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Controlling Bankruptcy: An Early Warning Signal Model

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ABSTRACT

The continued development to best fit the model in prediction of bankruptcy has been of substantial interest over the decades. In accounting models of bankruptcy predictions usually single model appears to be a generalized one for each industry, even when industries are structurally different in terms of their financial, operational, and investing needs. This study investigates the causes of financial failure of textile companies (Around 100 companies) delisted from PSX during 2002-2017. A firm is financially distressed due to improper working capital management which led the firm to go bankrupt in the long run. We used 2 sets of data; estimation sample 2002-2012 & cross validation sample 2014-2017 and examined 20 ratios from Liquidity, profitability, Leverage and efficiency, for a five-year period preceding liquidation. Multiple Discriminant Analysis (MDA) approach followed by Logit regression were used. Four ratios; working capital to total assets, acid test, sales to total assets, and sales growth as proxy of working capital, were identified as significant predictors. The resultant model has early forewarning signals for potential bankruptcy that can occur which could not be generalized one for each industry.

Key Words: Bankruptcy, Working Capital, Financial Ratios, Forewarning Signals, MDA, Logit.

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1. INTRODUCTION

Financial distress is a state when company has difficulty fulfilling its financial obligations when due. If this state continues then chances of financial failure may increase. Financial failure may perhaps take the form of short term

insolvency or bankruptcy. Insolvency is when the firm does not have sufficient resources to pay its obligations currently due. Bankruptcy is when total of the firm's assets are not enough to meet the current and future debts obligations of the firm when due (Muhammad and Kim-Soon,

2012). There are two sources of financing for the business; debt and equity. Business will be riskier if most of its projects are being financed by the outsiders.

Jayesh, Abhishek and Junare (2012) suggested financial failures will interrupt the growth of the economy which will result into great deal of financial loss to socio economic community as a whole. Corporate liquidity can be assessed using working capital measures (Naser et al., 2013). The effective management of working capital ensures sufficient cash flow to meet current financial accountabilities and hence is operationally efficient. Saghir, Hashmi and Hussain (2011); Mansoori and Muhammad, (2012) have found the strong relationship between them. A very profitable entity may go bankrupt due to not meeting the current year obligations to creditors. The manufacturing concerns are required to make sound valuations of given cash flows being used in business. This will help a corporate to device financing and investing related strategies timely in order to avoid possible bankruptcy (Anser and Malik 2013).

Ohlson (1980) stated that industries either in financial as well as non-financial systems organize differently and hence have different, operating, investing and financing needs which challenge the comparison and generalization of the tested results within different sectors. Valencia, et al., (2019) talk about the performance of different frameworks in different countries must be considered while Slefendorfas (2016) concluded that single model in forecasting

corporate failure for different sectors is a questionable decision.

Textile industry of Pakistan has a greater role to play in the development and growth of national economy. Pakistan is considered as 4th largest cotton producer. Textile sector is considered as the moral fiber of the financial system. The number of companies listed in stock exchange in 2002 were around 230 which further declined to 136 by the year end 2017³. In 2012 there was highest number of textile bankruptcies.

Financial performance over the time can best be measured through the use of ratio analysis which is considered as the most useful tool for understanding the financial results of the firms and hence is the key indicator of financial performance (Rezaei et al., 2015).

1.1- Objectives of Study:

This study revolves around the following points:

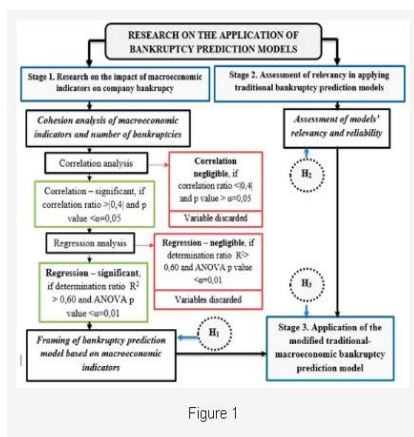
- To identify those financial indicators compatible with sectoral finding of bankruptcy.
- To identify the role of working capital in forecasting bankruptcy.
- To develop forewarning signal Model.

1- LITERATURE REVIEW

Akber, Tang and Qureshi (2019) investigated the relationship between possibilities of bankruptcy during the corporate life cycle. A sample of 301 non-financial firms in 12 multiple sectors listed in Pakistan during 2005 to 2014

³ Balance Sheet: An Analysis of “Joint Stock Companies”, State Bank of Pakistan

using Hierarchical Linear Mixed Model (HLM) was analyzed. This study reveal that firms during almost at all stages of their life-cycle experience higher (lower) level of risk for being bankruptcy. Authors conclude that the financial managers should at each stage of corporate life-cycle be thoughtful about the financial insubstantiality of the firm. Their results also entail that most of the Pakistani firms have the tendency to jump in between the stages business life-cycle not in a sequential manner. Giriuniene *at al* (2019) observed that same bankruptcy prediction models cannot be generalized for various economic environments that have different physical characteristics. Authors' conclude that the reliability of bankruptcy prediction model can be improved by model created using macroeconomic related indicators. This is also possible through a traditional bankruptcy's forecasting model which is a viable tool.



According to Muhammad and Kim-Soon (2012), Zeytinoglu and Akarim (2013) bankruptcy is when the fair value of resources of the company is less as compared to its debts. Altman (1983) classified the failure of the business as

insolvency, economic failure and bankruptcy while conducting day-to-day operations, a tradeoff between profitability and liquidity is required to keep track of the company for the survival in long run as well. The long-term survival of a company is dependent upon the satisfactory income earned by it (Narenhra 2013).

Alaka (2018) reviewed bankruptcy prediction models and found multiple discriminant analysis performed under six artificial intelligence tools i.e., case based reasoning, support vector machines, artificial neural network, rough sets, genetic algorithm and decision tree playing a key role such that no single tool is found to be principally better than other tools in bankruptcy prediction.

Son (2019) stressed on addressing bankruptcy prediction's importance and noted that models devised using machine learning cannot be applied in the field of business finance. Authors focused on explaining the skewness; characteristic of financial data. The financial distress or inefficiencies which lead a firm to bankruptcy can generate substantial losses to participants in economic development as whole (Jayesh, et al., 2012). When total debts exceed total assets, and also the persistent net losses are the most influential deterministic variables (Wang and Campbell, 2010).

Theses versatilities do not talk clearly on the inefficiencies on the part of financial management exclusively where the short run inability to pay debts will add to inability in long run. The short term inability to pay debts need careful evaluation of working capital that has momentous impact on the sustainability of the company. Efficiency on

⁴ <https://www.mdpi.com/2227-7099/7/3/82>

the part of the company in managing its working capital will not only resolve short term but also long term liquidity issues otherwise the consequences will be business failure or bankruptcy (Zeytinoglu and Akarim, 2013; Mansoori and Muhammad, 2012).

Optimum working capital amount is integral to financial management decision, therefore a firm manager must be able to control the tradeoff between Profitability (boost up sales, satisfy every customer) and Liquidity (arrange timely payments against debts) accurately (Saghir, et al., 2011).

In literature on managing the working capital, the effects have been explored by determining multiple relationships of management by holding working capital as an asset, with key corporate attributes. Chiou *et al.*, (2006) explore the relationship with size and industry type of firm, its growth and leverage position. Khamrui (2012) suggest that probability of bankruptcy may increase if working capital is not managed effectively. Another important aspect of this research that comes out of the study of the past researches is the significance of financial ratios in bankruptcy prediction. The accounting based data is able to anticipate financial torment in the companies. Analysis using financial ratios is the most versatile and powerful tool in measuring company's financial health (Jayesh, et al., 2012, Bhunia et al., 2012). This is also further suggested by Rezaei et al., (2015). The variables of research must reflect firm's stability, cash flow, growth, activity and profitability of corporation (XU and Wang, 2009). Since decade development of statistical models that can be true predictor are in process.

The numbers of ratios preferred in model estimations by the researchers are different. e.g., Bhunia et al., (2012) considered 16 ratios, Jayesh, et al., (2012) opted 13 financial ratios by applying careful selection criterion. The Altman Z score model is classified as the best predictor i-e 91 per cent accuracy was achieved. The Z-score model using MDA techniques by Altman - despite of the positive results of the study - has a key weakness of assuming normal sample data. This absence of normality usually results in picking unsuitable or undesirable predictors. Logit analysis is a better choice that corrects this problem and is considered more forceful (Lo, 1986). Several related studies are conducted to anticipate the accuracy of models those are already in the Literature.

The elective literature suggests the importance of sales and liquidity of a firm within a framework of working capital. The lacks in these vital indicators may cause financial failures and thus a possible bankruptcy. We in this paper thus attempts to determine the causes of financial failures and role of working capital which could prevent the bankruptcy in textile sector of Pakistan.

2- RESEARCH METHODOLOGY

The theoretical base of our research study is of "Altman's Z-score". Z-Score approach concludes that the efficiency of different sectors cannot be checked, compared and generalized with the single estimated model (Ohlson 1980). In addition the model must have ability to maximize the forewarning of impending financial difficulties by identifying firms that will experience financial failure due to severe financial difficulty (Goudie,

1987). This will forewarn the management to undertake all the stages to avoid such occurrences (Deakin, 1972). The estimation through the use of financial accounting based data has significantly shown more predictive advantage.

3.1- Model Specifications:

$$Z = \beta_1 \chi_1 + \beta_2 \chi_2 + \beta_3 \chi_3 + \dots \dots \dots \beta_n$$

Z = Discriminant score

$$\beta_1 + \beta_2 + \beta_3 \dots \dots \dots \beta_n =$$

discriminant coefficients

$$\chi_1 + \chi_2 + \chi_3 + \dots \dots \dots \chi_n =$$

discriminant variables (ratios)

Grounded on the value of Z – Scores, a bankrupt or otherwise firms will be identified, that take the value of dummy variable accordingly, i-e “0” for bankrupt and “1 for non-bankrupt.

3.2- Selection of Ratios:

The ratios are chosen as per their importance in the literature, (see e.g., Rashid and Abbas (2011), (Altman 1968, Jones 1987) and (Altman et al., 1977 and Ohlson 1980;) and relevance to study. Moreover, new ratios those will highlight the efficiency of management in managing each of its liquid assets and disposing of short term debts are also added. Twenty ratios are chosen from Liquidity, Leverage, Profitability sustainability and efficiency ratios.

We select 3 ratios for the study. Liquidity denotes to the capability on the part of the firm to

reimbursement its debts when due, higher the given ratio, greater the margin of safety for the firm or company to avoid a possibility of bankruptcy (5 ratios are selected for the study). Performance in terms of generating sufficient revenues and enough financial resources is required for a firm to continue serving its constituents for tomorrow as well as today. The firm's chances (probability) of bankruptcy falls as the firm's profitability increases. (9 ratios are selected). Operational efficiency is the efficiency on the part of managing assets and liabilities. The firm's probability of bankruptcy decreases as the firm's efficiency increases. (3 ratios are selected).

3.3- Hypotheses:

H-1: Financial Ratios under Liquidity, Leverage, Profitability and Operational Efficiency are significant predictors of bankruptcy via MDA approach.

H-2: Working Capital to Total Assets, Acid Test, Return on Equity, Sales Growth and Sales to Total Assets ratios are statistically significant independent variables Bankruptcy using Logit regression model.

H-3: There is a difference of strengths of the bankruptcy framework i.e., MDA & Logit regression.

3.4- Sample Data Characteristics:

The information on surviving textile firms were collected from Pakistan Stock Exchange while data / facts on defaulted corporate firms were gathered from the information available that were de-listed from Pakistan Stock Exchange due to failing to fulfill the requirements of listing

regulations and defaulter companies list from analysis of balance performed by “*Joint Stock Companies*” provided by central bank in Pakistani economy (i.e., *State Bank of Pakistan*).

Data was collected and analyzed at two different points of time. Estimation sample in which companies go bankrupt during years 2002-2012 were identified and matched with the surviving companies based on the asset size at the time of default. The sample of 48 firms (24 surviving firms and 24 financially distressed firms) was finalized and 5 years data prior bankruptcy was collected. Cross Validation sample in which companies go bankrupt during 2014-2017 were studied 10 surviving and 10 financially distressed firms were added to previous data. Annual Data was taken from BSA by SBP in both data sets.

3.5- Statistical Frameworks:

3.5.1- Multiple Discriminant Analysis: (MDA)

A method that has gained popularity in the literature; yields a lower-dimensional signal agreeable to classification by compressing a multivariate signal. In other words, over fitting problem may disastrously affect the classifier's performance when signals are represented in very-high-dimensional spaces. This technique find the discriminating variables, give weights to these independent variables and to each company in a sample, assigns a Z-score. The test statistics used for carrying out this analysis is Wilk's Lambda (which assesses the overall fitness of discriminant function).

3.5.2- Logit Model:

Logit model technique measures relationship between DV and IVs by using probability scores as the predicted value of DV and then classify observations that as they have predicted chances or probabilities higher or lesser the stated benchmark value i.e., 0.5 for (Non-Bankrupt) or below (Bankrupt) respectively.

Equation takes the following form:

3.6- Preferences of Logit Model over MDA:

For two groups logit estimations are considered more accurate and have ability to early warning to the impending problem due to the following reasons:

1. More robust to failure of MDA assumptions
2. More similar to regression which makes it instinctively more attractive.
3. Can easily handle non-linearity
4. Through dummy variable coding it can lodge non-metric independent variable.

3- RESULTS AND DISCUSSIONS

4.1- Multiple Discriminant Analysis: (MDA)

To find out the financial variables that can superlatively discriminate the clusters, the discriminant score was calculated using stepwise multiple discriminant analysis on Estimation sample.

Table 1- Variables Entered/Removed

Step	Entered	Wilks' Lambda	df1	df2	F-Statistics	df1.	df2	Sig
1	Working capital to Assets (Total) (X1)	.828	1	46	9.526	1	46	.003
2	Sales Growth(X2)	.675	1	46	10.854	2	45	.000
3	Acid Test(X3)	.617	1	46	9.107	3	44	.000
4	Return on Equity(X4)	.562	1	46	8.390	4	43	.000
5	Sales to Total Assets(X5)	.506	1	46	8.195	5	42	.000

From Table 1, it is found that only five out of 20 ratios i.e., (Working capital per total assets,

Acid Test, sales growth, sales to total assets and return on equity) accumulate total Z-Score that can discriminate between the troubled and non-troubled firms at 5 percent significance. How much each ratio contributes is determined by standardized canonical discriminant function coefficients.

4.1.1- MDA Model for Z - Score:

The model finally takes the following form:

$$Z = 0.465X_1 + 0.643X_2 + 0.587X_3 + 0.532X_4 + 0.487X_5$$

Out of 5 discriminating variables sales growth (discriminated the most with the magnitude 0.643) and working capital to total asset ratios which were used as representations for working capital proved the importance of working capital in the continuity of firm. The presence of sales growth ratio is the same as predicted by Raheman, et al., (2010). The score represented in the table 2 reveal the optimum Z score which best discriminate the two groups.

Table 2- Functions at Centroids Group

Group	Z-Score
Bankrupt	-0.967
Non-Bankrupt	0.967

Wilks Lambda in Table 3 tells about the within groups variability to total variability. And P-value indicates that group means are significantly different. 0.506 signifies the overall fitness of the model at 99% level of confidence which is considered high for this model.

Table 3- Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	DF	Sig.
1	.506	29.618	5	.000

Zero is the separating value for two groups in table 4 which indicate that firms with Z-score above the cutoff point is considered as non-bankrupt and below the cutoff point will conclude the firm as bankrupt. This can be well seen in the final classification table 4, 81.3% of the cases are correctly classified by 5 financial variables on the principal sample which wrap up the latent applicability of the model.

Table 4- Classification Results

	Group	Forecasted Group Membership		Total
		Bankrupt	Non-Bankrupt	
Original Count	Bankrupt (0)	21	3	24
	Non-Bankrupt (1)	6	18	24
%age	Bankrupt (0)	87.5	12.5	100.0
	Non-Bankrupt (1)	25.0	75.0	100.0

81.3% correct classification was achieved using actual sample.

4.2- Logistic Model:

Logit approach was used on both estimation and cross validation sample. Results of Estimation sample show that ratios named acid test, sales to total assets, sales growth, working capital to total assets remained significant under logit model estimation except return on equity ratio which is declared insignificant in Logit model estimation as shown in table given below.

Table 5 - Logit Model Estimation (Estimation sample)

Variable	Coefficient	Std. Error	Wald	Prob.	Exp(B)	Probability of Odds
C	-2.713891	1.365923	3.948	0.0469	0.066	0.06
Acid Test Ratio	2.065633	1.012332	4.164	0.0413	7.890	0.89
Working Capital to Total Assets	4.003194	2.370101	2.853	0.0912	54.773	0.98
Sales Growth	0.042387	0.018726	5.123	0.0236	1.043	0.51
Sales to Total Assets	1.546337	0.791257	3.819	0.0507	4.694	0.82
Return on Equity	1.506393	1.028655	2.145	0.1431	4.510	n/a*
McFadden R-squared	0.546805					
Obs with Dep=0	24		Total obs	48		
Obs with Dep=1	24					

* This estimator is not measured due to the insignificant beta coefficient of "ROE"

Table 5 above suggests that For intercept: keeping all other ratios at 0, the probability of non-bankruptcy is 0.06 keeping all

other ratios at level, the probability of non-bankruptcy is 89% for Acid Test, 98% for Working capital to Total Assets, 51% for Sales Growth and 82% for Sales to Total Assets for 1 unit increase in these ratios.

Table 6- Expectation-Prediction Evaluation for Binary Specification

	Group	Forecasted Group Membership		Percentage count
		Bankrupt	Non-Bankrupt	
Original Count	Bankrupt (0)	19	4	79.17
	Non-Bankrupt (1)	5	20	83.3
Overall %age				81.25

The cut value is 0.5

As shown in table 6 above, the predicted probability of the Logit model using cutoff point $c=0.5$, is such that concludes 81.25 % accuracy of the model which is almost the same as of the classification results produced using MDA model. The results suggest that both econometric techniques result in the similar estimation accuracy initially when applied to the aggregated data of 5 years.

In Cross validation a sample of 68 companies (34 bankrupt and 34 non-bankrupts) was taken for Logit model estimation. Results show that acid test, sales to total assets, sales growth and working capital to total assets ratios remained significant under Logit model estimation as shown in the table provided in Table given below:

Table 7: Logit Model Estimation (Cross Validation Sample)

Variable	Coefficient	Std. Error	Wald	Prob.	Exp(B)	Probability of Odds
Acid Test Ratio	2.231	1.229	3.294	0.070	9.306	0.90
Working Capital to Total Assets	3.160	1.844	2.937	0.087	23.562	0.96
Sales to Total Assets	1.348	0.593	5.167	0.023	3.849	0.79
Sales Growth	0.032	0.014	5.391	0.020	1.033	0.51
C	-2.466	1.093	5.089	0.024	0.085	0.08
Obs with Dep=0	34	Total obs	68			
Obs with Dep=1	34					

Table 7 given above suggests that for intercept: keeping all other ratios at 0, the

probability of non-bankruptcy is 0.08 keeping all other ratios at level, the probability of non-bankruptcy is 90% for Acid Test, 96% for Working capital to total assets, 51% for Sales Growth and 79% for Sales to total assets for 1 unit increase in these ratios.

Table 8- Expectation-Prediction Evaluation for Binary Specification

	Group	Forecasted Group Membership		Percentage count
		Bankrupt	Non-Bankrupt	
Original Count	Bankrupt (0)	28	5	82.4
	Non-Bankrupt (1)	6	29	85.3
Overall %age				83.8

As from table 8 above, the predicted probability of the Logit model using cutoff point $c=0.5$, is such that concludes 83.8% accuracy of the model which further confirms the validity of Logit model estimation on both of the samples (pre and post validation sample).

4.3- Testing Power of the Two Econometric Models:

Further analysis was also done to see whether these two models have the ability to early signal the probability of default. Early signals will help management to foresee problem so that timely corrective actions can always be taken to elude the chances of being defaulted. To reach the instinct of early warning signal these models were estimated on each year up till 5-year prior possibility of bankruptcy. The results are reported in table 9 as follows:

Table 9: Forecasting Performance of MDA Model vs Logit Model Across distress state 0 and 1

Year Prior Bankruptcy	MDA %age	Logit (Pre) %age	Logit(Post) %age
Overall	81.3	81.25	83.8
Last reporting period	66.7	71.11	79.4
2 nd year preceding Bankruptcy	70.8	73.91	80.9
3 rd year preceding Bankruptcy	68.8	72.92	79.4
4 th year preceding Bankruptcy	62.5	77.78	77.9
5 th year preceding Bankruptcy	-	70.73	72.1

Both logistic regression and MDA approaches converged in similar outcomes. It can be seen that the predictions for both approaches was good (see table 9). Logistic regression is somewhat healthier than discriminant analysis in the correct classification rate (George et al., 2009). The Logit model has the tendency to predict the chance of bankruptcy of a firm up to 5 years prior to the actual year of default. While MDA lost its ability to forecast the model as years prior bankruptcy moves farther from the year of default. Hence it was identified that the Logit model is more robust for early warning signals of default of the firms.

4. CONCLUSION AND RECOMMENDATIONS

This study identified 4 discriminating ratios; sales growth, acid test, working capital to total assets and sales to total assets. Collectively these ratios can significantly classify the group into two that is the bankrupts vs. the non-bankrupts firms in the textile sector of Pakistan. Among 4 significant ratios, sales growth ratio and working capital base to total available assets both served as proxies for working capital signifies the role of working capital management in modeling bankruptcy prediction.

The companies not managing their working capital efficiently will lead to bankruptcy, i.e., the company is likely to suffer if short term debt obligations not withstand then long run survival could not be possible (Beaver 1966). Five ratios were significant using MDA and 4 ratios were significant using Logit model. It was concluded that Z-Score presented by other researches using

the discriminating variables have no generalizability. This study finally concluded the following:-

- a. One model cannot be generalized on structurally different sectors due to their financial and operational differences.
- b. Effective working capital administration involves in a vigorous role for the steadiness of the firm. The firms with negative working capital since certain years headed towards bankruptcy.
- c. Logit Model can predict expected failure more accurately up-till 5 years prior to bankruptcy. The early signals of impending problems help management to take timely corrective actions to avoid failure.

According to Jones et al., (2017), Logit and LDA are the best predictor of bankruptcy. Logit model slightly show better performance and hence has a tendency to forecast failure 5 years prior to bankruptcy which MDA could not.

It is therefore recommended that the firms in Textile industry of Pakistan must focus on to the above four selected ratios to avoid failure and take necessary actions in monitoring performance of the firms around these ratios. Also proper and effective working management policies should be tailored according to the forthcoming requirements of the firm in Textile industry. This will help to avoid both the short as well as long run indebtedness that may be headed to failure of the firm.

REFERENCES

- Akbar, A., Akbar, M., Tang, W., & Qureshi, M. A. (2019). Is Bankruptcy Risk Tied to Corporate Life-Cycle? Evidence from Pakistan. *Sustainability*, 11(3), 678.
- Alaka, H. A., Oyedele, L. O., Owolabi, H. A., Kumar, V., Ajayi, S. O., Akinade, O. O., & Bilal, M. (2018). Systematic review of bankruptcy prediction models: Towards a framework for tool selection. *Expert Systems with Applications*, 94, 164-184.
- Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The journal of finance*, 23(4), 589-609.
- Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of accounting research*, 71-111.
- Bhunia, A., Bagchi, B., & Khamrui, B. (2012). The impact of Liquidity on Profitability: A Case Study of FMCG Companies in india. *Research and Social practices in Social Sciences*, 7(2), 44-58.
- Chiou, J. R., Cheng, L., & Wu, H. W. (2006). The determinants of working capital management. *Journal of American Academy of Business*, 10(1), 149-155.
- Deakin, E. B. (1972). A discriminant analysis of predictors of business failure. *Journal of accounting research*, 167-179.
- Giriūniene, G., Giriūnas, L., Morkunas, M., & Brucaite, L. (2019). A Comparison on Leading Methodologies for Bankruptcy Prediction: The Case of the Construction Sector in Lithuania. *Economies*, 7(3), 82.
- Jayesh, P., Abhishek, P., & Junare, S. O. (2012). Predicting Corporate Bankruptcy Using Financial Ratios: An Empirical Analysis, Indian Evidence from 2007-2010. *Ganpat University-Faculty of Management Studies Journal of Management & Research*, 4.
- Jones, S., & Hensher, D. A. (2004). Predicting firm financial distress: A mixed logit model. *The Accounting Review*, 79(4), 1011-1038.
- Jones, S., Johnstone, D., & Wilson, R. (2017). Predicting corporate bankruptcy: An evaluation of alternative statistical frameworks. *Journal of Business Finance & Accounting*, 44(1-2), 3-34.
- Khamrui, B. B. (2012). Impact of Working Capital Management on Firms performance. *Business and Economics Journal*, 19(4), 25-37
- Lo, A. W. (1986). Logit versus discriminant analysis: A specification test and application to corporate bankruptcies. *Journal of econometrics*, 31(2), 151-178.
- Mansoori, D. E., & Muhammad, D. (2012). The effect of working capital management on firm's profitability: Evidence from Singapore.

- Mohammed, A. A. E., & Kim-Soon, N. (2012). Using Altman's model and current ratio to assess the financial status of companies quoted in the Malaysian stock exchange. *International Journal of Scientific and Research Publications*, 2(7), 1-11.
- Naser, K., Nuseibeh, R., & Al-Hadeya, A. (2013). Factors influencing corporate working capital management: Evidence from an emerging economy. *Journal of Contemporary Issues in Business Research*, 2(1), 11-30.
- Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of accounting research*, 109-131.
- Raheman, A., Afza, T., Qayyum, A., & Bodla, M. A. (2010). Working capital management and corporate performance of manufacturing sector in Pakistan. *International Research Journal of Finance and Economics*, 47(1), 156-169.
- Rashid, A., & Abbas, Q. (2011). Predicting Bankruptcy in Pakistan. *Theoretical & Applied Economics*, 18(9).
- Rezaei, F., Marahemi, S., & Marahemi, K. (2015). Determining the Ability of Financial Ratio to Predict Firms' Bankruptcy by Mixed Methods of DANP and Logistic Regression, *Iranian Journal of Business and Economics*, 2(2)
- Saghir, A., Hashmi, F. M., & Hussain, M. N. (2011). Working capital management and profitability: evidence from Pakistan firms. *Interdisciplinary Journal of Contemporary Research in Business*, 3(8), 1092-1105.
- Slefendorfas, G. (2016). Bankruptcy prediction model for private limited companies of Lithuania. *Ekonomika (Economics)*, 95(1), 134-152.
- Son, H., Hyun, C., Phan, D., & Hwang, H. J. (2019). Data analytic approach for bankruptcy prediction. *Expert Systems with Applications*, 138, 112816.
- Valencia, C., Cabrales, S., Garcia, L., Ramirez, J., & Calderona, D. (2019). Generalized additive model with embedded variable selection for bankruptcy prediction: Prediction versus interpretation. *Cogent Economics & Finance*, 7(1), 1597956.
- Wang, Y., & Campbell, M. (2010). Financial ratios and the prediction of bankruptcy: The Ohlson model applied to Chinese publicly traded companies. *The Journal of Organizational Leadership and Business*, 17(1), 334-338
- Xu, X., & Wang, Y. (2009). Financial failure prediction using efficiency as a predictor. *Expert Systems with Applications*, 36(1), 366-373.
- Zeytinoglu, E., & Akarim, Y. D. (2013). Financial failure prediction using financial ratios: An

empirical application on Istanbul Stock Exchange. *Journal of Applied Finance and Banking*, 3(3), 107.