in their means.

Table 3 presents the correlation matrix among the independent variables. Pairwise correlation is uniformly low and insignificant except for several ratios: retain earnings to total assets against net income to total assets, EBIT to total assets against net income to total assets, working capital to total assets against net income to total assets, cash flow from operations to total liabilities against net income to total assets, EBIT to total assets against retained earnings to total assets, current assets to total liabilities against retained earnings to total assets, working capital to total assets against retained earnings to total assets, cash flow from operations to total liabilities against retained earnings to total assets, cash flow from operations to sales against retained earnings to total assets, working capital to total assets against EBIT to total assets, cash flow from operations to total liabilities against EBIT to total assets, cash flow from operations to sales against EBIT to total assets, net income total assets against total liabilities to total asset, retained earnings to total assets against total liabilities to total asset, current assets to current liabilities against total liabilities to total asset, working capital to total assets against total liabilities to total asset, cash flow from operations to total liabilities against total liabilities to total asset, and working capital to total assets against cash flow from operations to total liabilities.

TABLES 3. CORRELATIONS MATRIX

VARIABLES	NITA	RETA	ETA	CATL	WCTA	TLTA	CFOTL	CFOS
NITA	1							
RETA	.101**	1						
ETA	.826**	.126**	1					
CATL	.011	.042*	.007	1				
WCTA	.095**	.870**	.128**	.076**	1			
TLTA	-.075**	-.888**	-.092**	-.06**	-.91**	1		
CFOTL	.362**	.055**	.366**	-.156**	.137**	-.128**	1	
CFOS	.022	.046*	.028	.002	.017	-.034	.008	1

Note: ** - Correlation is significant at the 0.01 level (2-tailed). * - Correlation is significant at the 0.05 level (2-tailed).

Few of the variables are highly correlated and the existence of coefficient correlation probably indicates the existence of multicollinearity problem between the variables. It must be noted here that the identification of ratios is not based on any bankruptcy theory, instead it is based on their popularity in literature to predict financial distress. Thus, the variables that are highly correlated with each other could be dropped (Abdullah, Ahmad & Md-Rus, 2008).

The study has applied the variance inflation factor (VIF) to re-examine the seriousness of multicollinearity problem in the data set. VIF is the ratio of variables actual variance to the perfect variance of zero collinearity. Table 4 shows that VIF for all considered variables is less than 10 that is tolerable variance inflation factor (Gujarati & Porter, 2009) and indicates that there is no serious threat of multicollinearity to our data set.

TABLE 4. VARIANCE INFLATION FACTOR

VARIABLES	VIF
Net income to total assets	2.581
Retained earnings to total assets	4.295
EBIT to total assets	3.239
Current assets to total assets	1.010
Working capital total assets	4.365
Total liabilities to total asset	7.120
Cash flow from operations to sales	1.007
Cash flow from operations to total liabilities	2.630

TABLE 5. LOGIT REGRESSION RESULTS

VARIABLES	MEASURE	B	SIG
NITA	Proftiability	9.93	0.001
RETA	Proftiability	-2.303	.000**
ETA	Proftiability	-9.230	.000**
CATL	Liquidity	.227	.001**
WCTA	Liquidity	-2.248	.000**
TLTA	Leverage	8.377	.000**
CFOTL	Cash flow	.776	.003**
CFOS	Cash flow	.046	.025*
Constant	Constant	-7.013	.000**

Note: * - significant at 95%. ** - significant at 99%.

TABLE 6. CLASSIFICATION ACCURACY OF ESTIMATED MODEL

OBSERVED	PREDICTED		
	HEALTHY	DISTRESSED	PERCENTAGE CORRECT
Healthy	1717	34	98.1
Distressed	138	176	56.4
Overall Percentage			91.7

We analyze the relationship between financial distress and financial ratios by using Logit regression as stated in model 2. Results (Table 5) reveal that all ratios included in the models are highly significant in explaining the financial distress. The coefficient value of NITA is greater than all other variables included in the analysis as shown in Table 5.

The results from Table 5 depict that the retained earnings to total assets ratio and EBIT to total assets are significant in predicting financial distress and have a negative relation with probability of distress. These findings are in line with the findings of Altman (1968) and Altman et al. (2014). Meanwhile, net income to total asset is positively associated with the probability of distress. This finding contradicts with Ohlson (1980). Liquidity ratio measured by current asset to total liabilities is positively related to financial distress. This finding contradicts with Agarwal & Taffler (2007). The working capital to total asset ratio is negatively related to financial distress and these findings are in line with Altman (1968), and Xiao, Yang, Pang, & Dang (2012). Leverage ratio represented by total liabilities to total asset is positively related to the probability of default. This supports the argument that highly levered firms are more prone to financial distress (Altman, 1968; Shumway, 2001; Xu et al., 2014; Zmijewski, 1984). The cash flow to total liabilities ratio and cash flow from operations to sales are significant predictors in the estimated model. Cash flow from operations to sales ratio compares a firms' ability to turn sales into cash. Table reveals the positive relationship among cash flow from operation to sales ratio. This positive sign is in line with Bhunia, Khan, & MuKhuti (2011).

Classification accuracy presents the model accuracy in classifying the distressed firms as distressed and healthy firms as healthy. Table 6 presents the classification accuracy of the estimated model. The estimated logit model classifies the healthy firms with accuracy rate of 98.1 percent and distressed firms as distressed with accuracy rate of 56.4 percent. The overall accuracy for the estimated model is 91.7 percent.

Next, we try to examine whether the accuracy of the Ohlson (1980) model is similar when it is applied to developing country like Pakistan. We replicate the model by using O-Score coefficients as in model 3 and using Pakistani listed firms as the sample. The results are shown in Table 7.

TABLE 7. CLASSIFICATION ACCURACY OF O-SCORE IN PREDICTING FINANCIAL DISTRESS

OBSERVED	PREDICTED		
	HEALTHY	DISTRESSED	PERCENTAGE CORRECT
Healthy	1386	1067	56
Distressed	77	407	84
Overall Percentage			61

Table 7 reveals that the O-score classifies the healthy firms as healthy with accuracy rate of 56 percent, while distressed firms are classified as distress with accuracy rate of 84 percent. The overall classification accuracy of the O-score is 61 percent. The results show that the accuracy rate has reduced from 84 percent (as in Ohlson, 1980) to 61 percent.

A comparison in accuracy rate shows that the accuracy rate from the estimated model is higher than the accuracy rate using the coefficients from Ohlson model. Table 8 demonstrates that the overall classification of O-score model is less than the overall classification accuracy of estimated model. The overall classification accuracy for the estimated model is 91.7 percent which is greater than the overall accuracy of O-score model.

To examine the robustness of the estimated model, this study uses the hold out sample. The holdout sample consists of sample from the period of 2014 to 2016. The classification accuracy of the hold-out sample is presented in Table 9. These results are similar to the classification accuracy of estimated model.

TABLE 8. COMPARISON IN CLASSIFICATION ACCURACY RATE BETWEEN O-SCORE AND ESTIMATED MODEL

	ESTIMATED MODEL				O-SCORE		
	HEALTHY	DISTRESS	PERCENTAGE		HEALTHY	DISTRESS	PERCENTAGE
Healthy	1717	34	98.1	Healthy	1386	1067	56
Distress	138	176	56.4	Distress	77	407	84
Overall Percentage			91.7	Overall Percentage			61

TABLE 9. CLASSIFICATION ACCURACY OF HOLD-OUT SAMPLE

OBSERVED	PREDICTED		
	HEALTHY	DISTRESSED	PERCENTAGE CORRECT
Healthy	736	9	98.8
Distressed	50	84	62.7
Overall Percentage			93.3

The table demonstrates that the model classifies the healthy firms as healthy with an accuracy rate of 98.8 percent and distress firms as distressed with an accuracy rate of 62.7 percent. The overall classification accuracy of the hold-out model sample is 93.3 percent which is higher than the overall accuracy of Ohlson (1980).

5. Conclusions

Most of the literature on financial distress prediction emphasize on the use of multivariate discriminant model. However, most of the studies in developed countries have highlighted inadequacies of MDA model in predicting the financial distress and suggests that logit model provides more accurate results. Furthermore, MDA model suffers with few downsides based on its underlying statistical assumptions. These arguments provide ground to use the alternative statistical model which overcomes the shortcomings of MDA model and provides more precise results.

The study has used all the listed and delisted firms during the period 2007 to 2016. We did not use the matching sample technique in selecting the distressed and non-distressed firms to avoid the sampling bias as suggested by Ohlson (1980). The findings unfold that the estimated prediction model provided more precise results with overall accuracy of 91.7 and 93.3 percent for the estimation sample and the hold-out sample respectively, while the overall accuracy of the O-score model using the Pakistani data for the given sample period is 61 percent. The proposed logit model produced a better result than the O-score model, and this accuracy improved when it is applied to hold out sample.

The results show that all variables which represent the profitability ratios, liquidity ratios, leverage ratio, and cash flow ratios are important determinants of financial distress in

Pakistan. However, sign of the few ratios are not in line with previous studies. This might be because of some unexpected trading volume fluctuations (market liquidity) that Pakistani financial market faced during the sample period e.g. (rise of Pakistan Stock Exchange's KSE-100 index from 6400 to 39000). The role of market index value and market liquidity effect in predicting the financial distress can be analyzed in later studies. Furthermore, the market variables can also be used to predict financial distress for firms listed at Pakistan Stock Exchange.

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